Body mass predicts personality development across 18 years in middle to older adulthood

Received: 11 May 2022 | Revised: 26 September 2022 | Accepted: 25 January 2023

DOI: 10.1111/jopy.12816

ORIGINAL ARTICLE

WILEY

Body mass predicts personality development across 18 years in middle to older adulthood

Kadri Arumäe[1] | **René Mõttus**[1,2] | **Uku Vainik**[1,3,4]

[1]Institute of Psychology, University of Tartu, Tartu, Estonia

[2]Department of Psychology, University of Edinburgh, Edinburgh, UK

[3]Institute of Genomics, University of Tartu, Tartu, Estonia

[4]Montreal Neurological Institute, McGill University, Montreal, Quebec, Canada

Correspondence
Kadri Arumäe, Institute of Psychology, University of Tartu, Näituse 2, Tartu 50409, Estonia.
Email: kadri.arumae@ut.ee

Funding information
Eesti Teadusagentuur, Grant/Award Number: PSG759

Abstract

Objective: Various personality traits have longitudinal relations with body mass index (BMI), a measure of body weight and a risk factor for numerous health concerns. We tested these associations' compatibility with causality in either direction.

Method: Using three waves of the Wisconsin Longitudinal Study (N = 12,235, M_{age} = 53.33 at baseline), we tested how accurately the Five-Factor Model personality domains and their items could collectively predict BMI and change in it with elastic net models. With multilevel models, we tested (a) bidirectional and (b) within-person associations between BMI and personality traits.

Results: The five domains were able to predict concurrent (r = 0.08), but not future BMI. Twenty-nine personality items predicted concurrent and future BMI at r = 0.21 and r = 0.16 to 0.25, respectively. Neither the domains nor items could collectively predict change in BMI. Similarly, no individual trait predicted change in BMI, but BMI predicted changes in Conscientiousness, Agreeableness, and several items ($|b^*|$ = 0.03 to 0.08). BMI had within-person correlations with these same traits; time-invariant third factors like genetics or childhood environments therefore could not (fully) account for their relations.

Conclusions: Body weight may contribute to adults' personality development, but the reverse appears less likely.

KEYWORDS
body mass index, health, item-level analyses, multilevel modeling, personality development

1 | INTRODUCTION

Many studies have shown that personality traits can predict various indices of physical health (Charles et al., 2008; Hampson et al., 2015; Magee et al., 2013; Mueller et al., 2018; Turiano et al., 2012; Weston et al., 2015) but also that personality traits can be predicted from the onset of multiple common diseases (Jokela et al., 2014; Sutin, Zonderman, et al., 2013). Among the specific health indicators that can both predict and be predicted from personality traits is body mass index (BMI) (Gerlach et al., 2015; Jokela et al., 2014; Vainik et al., 2019), a measure of body weight that also indexes the various health issues that obesity is a risk factor for (Nuttall, 2015). Some evidence suggests that the longitudinal relations between BMI and personality traits could reflect causal associations beyond being merely predictive (Armon et al., 2013; Arumäe et al., 2021; Brummett et al., 2006; Lahti et al., 2013; Stephan et al., 2019; Sutin et al., 2011), but results are inconsistent as to which specific traits could potentially influence BMI and which traits could be influenced by it. Moreover, studies have not explicitly tested possible bidirectionality of the associations

which limits their interpretability; for instance, predictive associations in one direction could partly also reflect influences in the opposite direction or the effects of confounds. Once better understood, the relations between personality traits and body weight may have both theoretical and practical relevance as understanding them could clarify whether personality trait measurements could be useful in weight-management interventions as well as illuminate how personality traits develop following changes in body weight. In a large sample, we tested longitudinal associations between BMI and the Five-Factor Model (FFM; McCrae & John, 1992) domains and their items, and assessed whether they are consistent with causal influences in either direction.

