Beyond BMI

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Beyond BMI: Personality Traits' Associations With Adiposity and Metabolic Rate

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Abstract

Various personality traits are known to correlate with body mass index (BMI). However, this index of adiposity conflates fat mass with lean body mass and may therefore lead to biased estimates of correlations. Yet, rarely have studies looked beyond BMI to understand how adiposity and other physiological characteristics relate to these psychological traits. Using previously validated formulas, we calculated an improved measure of adiposity (relative fat mass, RFM), as well as basal metabolic rate (BMR); explored their associations with various personality traits; and assessed how personality traits' associations with RFM differ from their associations with BMI. In a subsample of the Estonian Biobank (*N* = 3,535), we compared how the five domains and 30 facets of NEO Personality Inventory-3 correlated with RFM, BMI, and BMR. Various traits, notably Openness to Experience and its facets, were associated with RFM above and beyond BMI; these traits may relate to lower adiposity through eating habits. Assertiveness, a facet of Extraversion, correlated more strongly with BMI than with RFM and also correlated with BMR. These correlations mirror associations of metabolic rate with conceptually similar traits in non-human animals and are consistent with Assertiveness being based on biological processes. Finally, BMI–personality trait correlations appeared to conflate personality traits' associations with fat mass and lean mass; the use of BMI as an indicator of adiposity can lead to both attenuated and inflated estimates of personality trait–adiposity associations.

Keywords: personality traits, obesity, basal metabolic rate, BMI, body composition

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1. Introduction

Health is among the most important factors shaping our everyday experiences—how we feel, what we think about, what we do and avoid doing. It is then unsurprising that various indices of physical health correlate with personality traits, defined as individuals' tendencies to think, feel, and behave in certain ways that make them differ from one another. Among the various health outcomes known to correlate with personality traits is body mass index (BMI), an indicator of adiposity that is simple to calculate from height and weight and is commonly used in studies when direct measures of body fat are unavailable. BMI is relevant for health outcomes beyond adiposity, also being a risk factor for various health conditions such as diabetes and cancer (Boles et al., 2017; Cercato & Fonseca, 2019). As many studies have shown, BMI correlates consistently with various personality traits (Sutin et al., 2011; Terracciano et al., 2009; Vainik et al., 2019), most prominently with the broad Conscientiousness domain and some of its sub-components, facets (Sutin et al., 2018). Yet, how exactly these associations arise remains unclear.

BMI and personality traits are sometimes thought to be causally associated (Sutin & Terracciano, 2017). For instance, personality traits may influence BMI (Friedman, 2019), perhaps through health behaviours such as diet and physical activity (Bogg & Roberts, 2004; Kim, 2016). But the causal associations may also run in reverse, as suggested by longitudinal studies (Lahti et al., 2013), or be bidirectional, as supported by genetic analyses (Arumäe et al., 2021). Therefore, although the correlations might also arise from common causes (Sutin et al., 2013; Nagel et al., 2018; Vainik et al., 2018), the longitudinal and genetic analyses suggest that causal associations may instead (or additionally) exist. If so, understanding personality traits' associations with BMI may not only explain health conditions like obesity but also shed some light on the elusive sources of differences in and development of personality traits. Further disentangling personality traits' associations with BMI and the health outcomes it is a proxy for is therefore of broad interest. However, there are other indices besides BMI that quantify related physiological characteristics that are simple to calculate but have received little attention in relation to personality traits so far.

1.1. Alternatives to BMI

Whatever mechanisms give rise to the BMI–personality trait associations, attempts to explain these links should begin with their accurate descriptions. However, as is well known, BMI is imprecise as an indicator of adiposity as it can conflate fat mass and lean mass. Not only does BMI overestimate fat mass in individuals with high muscle mass (Rothman, 2008), it may even correlate more strongly with lean body mass (i.e., the mass of skeletal muscle and organs, or fat-free mass) than with fat mass in men (Romero-Corral et al., 2008). Ignoring this limitation leaves researchers open to misinterpreting BMI's associations with personality traits. On one hand, some of the associations may be driven by lean mass rather than fat mass; for instance, BMI correlates with Assertiveness (Vainik et al., 2019), which may well be due to more muscular individuals being able to act dominantly rather than those with higher fat mass being able to assert themselves. On the other hand, if BMI tends to misrepresent adiposity, the use of BMI as its proxy may result in attenuated estimates of personality trait–adiposity correlations or in missing such links altogether. Using a more accurate measure of adiposity could clarify this issue.

Although adiposity is most accurately measured using methods like dual-energy X-ray absorptiometry (DEXA), computed tomography, and magnetic resonance imaging (MRI) (Borga et al., 2018; Denton & Karpe, 2016), research on the relations between adiposity and psychological characteristics rarely employs objective measures of body fat, relying instead on BMI, the most convenient-to-use index of adiposity. Although personality traits' correlations with BMI track their correlations with adiposity as measured via skinfold thickness fairly closely (Sutin et al., 2011), few studies have made such comparisons and the accuracy of BMI in assessing personality trait–adiposity correlations is still uncertain. Because of this, additional studies are warranted.

When objective measurements of adiposity or body composition are not available, there may be alternatives to BMI that are not only more accurate but, crucially, also available in large datasets or can realistically be incorporated in large research projects. For instance, relative fat mass (RFM) is a new formula that estimates whole-body adiposity via height, waist circumference, and sex, and tracks adiposity more accurately than BMI does (Woolcott & Bergman, 2018). Granted, any index of body composition indirectly estimated with a formula is unlikely to be as accurate as objective measurements via, for instance, MRI or DEXA. But if different formulas with differing degrees of accuracy are available, those that estimate adiposity more closely should also describe personality trait–adiposity associations more accurately.

1.2. Beyond Adiposity

While personality traits' correlations with adiposity (as approximated by BMI) have been the subject of extensive research, other physiological characteristics have received less attention in relation to personality traits. Yet, given the interest in understanding the causes and consequences of personality traits as well as health outcomes, attention to such relations is justified. As personality traits are sometimes thought to be in substantial part based on biology (McCrae & Sutin, 2018), associations between physiology and behavioural traits in non-human animal species may hint at similar associations in humans. For instance, studies in behavioural ecology have repeatedly shown correlations between basal metabolic rate (BMR)—the amount of energy needed to power life-sustaining functions—and behavioural traits like dominance, aggressiveness, exploration, and activity in various species (Careau & Garland, 2012). If metabolism and behaviour are genetically or functionally linked (Careau et al., 2011) or causally associated (Biro & Stamps, 2010; Réale et al., 2010), such associations may clarify where individual differences in these traits originate.

To our knowledge, two studies have so far explored the associations between BMR and personality traits in humans. The first of the two found metabolic rate to be largely uncorrelated with personality traits (Terracciano et al., 2013), and the second found it to negatively correlate with Extraversion (Bergeron et al., 2021). However, the sample sizes of these studies may not have allowed to accurately estimate the associations as they likely have small effect sizes—for comparison, the correlation between BMI and Conscientiousness, robust as it appears to be, has been meta-analytically estimated to be r = –.04 (Vainik et al., 2019). And yet, given the ongoing discussion surrounding energy metabolism and personality in non-human species (Biro et al., 2020) fueled by the many empirical findings on such associations, a new look at the correlations in humans seems warranted.