1.1 | Personality traits and BMI: Longitudinal associations

Some personality traits of the FFM correlate with BMI cross-sectionally (Kim, 2016; Sutin et al., 2015; Vainik et al., 2019) and predict future BMI (Armon et al., 2013; Bagnjuk et al., 2019; Brummett et al., 2006; Jokela et al., 2013; Sutin et al., 2011), suggesting that they may have a role in the development of body weight. If such causal associations indeed exist, they could operate through, for instance, health-relevant behaviors associated with these traits or through physiological processes like inflammation or the stress response (Sutin & Terracciano, 2017; Wright et al., 2022). Cross-sectionally, BMI is most consistently correlated with Conscientiousness and related traits (Gerlach et al., 2015; Jokela et al., 2013; Vainik et al., 2019). Some longitudinal studies have shown that similar associations exist across time: Lower Conscientiousness has been found to relate to higher obesity risk (Jokela et al., 2013), larger increases in BMI over time (Brummett et al., 2006), and weight fluctuations (Sutin et al., 2011). However, not all longitudinal studies have found associations between BMI and Conscientiousness, finding instead that BMI can be predicted from other personality domains—but these associations, too, have been inconsistent across studies (Armon et al., 2013; Bagnjuk et al., 2019; Magee & Heaven, 2011). Given these divergent findings, generalizable conclusions regarding which traits can predict or potentially influence body weight are hard to make yet.

Fewer studies have tested personality traits' associations with body weight in the opposite direction—that is, whether indices of body weight can predict personality traits. For example, weight gain may influence aspects of personality, because people with overweight face stigma and discrimination in the job market, interpersonal relationships, and other domains of life (Puhl & King, 2013), and insomuch as aspects of the social environment have an impact on personality (Sutin & Terracciano, 2017), the unequal treatment could eventually manifest as personality differences that depend on body weight. There is indeed some evidence that BMI can predict personality traits or changes in them. Measured in adulthood, for example, all FFM domains but Openness have been associated with either birth weight or weight growth trajectories in earlier life (Lahti et al., 2013). Some studies have linked weight changes in adulthood to deviations from average patterns of personality development in the FFM domains (Stephan et al., 2019) or changes in narrower traits such as impulsiveness and deliberation (Sutin, Costa, et al., 2013). It is thus possible that body weight plays a role in personality development, but the design of these studies does not warrant strong causal inferences and their results might additionally reflect influences in the opposite direction.

1.2 | Assessing prediction and causation: Methodological considerations

When studying the longitudinal associations between BMI and personality traits, various issues relating to measurement and statistical modeling need to be considered. First, thought should be given to how exactly personality traits are operationalized. For instance, broad-bandwidth traits like domains may not be sufficient to capture personality domains' possibly nuanced associations with outcomes, whereas the individual items that make up domains could be more useful. With the necessary trait-properties of rank-order stability, heritability, and cross-rater agreement (Mõttus et al., 2019), many items represent unique narrow traits themselves. In view of that, item-level analyses can clarify personality trait–BMI relations: For instance, BMI tends to correlate more strongly with individual personality items than with domains, and items within a domain vary not only in the strength, but also the direction of their correlations with BMI (Arumäe, Vainik, et al., 2022). As domains' correlations with an outcome may therefore be driven by certain items in some cases and suppressed by them in others, their constituent items can be useful in predicting the outcome as they often enable more accurate prediction than domains. Combining items in a single model can be especially beneficial for predictive accuracy (Mõttus et al., 2020; Seeboth & Mõttus, 2018) with machine learning methods that weight the predictors according to their relevance—like elastic net (Yarkoni & Westfall, 2017)—being particularly useful in maximizing prediction. Owing to their comparatively stronger relations with outcomes, items can also provide more power for testing causal hypotheses (Arumäe et al., 2021).

Second, the time intervals between the measurements of the predictors and the outcomes in longitudinal data can affect prediction strength and researchers' ability to detect possible causal associations. If a variable precedes or influences another, then it should predict not only the outcome's future values but also its changes. For this, however, it is necessary that the relevant (causal) processes have had enough time to play out for the association to be detectable, so the time interval between the longitudinal measurements should be sufficiently long. Additionally, because both personality traits and body weight tend to change slowly (Anusic & Schimmack, 2016; Herman et al., 2009), short time intervals may not be sufficient to study their longitudinal relations. Although permissible time intervals for detecting personality traits' associations with BMI may be flexible as past studies have found links between them with time intervals ranging from 2 years (Magee & Heaven, 2011) to over half a century (Lahti et al., 2013; Sutin et al., 2011), the strength of the associations may increase with time when a variable has a cumulative effect on the outcome. Thus, a measurement interval of at least several years seems justified for studies aiming to assess the longitudinal relations between personality traits and body weight.

Third, when using longitudinal associations to test causality, approaches to statistical modeling should be considered carefully. Longitudinal studies often aim to establish the temporal precedence of one variable over another, but one variable predicting another variable's future values can only offer tentative support for causality: Besides one variable influencing another, such associations may reflect effects of third factors (confounds) that influence both in a way that persists over time. For instance, even if people who are more conscientious in middle adulthood come to have a lower average body weight in older adulthood (a between-person association), this does not necessarily mean that an individual's increase in Conscientiousness leads to their having lower weight subsequently (a within-person association). Many factors, including genetics, childhood experiences, and education, could mutually influence personality traits and body weight and their developmental trajectories throughout life, confounding both their cross-sectional and longitudinal associations. Even if some potential confounds like age, sex, and education are controlled for, in statistical models, unknown or unmeasured other variables could still confound the associations.

To tackle this issue, it is often helpful to consider intraindividual or within-person associations. For instance, repeated-measurements data enable assessing whether changes in two variables over time are correlated. Unlike the standard longitudinal modeling approach where one variable is used to predict another, such within-person correlations do not reveal the temporal direction of the association, but rather indicate whether within-person changes in one variable are related to within-person changes in another, which would be expected if the two are causally linked. These within-person models have a notable advantage in terms of causal inference. Just like individual differences—that is, stable, person-level, or *time-invariant* factors—do not contribute to associations observed in within-subject experiments, they also do not contribute to within-person associations in observational studies as, by definition, they remain stable for the study period. Thus, unmeasured time-invariant variables like genetics and childhood environments are inherently controlled for (Rohrer & Murayama, 2021). True, even within-person associations are not free of all confounding—*time-varying* third factors like age or employment status could plausibly still account for within-person associations—but they can help strengthen causal inference by providing a way to control for a broad range of potential unmeasured confounds. Thus, if a within-person association is found between BMI and a personality trait, this would provide stronger evidence for causality between them than standard between-person approaches can.

1.3 | The current study

Here, we relied on a large sample of the Wisconsin Longitudinal Study (WLS) to clarify personality trait–BMI associations, testing whether either can predict changes in the other and whether within-person correlations exist between them. Because narrower traits, such as those represented by the items of an inventory, can either drive or suppress their domains' associations with BMI, we also tested BMI's associations with (a) the individual items most relevant to BMI (i.e., most strongly correlated with it) and (b) the domains with the most relevant items excluded (domains' associations not driven solely by certain items should survive excluding a few items).

First, we used elastic net models to estimate the overall strength of BMI's cross-sectional and longitudinal associations with the personality domains and items collectively and to select items for further analyses. Knowing items' and domains' predictive ability for BMI can calibrate expectations about which association strengths to anticipate in other analyses besides showing the phenomena's overall overlaps. Next, we assessed BMI's cross-sectional and longitudinal associations with the domains and selected items using a series of multilevel models (MLMs).[1] We estimated cross-sectional correlations to test whether BMI related to personality traits similarly cross-sectionally and longitudinally. Then, we tested whether personality traits could predict longitudinal changes in BMI and vice versa,

to clarify the likely direction of any influences between them. Finally, we used MLMs to test within-person correlations (correlated changes) between BMI and personality traits. If within-person correlations—i.e., associations where a broad range of confounds is controlled for—are found between BMI and a personality trait, this would be consistent with causality between them unfolding over time, while the bidirectional longitudinal models can indicate the likelier direction of these influences (see Daly et al., 2015 for a similar multi-step approach). Together, the analyses can test whether personality traits can predict BMI and vice versa and provide clearer evidence in regards to possible causal relations between them than has been reported in previous longitudinal studies.

2 | METHOD

2.1 | Participants

We used data of the WLS (Hauser et al., 2020; Herd et al., 2014), a longitudinal study that followed a random sample of 10,317 people who graduated from Wisconsin high schools in 1957 (most of them born in 1939). The graduates are broadly representative of White, non-Hispanic American men and women with at least a high school education. Data collection began in 1957; follow-up data were collected via surveys on multiple occasions. In addition to the graduates, data were collected on a sample of randomly selected siblings of the graduates. In the current study, we used data from three data collection waves in which the respondents' personality was assessed: 1993–1994, 2004–2005, and 2011, to which we refer as waves 1, 2, and 3, respectively. In total, data of 12,235 participants (7757 graduates and 4472 siblings) were included for whom information on personality traits, BMI, and the necessary demographic variables were available in at least one wave. At baseline (wave 1), mean age of the sample was 53.33 years (SD = 4.30), and mean BMI was 26.77 kg/m^2 (SD = 4.53); most people fell within the normal-weight or overweight (pre-obesity) range. Sample characteristics are reported in more detail in Table 1 for the total sample and in Table S1 for the graduates and their siblings separately.