Just like adiposity, BMR is laborious to measure objectively, but can be estimated using existing formulas through height, weight, age, and sex (e.g., Mifflin et al., 1990). As with adiposity, there is a trade-off between measurement accuracy of BMR and sample size—datasets with large samples are unlikely to have objectively measured BMR available. But indirect estimation of BMR does enable the use of BMR in the large samples required to assess personality–physiology correlations. Importantly, because BMR is tightly linked with lean body mass (Dulloo et al., 2010; Weinsier et al., 1992), personality traits' correlations with BMR are also expected to reflect their associations with lean mass.

1.3. The Current Study

In this study, we assessed personality traits' correlations with three physiological characteristics—RFM, BMI, and BMR—and tested whether the correlations between BMI and personality traits likely reflect associations with adiposity or, instead, lean body mass. Although numerous studies have attempted to characterize personality traits' associations with adiposity relying on BMI, we aimed to provide an alternative and potentially less biased description of the associations using RFM. Additionally, we aimed to describe personality traits' associations with BMR. We assumed that BMI, a composite measure of fat mass and lean mass, is not as accurate as RFM as an index of adiposity and its correlations with personality traits conflate the associations of the traits with fat mass and lean mass.

First, we estimated RFM, BMI, and BMR, and assessed their correlations with the five personality domains of the Five-Factor Model (FFM) and their 30 facets. Second, we aimed to assess whether the associations between BMI and personality traits are likely driven by adiposity (as commonly assumed in studies where BMI is used) or with lean mass instead. To this end, we compared the traits' correlations with RFM and BMI: because BMI is a composite of adiposity and lean mass, traits that more strongly correlate with RFM are more likely to associate with adiposity than with lean mass; traits that more strongly correlate with BMI may instead have stronger correlations with lean mass than with adiposity. Third, to further clarify to what extent personality traits' associations with BMI resemble their associations with adiposity and lean mass, we assessed the overlap between the personality profiles of the three physiological characteristics: RFM, BMI, and BMR. And finally, beyond these descriptive analyses, we tested how strongly the three physiological characteristics can be predicted from a linear composite of the facets of the FFM personality traits. Altogether, these analyses not only describe personality traits' associations with adiposity and BMR but also clarify how accurately studies using BMI have represented personality traits' associations with adiposity.

2. Materials and Methods

2.1. Participants

The sample for this study consisted of a subsample of the Estonian Biobank—a cohort of Estonian residents recruited by medical personnel throughout the country (Leitsalu et al., 2015) from whom various medical data have been collected. All participants have given informed consent. Analyses included data from 3,535 individuals in total (2,110 women) for whom NEO–PI–3 personality data were available along with their height and weight. The participants were on average 46.75 years old (SD = 16.98) with mean BMI 25.97 kg/m^2 (SD = 4.88) and mean BMR 1,505.68 kcal/day (SD = 262.72). Analyses including RFM were done on a subsample of 2,547 persons (1,447 women) for whom waist circumference data were additionally available; mean RFM was 30.25% (SD = 7.60) among the individuals for whom it could be calculated. Characteristics of the full sample, as well as this subsample, are detailed in Supplementary Table 1.

2.2. Materials

2.2.1. Personality traits. Personality traits were assessed using the Estonian version of the NEO Personality Inventory-3 (NEO–PI–3; McCrae et al., 2005), a slightly modified version of the NEO–PI–R (Kallasmaa et al., 2000). The NEO–PI–3 is a 240-item personality inventory covering the five domains and 30 facets of the FFM. This inventory assesses the domains of Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness, as well as six narrower facets within each domain. The answers were provided on a 5-point Likert scale ranging from 0 (*strongly disagree*) to 4 (*strongly agree*).

2.2.2. Physiological variables. RFM was calculated using the formula 64 − (20 × height/waist circumference) + (12 × sex), where sex = 0 for men and sex = 1 for women (Woolcott & Bergman, 2018). The formula used to calculate RFM has been validated using DEXA, shown to be a more accurate measure of adiposity, and reduce obesity misclassification compared to BMI (Woolcott & Bergman, 2018). BMI was calculated as body mass in kilograms divided by height in meters squared (kg/m^2). Finally, BMR was calculated using the Mifflin–St Jeor formula: 9.99 × weight + 6.25 × height − 4.92 × age + 166 × sex − 161, where sex = 1 for men and sex = 0 for women (Mifflin et al., 1990). Participants’ height, weight, and waist circumference used in the calculations were measured directly in the Estonian Biobank sample.

2.3. Statistical Analyses

To test the associations of the physiological variables and personality traits (the five domains and 30 facets), we first residualized each personality trait as well as RFM, BMI, and BMR for age, age^2, and sex. We then calculated Spearman's *rho*s between the residualized physiological variables and personality traits. We compared RFM's and BMI's associations with each individual personality trait with Williams' test. These comparisons were done with the R package "cocor" using dependent groups with overlapping correlations (Diedenhofen & Musch, 2015).

Because adiposity and BMR are correlated (i.e., people with higher fat mass also tend to have higher BMR as they also have higher lean mass), we ran an additional set of correlation analyses on personality traits on one hand and RFM or BMR on the other where, in addition to age, age^2, and sex, RFM was also residualized BMR and BMR for RFM. This would give "cleaner" estimates of correlations with adiposity and BMR that are presumably less dependent on or confounded with each other.

Next, we estimated the personality trait correlation profiles (henceforth called "personality profiles" for simplicity) for RFM, BMI, and BMR, and assessed their similarity. Personality profiles of the physiological variables reflect the configurations of personality traits that tend to accompany higher values on the respective physiological variables. Each physiological variable's correlations with the 30 personality facets served as its personality profile (all variables were first residualized for age, age^2, and sex as in previous analyses). For instance, the personality profile of BMI consisted of BMI's correlations with the 30 facets after BMI and each facet had been residualized for the covariates. To estimate the correlations between the profiles of RFM, BMI, and BMR, the correlations (*rho*s) were first transformed to z scores using Fisher's transformation, and Pearson's correlations as well as Euclidean distances were then found between the transformed scores to assess the similarity between the profiles' shapes as well as their distances from each other. Prior to calculating the profile correlations, scores of the six Neuroticism facets were reversed to avoid inflation of the estimates. Further details on personality profile analysis can be found in Vainik et al. (2019).

Additionally, we tested how well RFM, BMI, and BMR can be predicted from the personality facets of the FFM. Because narrower personality traits (e.g., facets) are known to have considerable incremental predictive accuracy over domains in predicting many outcomes (including BMI; Seeboth & Mõttus, 2018; Vainik et al., 2019), we used the 30 facets instead of the five domains to predict the three physiological characteristics. For each person in the sample, a "polyfacet score" was calculated for each RFM, BMI, and BMR to summarize their personality-based propensity for higher values in the respective phenotypes. Each polyfacet score was calculated as the sum of the 30 facets' weighted correlations with the physiological characteristic. The weights for the polyfacet scores were calculated using LASSO, a regression-based procedure that estimates an outcome's (physiological characteristic's) correlations with each predictor (facet), shrinking some of the predictors' weights towards zero based on their intercorrelations to counteract overfitting of the models (Yarkoni & Westfall, 2017). Prior to calculating the polyfacet scores, each facet and physiological variable was residualized for age, age^2, and sex. Importantly, to further avoid overfitting, the sample was randomly divided into 10 parts and the polyfacet scores were calculated separately for participants in each partition of the sample (10%) using the weights calculated in the rest of the sample (90%). To quantify the polyfacet scores' predictive accuracy, their correlations with their respective target phenotypes (RFM, BMI, or BMR) were calculated. We additionally compared whether predictive accuracies of the three indicators were different with the "cocor" package, using dependent groups with nonoverlapping correlations.

Finally, as further tests of robustness, the analyses were repeated after additionally residualizing the personality traits and physiological variables for education. This covariate was included because, similarly with age and gender, it may influence personality traits as well as the physiological variables; however, should the variables of interest influence educational attainment (for instance, personality traits might; Mõttus et al. 2017), including this covariate would lead to an underestimation of the correlations due to statistical overcontrol (Kim, 2016). Including education therefore is likely to lead to more conservative estimates. Including this covariate also controls for other socioeconomic or lifestyle factors in addition to academic attainment to the extent that people with different levels of education are exposed to different environmental circumstances and lead different lives in general. Information on education was available for 3,530 individuals (including 2,544 individuals with waist circumference data available).

All statistical procedures were conducted in the RStudio environment using R version 3.6.1. All *p*-values were adjusted using false discovery rate.

3. Results

Prior to calculating their correlations with personality traits, we assessed the extent to which the three physiological characteristics correlated with each other. BMI correlated with RFM at r = .60/.86/.84 (total sample/females/males), and with BMR at r = .41/.51/.53; RFM correlated with BMR at r = –.37/.23/.16. This suggests a high degree of overlap between BMI and RFM, a moderate overlap between BMI and BMR, and a relatively modest overlap between RFM and BMR. Further, this confirms that RFM was distinguished from BMR fairly well and better than BMI was. Crucially, however, these correlations also suggest that the similarity of RFM and BMR was not inflated due to using a partially overlapping set of anthropometric measurements to calculate them. Specifically, fat mass has been reported to explain 7% or less of the variation in BMR (Dulloo et al., 2010; Johnstone et al., 2005) which translates to a maximum expected correlation of r = .26 between RFM and BMR. Because their observed correlation in both men and women was lower than .26, this suggests that the formulas can appropriately distinguish fat mass and metabolic rate/fat-free mass.

3.1. Personality Traits' Correlations With Physiological Variables

Table 1 shows the personality traits' correlations with RFM, BMI, and BMR, as well as the comparison of their correlations with RFM and BMI. Of statistically significant associations, Conscientiousness correlated negatively with all three physiological variables, Neuroticism correlated positively with RFM and BMI, Openness correlated negatively with RFM, and Extraversion correlated positively with BMR and BMI. All of the correlations were relatively weak ($|r|$ = .04 … .08). Each physiological variable also correlated with at least one facet within each domain. Additionally adjusting for education tended to attenuate the correlations (Supplementary Table 2), but many associations remained significant. These results indicate that even if the individual associations are modest in size, the three physiological characteristics correlate with distinguishable sets of personality traits.

The comparison of correlations indicated that RFM had a stronger correlation than BMI with the domains Neuroticism and Openness as well as with various facets. In contrast, the facets E3: Assertiveness, E5: Excitement-Seeking, and N6: Vulnerability had stronger correlations with BMI than RFM (although the correlations of E5 and N6 with BMI were nonsignificant). The median absolute correlation across all facets was .04 (M = .05) with RFM, whereas the median absolute correlation was .03 (M = .04) with BMI. Together, these results suggest that BMI–personality trait correlations are mostly driven by fat mass, but the correlation with E3: Assertiveness may instead be attributable to lean mass. BMI appears to conflate the associations of personality traits with fat mass and lean body mass, and can both underestimate and overestimate personality traits' links with adiposity to some degree.

Table 1

Personality Traits' Associations With Physiological Characteristics

Trait	Correlations			Comparison of correlations with RFM and BMI	
	RFM	BMI[1]	BMR	*t*[2]	Stronger correlation
Neuroticism	.07***	.04*	.01	2.82*	RFM
Extraversion	.02	.04*	.05*	-2.04	
Openness	-.08***	-.02	.01	-4.96***	RFM
Agreeableness	.01	-.01	-.03	1.79	
Conscientiousness	-.08***	-.06**	-.05**	-1.83	
N1: Anxiety	.04	.02	-.01	1.88	
N2: Angry Hostility	.06*	.03	.01	2.59*	RFM
N3: Depression	.04	.01	-.01	2.72*	RFM
N4: Self-Consciousness	.04	.03	.00	1.47	
N5: Impulsiveness	.15***	.14***	.12***	0.21	
N6: Vulnerability	.00	-.04	-.05*	3.17**	BMI
E1: Warmth	.05*	.05**	.04*	-0.27	
E2: Gregariousness	.02	.02	.01	0.23	
E3: Assertiveness	.02	.06**	.10***	-2.83*	BMI

E4: Activity	-.04	-.02	-.02	-1.2	
E5: Excitement-Seeking	.00	.03	.04	-2.61*	BMI
E6: Positive Emotions	.03	.06**	.04*	-2.12	
O1: Fantasy	.01	.04*	.05*	-2.21	
O2: Aesthetics	-.04	-.01	-.01	-2.55*	RFM
O3: Feelings	-.04	-.02	-.02	-1.17	
O4: Actions	-.10***	-.04*	.00	-4.86***	RFM
O5: Ideas	-.07**	-.01	.02	-5.23***	RFM
O6: Values	-.11***	-.06**	-.01	-4.81***	RFM
A1: Trust	-.07**	-.04*	-.01	-2.39*	RFM
A2: Straightforwardness	-.01	-.03	-.02	1.19	
A3: Altruism	.02	.00	-.01	1.05	
A4: Compliance	-.01	-.03	-.05*	1.99	
A5: Modesty	.04	.02	.00	1.59	
A6: Tender-Mindedness	.09***	.05**	.00	3.36**	RFM
C1: Competence	-.03	.00	.01	-2.39*	RFM
C2: Order	-.09***	-.08***	-.08***	-0.33	
C3: Dutifulness	-.06**	-.06**	-.06**	-0.36	
C4: Achievement Striving	-.05*	-.03	-.04	-1.26	
C5: Self-Discipline	-.06*	-.05*	-.04*	-0.92	

C6: Deliberation	-.07**	-.04*	-.04*	-2.32*	RFM

Note. Coefficients are Spearman's *rho*s between the personality trait and RFM, BMI, or BMR. The physiological characteristics as well as personality traits are residualized for age, age^2, and sex. The comparison of correlations is based on Williams' test. Column "Stronger correlation" indicates whether RFM or BMI correlated with the trait significantly more strongly than the other; if blank, then the comparison indicated no statistically significant difference. Analyses with RFM and comparison of correlations with RFM and BMI were done on the subsample for which we were able to calculate RFM (N = 2,547). RFM = relative fat mass, BMI = body mass index, BMR = basal metabolic rate. All p-values are adjusted for false discovery rate.