WLS data have been used previously to test links between FFM personality domains and health outcomes (listed on the study's web page, https://www.ssc.wisc.edu/wlsresearch/publications/pubs.php?topic=ALL), including one meta-analysis where personality domains were used to predict various health indicators including BMI (Jokela et al., 2018). However, the authors of the meta-analysis noted that their approach was limited in that it was cross-sectional and did not incorporate lower-level personality traits, and called for further exploration of the associations using different analytic approaches. With a focus on longitudinal associations and personality items besides domains, the current study addresses these limitations.

TABLE 1 Sample characteristics.

Characteristics	Wave 1 (N = 9977)	Wave 2 (N = 9228)	Wave 3 (N = 7435)
Age (years)	53.33 (4.30)	64.76 (4.09)	71.09 (4.00)
Sex—*n* (%)			
Male	4717 (47.28%)	4307 (46.67%)	3468 (46.64%)
Female	5260 (52.72%)	4921 (53.33%)	3967 (53.36%)
Education—*n* (%)			
Less than high school	174 (1.74%)	137 (1.48%)	96 (1.29%)
High school	6934 (69.50%)	6323 (68.52%)	4973 (66.89%)
Bachelor's degree	1423 (14.26%)	1378 (14.93%)	1140 (15.33%)
Master's degree	1242 (12.45%)	1171 (12.69%)	1035 (13.92%)
PhD	204 (2.04%)	219 (2.37%)	191 (2.57%)
BMI (kg/m^2)	26.77 (4.53)	27.88 (4.99)	28.75 (5.51)
Agreeableness	4.73 (0.75)	4.77 (0.70)	4.79 (0.72)
Conscientiousness	4.84 (0.70)	4.77 (0.69)	4.73 (0.72)
Extraversion	3.81 (0.90)	3.78 (0.86)	3.78 (0.89)
Neuroticism	3.21 (0.98)	3.03 (0.90)	3.03 (0.93)
Openness	3.62 (0.80)	3.57 (0.75)	3.46 (0.76)

Note: Means and SDs are presented unless otherwise noted.

2.2 | Measures

2.2.1 | Personality traits

Personality traits were assessed using a 29-item version of the Big Five Inventory (BFI; John et al., 1991). The BFI assesses Neuroticism with five items and the other four domains with six items each. The inventory uses a 6-point scale from 1 (*agree strongly*) to 6 (*disagree strongly*); in the current study, the scale was reversed so that higher values reflected higher agreement with the item. Cronbach's α was 0.67 for Agreeableness, 0.66 for Conscientiousness, 0.75 for Extraversion and Neuroticism, and 0.60 for Openness. Personality data were collected via mail.

2.2.2 | BMI

Height and weight used to calculate BMI (kg/m^2) were self-reported via mail in waves 1 and 2 and measured objectively in wave 3.

2.3 | Statistical analyses

2.3.1 | Elastic net

To begin, elastic net was used to test how accurately personality traits (domains and items) could collectively predict (a) BMI and (b) change in BMI, and (c) to find items that have unique links with BMI for inclusion in further analyses. Elastic net (Zou & Hastie, 2005) is a form of penalized regression where predictors (personality traits) are weighted by their correlations with the outcome (BMI) to produce the strongest prediction of the outcome while shrinking some of the predictors' weights toward zero, thereby counteracting overfitting. In cross-sectional models, either the five personality domains or the 29 items of the BFI were used as predictors of BMI, all measured at wave 1; in longitudinal models, earlier measurements of personality (waves 1, 2, and 3) were used to predict later measurements of BMI (waves 2 and 3). For all models, personality traits were residualized for age, age^2, sex, and highest level of education (measured in the same wave) before they were entered into the models. In all elastic net models, the mixing hyperparameter α was set to 0.50; the default value of the regularization hyperparameter λ was used, with the hyperparameters' values set a priori (i.e., without tuning). Weights were calculated separately for the predictors in 10 random partitions of the sample to further minimize the risk of overfitting the models and thus making them less generalizable. Predictive accuracy of combined personality traits was quantified as the correlation between observed BMI and BMI as predicted by the elastic net models.

Change in BMI was predicted with elastic net models otherwise identical to those described above, but personality traits were additionally residualized for BMI measured concurrently with the personality traits.

Items were selected for subsequent analyses based on the models where personality traits were used to predict BMI's future values. An item was selected if it had nonzero weights in all four elastic net models (i.e., those predicting concurrent BMI at wave 1 as well as future BMI in all combinations of waves). To clarify whether the domains' associations with BMI were unitary or driven by specific items, the domains were recalculated for further analyses after excluding the selected items.