[1]Correlations with BMI in an overlapping sample have previously been published by Vainik et al. (2015) and used in the meta-analysis by Vainik et al. (2019), although their objectives and analytic strategy were different from those of the current study.

[2]df = 2,544.

*** $p < .001$, ** $p < .01$, * $p < .05$.

3.2. Correlations With Adjusted RFM and BMR

Table 2 indicates the personality traits' correlations with RFM (adjusted for BMR) and BMR (adjusted for RFM); results after also adjusting for education are reported in Supplementary Table 3. Most of the significant associations between RFM and personality traits found in previous analyses remained significant, suggesting that adiposity associates with a variety of personality traits even after accounting for BMR. However, the associations with the facets E1: Warmth and C3–C6 were no longer significant, suggesting that these traits largely associate with the common variance of RFM and BMR. At the same time, an additional association emerged with N4: Self-Consciousness.

Table 2

Differential Associations of RFM and BMR With Personality Traits

Trait	RFM	BMR
Neuroticism	.07**	-.01
Extraversion	-.01	.03
Openness	-.07**	.03
Agreeableness	.03	-.03
Conscientiousness	-.05*	-.03
N1: Anxiety	.04	-.01
N2: Angry Hostility	.05	.01
N3: Depression	.04	.01
N4: Self-Consciousness	.05*	-.03
N5: Impulsiveness	.09***	.05
N6: Vulnerability	.03	-.04
E1: Warmth	.03	.02
E2: Gregariousness	.02	-.01
E3: Assertiveness	-.05	.10***
E4: Activity	-.03	-.02

E5: Excitement-Seeking	-.02	.02
E6: Positive Emotions	.02	.00
O1: Fantasy	.00	.03
O2: Aesthetics	-.03	.01
O3: Feelings	-.03	-.01
O4: Actions	-.09***	.02
O5: Ideas	-.08***	.04
O6: Values	-.10***	.03
A1: Trust	-.06*	.01
A2: Straightforwardness	-.01	-.01
A3: Altruism	.03	-.03
A4: Compliance	.02	-.05
A5: Modesty	.04	.00
A6: Tender-Mindedness	.10***	-.05
C1: Competence	-.03	.01
C2: Order	-.05*	-.04
C3: Dutifulness	-.03	-.03
C4: Achievement Striving	-.03	-.03
C5: Self-Discipline	-.04	-.02
C6: Deliberation	-.04	-.03

Note. Coefficients are Spearman's *rho*s between the personality trait and RFM or BMR. The physiological variables as well as personality traits are residualized for age, age^2, and sex. Analyses were done on the subsample for which we were able to calculate RFM (N = 2,547). RFM = relative fat mass, BMR = basal metabolic rate. All p-values are adjusted for false discovery rate.

*** $p < .001$, ** $p < .01$, * $p < .05$.

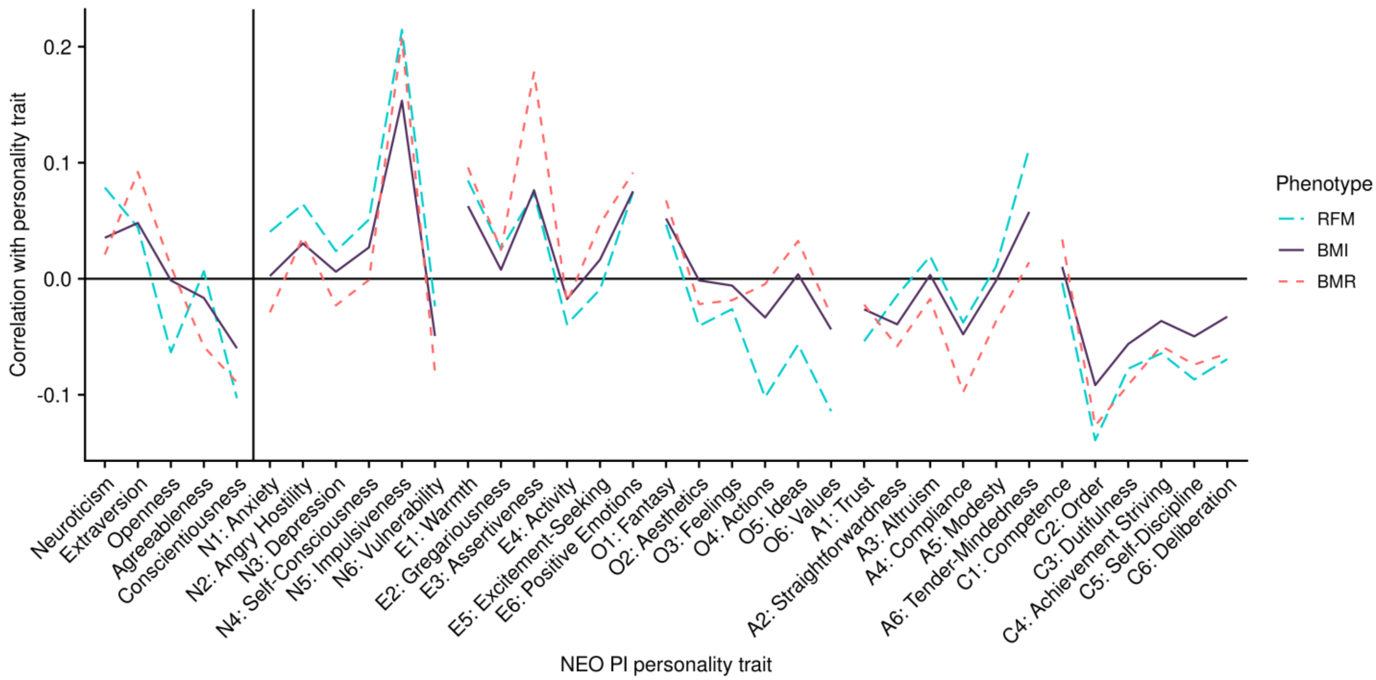
A different pattern emerged for BMR. The only association of BMR that remained significant after controlling for RFM was with E3: Assertiveness. This could suggest that either a) many of the correlations between BMR and personality traits can be attributed to the variance BMR shares with RFM, or b) both RFM and BMR may independently associate with the traits, but the effects of the latter are smaller than can be detected with our sample. However, it should be noted that the analyses reported in Table 2 were run on a subsample of those involving BMR in Table 1. Therefore, some of the associations may have become nonsignificant due to decreased sample size. To test this possibility, we reran the regressions of BMR reported in Table 1 on the smaller subsample (N = 2,547). Indeed, most of the BMR–personality trait correlations became statistically nonsignificant (specifically, the correlations with the Extraversion domain and the facets N6, E1, E6, O1, A4, C5, and C6). These results suggest that the p-values of these correlations were elevated because of the smaller sample size, while other formerly-significant associations (with the Conscientiousness domain, as well as the facets N5, C2, and C3) were no longer significant due to accounting for RFM. Therefore, BMR may still associate with other traits beyond Assertiveness, but detecting these associations may require larger sample sizes.

3.3. Personality Profiles

The personality profiles of RFM, BMI, and BMR are depicted in Figure 1. BMI's profile correlated with RFM's and BMR's equally: r = .89 ($p < .001$), suggesting that the shape of BMI's personality profile was highly similar with both. BMI's profile was also at roughly equal distances from RFM's and BMR's profiles (Euclidean distances of .16 and .12, respectively). Further, the profiles of RFM and BMR were less similar to each other (r = .62, p < .001) than they were to BMI's profile; their distance from each other was also somewhat higher (.26) than their distance from BMI's profile. It therefore seems that although BMI correlated more strongly with RFM than BMR, its personality profile was nearly equally similar to the profiles of RFM and BMR. Indeed, as Figure 1 illustrates, the profile of BMI tends to roughly represent the average of the profiles of RFM and BMR. In sum, BMI's correlations with a range of personality traits conflate the traits' correlations with RFM, a measure of fat mass, and BMR, a proxy for lean body mass. It should be noted that the correlations between personality profiles tend to be higher than the correlations between their respective phenotypes (e.g., physiological characteristics) because different profiles are calculated based on the same trait ratings (see Revelle et al., 2021).

Figure 1

Personality Profiles of the Physiological Variables



Note. The personality profiles presented in the figure include the physiological variables' correlations with the five domains and 30 facets of the NEO–PI–3. In contrast, correlations between the profiles were calculated based on only the pysiological variables' correlations with the thirty facets. RFM = relative fat mass, BMI = body mass index, BMR = basal metabolic rate.

3.4. Facets as Predictors of the Physiological Variables

After adjusting for age, age^2, and sex, the polyfacet scores for RFM, BMI, and BMR correlated with their target phenotypes (i.e., formula-estimated RFM, BMI, or BMR) at r = .22, r = .20, and r = .18, respectively; comparisons of these correlations indicated that the three predictive accuracies were statistically no different, suggesting that the three indicators can be predicted from personality facets with approximately equal accuracy (Table 3). After additionally accounting for education, the correlations between the polyfacet scores and their target phenotypes were .18, .18, and .17 for RFM, BMI, and BMR, respectively; again, there were no statistically significant differences between the predictive accuracies of the three variables (Supplementary Table 4).

Table 3

Prediction of Physiological Characteristics from Polyfacet Scores

	Predictive accuracy[1]		Comparison of predictive accuracies[2]	
Characteristic	*r*	95% CI	BMI (*z*)	BMR (*z*)
RFM	.22	.18; .26	1.12	1.34
BMI	.20	.17; .24		0.90
BMR	.18	.14; .21		

Note. Predictive accuracies are Pearson's correlations between the physiological characteristics and their respective polyfacet scores after adjusting for age, age^2, and sex. Comparisons of predictive accuracies indicate whether there were pairwise differences in the predictive accuracies of the three physiological characteristics. Predictive accuracies of the three physiological characteristics were calculated and compared in the subsample for which we were able to calculate RFM and RFM polyfacet scores (N = 2,539). RFM = relative fat mass, BMI = body mass index, BMR = basal metabolic rate.

[1]All p-values are < .001 (adjusted for false discovery rate).

[2]All p-values are .369 (adjusted for false discovery rate).

4. Discussion

Various personality traits are hypothesized to be linked with adiposity, but the common practice of using BMI to quantify adiposity may have led to a biased understanding of such associations. Meanwhile, personality traits' possible associations with other physiological characteristics like BMR have received little attention. The current study aimed to explore these correlations and to clarify whether correlations between personality traits and BMI could be attributable to lean mass rather than fat mass. Given that both adiposity and lean mass contribute to BMI (Romero-Corral et al., 2008), we reasoned that some BMI–personality trait associations may be driven by lean mass, but be misattributed to adiposity, while other, true associations with adiposity, may go undetected.

The results are broadly in line with these expectations. First, RFM—a more accurate index of whole-body adiposity (Woolcott & Bergman, 2018)—correlated with various traits, notably with Openness and a subset of its facets, more strongly and consistently than BMI did, suggesting that the use of BMI can lead to underestimation of some personality–adiposity links. Second, Assertiveness correlated more strongly with BMI than with RFM and also correlated consistently with BMR, suggesting that this trait associates with lean mass and metabolic rate rather than fat mass. Third, comparisons of personality profiles showed that people with high BMI are nearly equally similar in their personality traits to those with high RFM and those with high BMR. Fourth and finally, personality facets were able to predict each physiological characteristic above and beyond age, sex, and education. Collectively, results also suggest that estimating additional physiological variables instead of solely relying on BMI helps us better understand how psychological traits relate to physiology.

4.1. Personality Traits' Associations With Adiposity

We found BMI's associations with personality traits to be broadly similar to what past studies have found them to be (Gerlach et al., 2015; Jokela et al., 2013; Kim, 2016; Sutin et al., 2011; Sutin et al., 2018; Sutin & Terracciano, 2017): BMI most consistently associated with Conscientiousness and several of its facets, but also with Impulsiveness and certain facets of Extraversion (Warmth, Assertiveness, and Positive Emotions). BMI's association with Neuroticism was driven by its facet Impulsiveness which, as has been previously noted, includes two items related to excessive eating (Terracciano et al., 2009). BMI also correlated with some facets of Openness, but, as also observed by Jokela et al. (2013), these associations tended to become nonsignificant after accounting for education.

Comparing personality traits' correlations with BMI and RFM, we found that both were largely related to the same personality traits. The personality profiles of BMI and RFM also correlated highly—as indicators of the same phenotype should. There were, however, some differences in which traits RFM and BMI related to. Facets of Extraversion did not relate to RFM as consistently as they did to BMI, suggesting that the BMI–Extraversion links may be driven by lean mass or body size in general: more extraverted individuals are physically stronger, possibly due to their higher activity levels (Fink et al, 2016; Tolea et al., 2012), suggesting they should also have higher muscle mass. More notably, however, RFM also correlated with Openness and several of its facets; these traits' associations with RFM were stronger than with BMI and, despite some attenuation, correlations with Openness to Actions and Openness to Values persisted after adjusting for education. Education therefore seems to partially, but not entirely, account for the Openness–adiposity association. These results also offer a potential resolution to the inconsistency that Openness relates to healthier eating habits, but does not reliably link with BMI (Jokela et al., 2013; Lunn et al., 2014; Sutin & Terracciano, 2017): Openness did, after all, track with lower body fat as estimated by RFM, but BMI was not able to reliably capture this association. One could speculate that higher Openness may prevent excess adiposity through healthier eating habits; if so, the facets Openness to Action and Openness to Values, both of which relate to decreased frequency of consumption of traditional or convenience foods (Mõttus et al., 2012), largely seem to drive these associations. These facets could therefore be relevant in dietary choices that promote healthy body weight.

Finally, beyond the domains' and facets' correlations with adiposity, we were interested in whether or to what extent adiposity as measured by RFM and BMI can be predicted from personality traits. We found that the polyfacet scores were able to predict RFM and BMI with about equal accuracy: the 30 facets explained 4.8% ($.22^2$) of the variance in RFM and 4% ($.20^2$) of the variance in BMI after adjusting for age, age^2, and sex. To compare, the predictive accuracy for BMI was about as high as in a previous study where 50 personality items explained 3.7% of the variance in BMI in a similar approach based on penalized regression (Seeboth & Mõttus, 2018). In sum, the current results suggest that adiposity can be predicted from the personality facets at least as accurately as BMI can.

4.2. Personality Traits and Metabolic Rate

BMR, similarly with RFM and BMI, also correlated with various personality traits. BMR was similar to BMI in its correlations with personality traits: firstly, BMR and BMI shared correlations with many of the individual traits, and secondly, the personality profile of BMI was as similar to the profile of BMR as it was to the profile of RFM. Considering these results, BMI's correlations with personality traits seem to reflect the contribution of lean mass about as strongly as that of fat mass. However, across all analyses (i.e., after accounting for RFM and education), BMR was only associated consistently with one facet of personality: Assertiveness. Given that Assertiveness also correlated more strongly with BMI than with RFM, this trait appears to relate to lean mass/BMR rather than adiposity. Although previous studies have found Assertiveness to correlate with both BMI and skinfold thickness (Terracciano et al., 2009; Sutin et al., 2011), the current results suggest that such associations may have arisen due to shared variance between fat mass and lean mass rather than a true correlation with adiposity in specific.

The current results differ from those of the two studies that have previously tested personality traits' associations with BMR in humans. In the first of the two, energy expenditure at rest was mostly uncorrelated to NEO–PI–R personality domains and facets in a sample of 441 individuals (Terracciano et al., 2013); in the second, resting metabolic rate was negatively correlated with Extraversion as measured with the Big Five Inventory in a sample of 40 college students (Bergeron et al., 2021). Although metabolic rate was measured objectively in both studies, the sample size may have been insufficient to detect the modestly sized association in the first study and was small enough to lead to spurious associations in the second. In sum, both of the studies were likely unable to detect associations between metabolic rate and personality traits as they are.

The current results are, however, in line with the associations between metabolic rate and behaviour that various studies have found in non-human species. BMR's positive correlation with Assertiveness, the facet of Extraversion reflecting dominance, forcefulness, and leadership tendencies, is consistent with studies that have linked energy metabolism to behavioural traits like activity, dominance, and aggressiveness in various other animal species (Careau & Garland, 2012). Because of the evident conceptual similarity of these traits with Assertiveness, the current findings suggest that the association present in various species from fish to mice to dogs (Careau & Garland, 2012) can also be found in humans.

Although the specific mechanisms that link Assertiveness to metabolic rate cannot be ascertained from cross-sectional associations, the result is consistent with the idea that higher metabolic rate enables an individual to engage in energetically costly behaviours (Biro & Stamps, 2010)—that is, metabolic rate could be a potential influence on interindividual variation in Assertiveness. If so, then the association is also consistent with the personality theories that postulate a biological basis of personality traits (e.g., the Five-Factor Theory; McCrae & Sutin, 2018). Indeed, the very fact that similar associations are found across species suggests that the association may have biological underpinnings. It seems plausible that the same genetic variants that underlie individual differences in metabolic rate might also influence assertive or dominant behaviour: for instance, a positive genetic correlation has been found between resting metabolic rate and exploratory behaviour, a trait that similarly represents activity and risk-taking, in deer mice (Careau et al., 2011). Further, because adjusting for education had no effect on the Assertiveness–BMR correlation, it also appears to be independent of certain socioeconomic or lifestyle factors.

Even though BMR only correlated consistently with one personality facet of the FFM (Assertiveness), the 30 facets were collectively able to predict BMR about as strongly as they could predict RFM and BMI: the polyfacet score explained 3.2% ($.18^2$) of the variance in BMR. This suggests that personality traits, at least as measured by the NEO–PI–3, may contain about as much information relevant to metabolic rate or lean mass as they contain information relevant to fat mass—although this predictive accuracy may be, in part, due to the variance shared between lean mass and fat mass. Still, regardless of the interpretation of the associations, it appears that personality facets can predict metabolic rate/lean mass. Future studies could attempt to further maximize predictive accuracy relying on even more detailed measures of personality (e.g., Seeboth & Mõttus, 2018).

4.3. Implications for Estimating Physiological Characteristics With Formulas

Based on the associations we found, it appears that indirectly estimated indicators of physiological variables beyond BMI can be useful for delineating the associations between personality and physiology. However, the suitability of using RFM, BMI, and BMR as indicators of their target phenotypes should also be explicitly discussed in order to better evaluate the results of the current study, as well as for the purposes of possible future studies. In this final section, we therefore discuss the advantages and limitations of using the three indirectly-estimated indicators.

Adiposity (RFM) and metabolic rate (BMR) as estimated from simple anthropometric measurements are inevitably less accurate estimates of their target phenotypes than more objective measurements would be—as is the case for BMI. However, although BMI may be a poor measure of adiposity at the individual level, it tracks the average adiposity of populations fairly closely (Speakman et al., 2018) and is therefore suitable for discovering sample-level associations. The same should apply to

RFM and BMR: despite less-than-ideal accuracy, they can be used to study statistical associations. Moreover, RFM and BMR both capture a larger proportion of the variance in their target phenotypes than BMI does (Mifflin et al., 1990; Woolcott & Bergman, 2018); any measure that exceeds the accuracy of the standard index (BMI) should be assumed to be at least as useful, if not more so. And finally, as exemplified by the BMR–Assertiveness link, our results suggest that personality–physiology associations similar to those that have been found in other species via observation and experiments can be discovered in humans using self-report personality inventories. This additionally supports the utility of using formulas to estimate physiological variables.

It is worth reiterating that the current results also suggest that adiposity and metabolic rate assessed with the formulas can be distinguished appropriately from each other. Although the personality profiles of RFM and BMR correlated strongly and the two indicators shared correlations with various personality traits (e.g., facets of Conscientiousness), such overlap is to be expected because individuals with higher fat mass also have higher lean mass and metabolic rate on average (Hopkins et al., 2016; Johnstone et al., 2005). That the RFM and BMR formulas can capture their target phenotypes is also seen in their personality profiles: if RFM represents adiposity, BMR reflects lean mass, and BMI is a composite index of the two, we would expect personality traits' correlations with BMI to lie somewhere between their correlations with RFM and BMR. This is indeed what the results show (as is evident in Figure 1).

Finally, something can also be said about the suitability of BMI as an indicator of adiposity based on the three indicators' correlations with personality traits. Despite correlating with a somewhat different set of traits, RFM and BMI broadly led to similar conclusions as to which personality traits correlate with adiposity. Still, assuming that RFM is indeed a more accurate index of adiposity than BMI is, the results suggest that the strength of some personality traits' correlations with adiposity can be both over- and underestimated when using BMI. Because various personality traits associated with RFM more strongly than with BMI, more correlations seemed to be underestimated than overestimated when using BMI (this was most clearly the case for facets of Openness), although BMI correlated more strongly with facets of Extraversion, suggesting that this index tends to overestimate the Extraversion–adiposity correlation. Meanwhile, the difference between the correlations of the facets of Conscientiousness with RFM and BMI was small, supporting the results of previous studies (mostly done using BMI) that have suggested reliable associations between Conscientiousness and adiposity (e.g., Gerlach et al., 2015; Jokela et al., 2013; Kim, 2016; Sutin & Terracciano, 2017). All in all the results underscore that when interpreting BMI's correlations with personality traits, it should be kept in mind that these associations reflect the contribution of not only fat mass but also lean mass to BMI.

4.4. Limitations

In characterizing personality traits' associations with adiposity and BMR, the main limitation was that these characteristics were estimated using formulas and therefore were likely less accurate than objective measurements would have been. Still, as discussed above, the results suggest that it is possible to gain additional insight into personality–physiology associations using RFM and BMR besides BMI. When it comes to prediction, more nuanced analyses would likely contribute to better predictive accuracy of the phenotypes—for instance, the items of a personality inventory could be used instead of facets (Seeboth & Mõttus, 2018). Finally, although the current sample was relatively homogeneous in terms of ethnic background, formulas that estimate physiological characteristics should be used cautiously in more diverse samples because they may perform differently in different populations (e.g. Hasson et al., 2011).

5. Conclusions

Altogether, we found that adiposity and BMR were associated independently with personality traits. For instance, people with higher adiposity scored lower on Openness, and people with higher BMR scored higher on Assertiveness; these associations were consistent with what might have been theoretically expected. Despite the similarity of the personality profiles of BMI and RFM, we found that the use of BMI led to over- and underestimation of the associations between adiposity and certain personality traits. Facets of personality can be used to predict adiposity and metabolic rate with similar accuracy. All in all, the results also suggest that assessing the correlations of personality traits with different physiological characteristics, even if the latter are estimated with formulas, can advance knowledge on the possible contributors to differences in personality traits as well as health outcomes.

References

Arumäe, K., Briley, D., Colodro-Conde, L., Mortensen, E. L., Jang, K., Ando, J., Kandler, C., Sørensen, T. I. A., Dagher, A., Mõttus, R., & Vainik, U. (2021). Two genetic analyses to elucidate causality between body mass index and personality. *International Journal of Obesity*. https://doi.org/10.1038/s41366-021-00885-4

Bergeron, P., Pagé, A., & Trempe, M. (2021). Integrating humans into pace-of-life studies: The Big Five personality traits and metabolic rate in young adults. *PLOS ONE*, *16*(4), e0248876. https://doi.org/10.1371/journal.pone.0248876

Biro, P. A., & Stamps, J. A. (2010). Do consistent individual differences in metabolic rate promote consistent individual differences in behavior? *Trends in Ecology & Evolution*, *25*(11), 653–659. https://doi.org/10.1016/j.tree.2010.08.003

Biro, P. A., Thomas, F., Ujvari, B., Adriaenssens, B., & Beckmann, C. (2020). Spontaneous activity rates and resting metabolism: Support for the allocation model of energy management at the among-individual level. *Ethology*, *126*(1), 32–39. https://doi.org/10.1111/eth.12957

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

Boles, A., Kandimalla, R., & Reddy, P. H. (2017). Dynamics of diabetes and obesity: Epidemiological perspective. *Biochimica Et Biophysica Acta (BBA) - Molecular Basis of Disease*, *1863*(5), 1026–1036. https://doi.org/10.1016/j.bbadis.2017.01.016

Borga, M., West, J., Bell, J. D., Harvey, N. C., Romu, T., Heymsfield, S. B., & Leinhard, O. D. (2018). Advanced body composition assessment: From body mass index to body composition profiling. *Journal of Investigative Medicine*, *66*(5), 1–9. https://doi.org/10.1136/jim-2018-000722

Careau, V., & Garland, T. (2012). Performance, personality, and energetics: Correlation, causation, and mechanism. *Physiological and Biochemical Zoology*, *85*(6), 543–571. https://doi.org/10.1086/666970

Careau, V., Thomas, D., Pelletier, F., Turki, L., Landry, F., Garant, D., & Réale, D. (2011). Genetic correlation between resting metabolic rate and exploratory behaviour in deer mice (peromyscus maniculatus): Pace-of-life in a muroid rodent. *Journal of Evolutionary Biology*, *24*(10), 2153–2163. https://doi.org/10.1111/j.1420-9101.2011.02344.x

Cercato, C., & Fonseca, F. A. (2019). Cardiovascular risk and obesity. *Diabetology & Metabolic Syndrome*, *11*(1), 74. https://doi.org/10.1186/s13098-019-0468-0

Denton, N., & Karpe, F. (2016). Measuring body composition and regional fat mass accurately. *Practical Diabetes*, *33*(7), 224–226. https://doi.org/10.1002/pdi.2043

Diedenhofen, B., & Musch, J. (2015). Cocor: A comprehensive solution for the statistical comparison of correlations. *PLOS ONE*, *10*(4), e0121945. https://doi.org/10.1371/journal.pone.0121945

Dulloo, A. G., Jacquet, J., Solinas, G., Montani, J.-P., & Schutz, Y. (2010). Body composition phenotypes in pathways to obesity and the metabolic syndrome. *International Journal of Obesity*, *34*(2), S4–S17. https://doi.org/10.1038/ijo.2010.234

Fink, B., Weege, B., Pham, M. N., & Shackelford, T. K. (2016). Handgrip strength and the Big Five personality factors in men and women. *Personality and Individual Differences*, *88*, 175–177.

Friedman, H. S. (2019). Neuroticism and health as individuals age. *Personality Disorders: Theory, Research, and Treatment*, *10*(1), 25–32. https://doi.org/10.1037/per0000274

Gerlach, G., Herpertz, S., & Loeber, S. (2015). Personality traits and obesity: A systematic review. *Obesity Reviews*, *16*(1), 32–63. https://doi.org/10.1111/obr.12235

Hasson, R. E., Howe, C. A., Jones, B. L., & Freedson, P. S. (2011). Accuracy of four resting metabolic rate prediction equations: Effects of sex, body mass index, age, and race/ethnicity. *Journal of Science and Medicine in Sport*, *14*(4), 344–351.

Hopkins, M., Finlayson, G., Duarte, C., Whybrow, S., Ritz, P., Horgan, G. W., Blundell, J. E., & Stubbs, R. J. (2016). Modelling the associations between fat-free mass, resting metabolic rate and energy intake in the context of total energy balance. *International Journal of Obesity*, *40*(2), 312–318.

Johnstone, A. M., Murison, S. D., Duncan, J. S., Rance, K. A., & Speakman, J. R. (2005). Factors influencing variation in basal metabolic rate include fat-free mass, fat mass, age, and circulating thyroxine but not sex, circulating leptin, or triiodothyronine. *The American Journal of Clinical Nutrition*, *82*(5), 941-948. https://doi.org/10.1093/ajcn/82.5.941

Jokela, M., Hintsanen, M., Hakulinen, C., Batty, G. D., Nabi, H., Singh-Manoux, A., & Kivimäki, M. (2013). Association of personality with the development and persistence of obesity: A meta-analysis based on individual-participant data. *Obesity Reviews*, *14*(4), 315–323. https://doi.org/10.1111/obr.12007

Kallasmaa, T., Allik, J. R., Realo, A., & McCrae, R. R. (2000). The Estonian version of the NEO-PI-R: An examination of universal and culture-specific aspects of the five-factor model. *European Journal of Personality*, *14*(3), 265-278.

Kim, J. (2016). Personality traits and body weight: Evidence using sibling comparisons. *Social Science & Medicine*, *163*, 54–62. https://doi.org/10.1016/j.socscimed.2016.06.054

Lahti, M., Räikkönen, K., Lemola, S., Lahti, J., Heinonen, K., Kajantie, E., Pesonen, A.-K., Osmond, C., Barker, D. J. P., & Eriksson, J. G. (2013). Trajectories of physical growth and personality dimensions of the Five-Factor Model. *Journal of Personality and Social Psychology*, *105*(1), 154–169. https://doi.org/10.1037/a0032300

Leitsalu, L., Haller, T., Esko, T., Tammesoo, M.-L., Alavere, H., Snieder, H., Perola, M., Ng, P. C., Mägi, R., Milani, L., Fischer, K., & Metspalu, A. (2015). Cohort profile: Estonian Biobank of the Estonian Genome Center, University of Tartu. *International Journal of Epidemiology*, *44*(4), 1137–1147. https://doi.org/10.1093/ije/dyt268

Lunn, T. E., Nowson, C. A., Worsley, A., & Torres, S. J. (2014). Does personality affect dietary intake? *Nutrition*, *30*(4), 403–409. https://doi.org/10.1016/j.nut.2013.08.012

McCrae, R. R., Costa, P. T., Jr., & Martin, T. A. (2005). The NEO-PI-3: A more readable revised NEO Personality Inventory. *Journal of Personality Assessment*, *84*(3), 261–270. https://doi.org/10.1207/s15327752jpa8403_05

McCrae, R. R., & Sutin, A. R. (2018). A Five–Factor Theory perspective on causal analysis. *European Journal of Personality*, *32*(3), 151–166. https://doi.org/10.1002/per.2134

Mifflin, M. D., St Jeor, S. T., Hill, L. A., Scott, B. J., Daugherty, S. A., & Koh, Y. O. (1990). A new predictive equation for resting energy expenditure in healthy individuals. *The American Journal of Clinical Nutrition*, *51*(2), 241–247. https://doi.org/10.1093/ajcn/51.2.241

Mõttus, R., Realo, A., Allik, J., Deary, I. J., Esko, T., & Metspalu, A. (2012). Personality traits and eating habits in a large sample of Estonians. *Health Psychology*, *31*(6), 806. https://doi.org/10.1037/a0027041

Mõttus, R., Realo, A., Vainik, U., Allik, J., & Esko, T. (2017). Educational attainment and personality are genetically intertwined. *Psychological Science*, *28*(11), 1631–1639. https://doi.org/10.1177/0956797617719083

Nagel, M., Watanabe, K., Stringer, S., Posthuma, D., & van der Sluis, S. (2018). Item-level analyses reveal genetic heterogeneity in neuroticism. *Nature Communications*, *9*(1), 905. https://doi.org/10.1038/s41467-018-03242-8

Réale, D., Garant, D., Humphries, M. M., Bergeron, P., Careau, V., & Montiglio, P.-O. (2010). Personality and the emergence of the pace-of-life syndrome concept at the population level. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1560), 4051–4063.

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

Romero-Corral, A., Somers, V. K., Sierra-Johnson, J., Thomas, R. J., Collazo-Clavell, M. L., Korinek, J., Allison, T. G., Batsis, J. A., Sert-Kuniyoshi, F. H., & Lopez-Jimenez, F. (2008). Accuracy of body mass index in diagnosing obesity in the adult general population. *International Journal of Obesity*, *32*(6), 959–966. https://doi.org/10.1038/ijo.2008.11

Rothman, K. J. (2008). BMI-related errors in the measurement of obesity. *International Journal of Obesity*, *32*(3), S56–S59. https://doi.org/10.1038/ijo.2008.87

Seeboth, A., & Mõttus, 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

Speakman, J. R., Loos, R. J. F., O'Rahilly, S., Hirschhorn, J. N., & Allison, D. B. (2018). GWAS for BMI: A treasure trove of fundamental insights into the genetic basis of obesity. *International Journal of Obesity*, *42*(8), 1524–1531. https://doi.org/10.1038/s41366-018-0147-5

Sutin, Angelina R., Costa, P. T., Chan, W., Milaneschi, Y., Eaton, W. W., Zonderman, A. B., Ferrucci, L., & Terracciano, A. (2013). I know not to, but I can't help it: Weight gain and changes in impulsivity-related personality traits. *Psychological Science*, *24*(7), 1323–1328. https://doi.org/10.1177/0956797612469212

Sutin, A. R., Ferrucci, L., Zonderman, A. B., & Terracciano, A. (2011). Personality and obesity across the adult life span. *Journal of Personality and Social Psychology*, *101*(3), 579–592. https://doi.org/10.1037/a0024286

Sutin, A. R., Stephan, Y., & Terracciano, A. (2018). Facets of conscientiousness and objective markers of health status. *Psychology & Health*, *33*(9), 1100–1115. https://doi.org/10.1080/08870446.2018.1464165

Sutin, A. R., & Terracciano, A. (2017). Personality and body weight: Mechanisms, longitudinal associations and context. *The Japanese Journal of Personality*, *26*(1), 1–11. https://doi.org/10.2132/personality.26.1.1

Terracciano, A., Schrack, J. A., Sutin, A. R., Chan, W., Simonsick, E. M., & Ferrucci, L. (2013). Personality, metabolic rate and aerobic capacity. *PLoS ONE*, *8*(1), e54746. https://doi.org/10.1371/journal.pone.0054746

Terracciano, A., Sutin, A. R., McCrae, R. R., Deiana, B., Ferrucci, L., Schlessinger, D., Uda, M., & Costa, P. T. (2009). Facets of personality linked to underweight and overweight. *Psychosomatic Medicine*, *71*(6), 682–689. https://doi.org/10.1097/PSY.0b013e3181a2925b

Tolea, M. I., Terracciano, A., Simonsick, E. M., Jeffrey Metter, E., Costa, P. T., & Ferrucci, L. (2012). Associations between personality traits, physical activity level, and muscle strength. *Journal of Research in Personality*, *46*(3), 264–270.

Vainik, U., Baker, T. E., Dadar, M., Zeighami, Y., Michaud, A., Zhang, Y., García Alanis, J. C., Misic, B., Collins, D. L., & Dagher, A. (2018). Neurobehavioral correlates of obesity are largely heritable. *Proceedings of the National Academy of Sciences*, *115*(37), 9312–9317. https://doi.org/10.1073/pnas.1718206115

Vainik, U., Dagher, A., Realo, A., Colodro-Conde, L., Mortensen, E. L., Jang, K., Juko, A., Kandler, C., Sørensen, T. I. A., & Mõttus, 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

Vainik, U., Mõttus, R., Allik, J., Esko, T., & Realo, A. (2015). Are trait–outcome associations caused by scales or particular items? Example analysis of personality facets and BMI. *European Journal of Personality*, *29*(6), 622–634. https://doi.org/10.1002/per.2009

Weinsier, R. L., Schutz, Y., & Bracco, D. (1992). Reexamination of the relationship of resting metabolic rate to fat-free mass and to the metabolically active components of fat-free mass in humans. *The American Journal of Clinical Nutrition*, *55*(4), 790–794. https://doi.org/10.1093/ajcn/55.4.790

Woolcott, O. O., & Bergman, R. N. (2018). Relative fat mass (RFM) as a new estimator of whole-body fat percentage - A cross-sectional study in American adult individuals. *Scientific Reports*, *8*(1), 10980. https://doi.org/10.1038/s41598-018-29362-1

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science, 12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393