2.3.2 | Multilevel models

Next, a series of MLMs were used to assess cross-sectional and longitudinal links between BMI and personality traits, and to test, using within-person models, whether changes in them were correlated.

First, we used random-coefficients MLMs to assess cross-sectional correlations between BMI and personality traits. By accounting for the nested structure of the longitudinal data (specifically, the waves of measurement were nested within individuals) and for the sibling family structure, these models gave more realistic estimates of the associations than regular (e.g., ordinary least squares) regression models would have when used on longitudinal data. The association of each trait of interest was tested in a separate model with BMI as the dependent variable, adjusting for age and highest level of education (level 1, i.e., time-variant or within-person covariates) and sex (level 2, i.e., time-invariant or between-person covariate). These cross-sectional models are described with Equations 1–3.

Level 1:

$$\begin{aligned}\text{BMI}_{ti} = \beta_{0i} + \beta_{1i}(\text{personality trait})_{ti} + \beta_{2i}(\text{age})_{ti} \\ + \beta_{3i}(\text{education})_{ti} + \beta_4(\text{wave})_t + e_{ti}\end{aligned} \quad (1)$$

Level 2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{sex})_i + u_{0i} \quad (2)$$

$$\beta_{1i} = \gamma_{10} + u_{1i} \quad (3)$$

Second, we assessed longitudinal relations between BMI and personality traits with random-coefficients MLMs in both directions. We tested whether each trait, measured at a given wave t, predicted change in BMI between waves t and its following wave, $t+1$, and vice versa. Because we were interested in predicting *change* in BMI, earlier measurements of the dependent variable were adjusted for besides age, sex, and highest level of education. A first-order autoregressive correlation structure was used. Because a personality trait may be more relevant in shaping the body weight in some people than others (or vice versa), random slopes were included in the models in addition to random intercepts to allow the trait–BMI relationships to vary between people. To formally assess the appropriateness of these random-coefficients models, we fit a series of nested models for each personality trait in order of increasing complexity: (a) model with intercept only, (b) model with level 1 predictors, (c) model with level 1 and level 2 predictors, and (d) the final random-coefficients model with random intercepts and slopes. Where the final, most complex model fit statistically better than the simpler ones, this was taken as evidence that the within-individual BMI–personality trait associations differed between people and the random-coefficients model was appropriate.

The bidirectional models are described with Equations 4–6 (with either BMI or a personality trait being the dependent variable and the other being the independent variable).

Level 1:

$$\begin{aligned}\mathrm{DV}_{(t+1)i} = {} & \beta_{0i} + \beta_{1i}(\mathrm{IV})_{ti} + \beta_{2i}(\mathrm{DV})_{ti} + \beta_{3i}(\mathrm{age})_{ti} \\ & + \beta_{4i}(\mathrm{education})_{ti} + \beta_5(\mathrm{wave})_t + e_{ti}\end{aligned} \quad (4)$$

Level 2:

$$\beta_{0i} = \gamma_{00} + \gamma_{01}(\mathrm{sex})_i + u_{0i} \quad (5)$$

$$\beta_{1i} = \gamma_{10} + u_{1i} \quad (6)$$

Importantly, although these longitudinal models clarify the likely direction of the BMI–personality trait associations, they cannot distinguish between the contributions of within- and between-person processes to them. Should the associations be primarily due to between-person processes, this would suggest that there are no causal relations between them that unfold over time within individuals. To test of this possibility, we assessed the proportions of within- and between-person variance in the final bidirectional models using Nakagawa's conditional and marginal R^2 (Nakagawa et al., 2017). Where non-negligible proportions of within-person variance were found, this was taken as evidence that the associations are not entirely due to spurious between-person processes.

Third and finally, to provide a more straightforward test of within-person associations, we used a set of fixed-coefficients MLMs to estimate correlations between changes in BMI and personality traits—that is, within-person correlations—including age and education as covariates. Within-person changes in BMI were calculated by subtracting an individual's mean BMI across the three waves from their BMI at a specific wave; within-person changes in personality traits and the covariates were calculated analogously. As these models rely on within-person changes, unmeasured time-invariant confounds like genetics, childhood environment, birth weight, and sex do not contribute at all to the associations in these models. This also means that the addition of a time-invariant covariate like sex or a person's mean of a personality trait or BMI would not change the results of the model. Because measurement error can be higher in models that use change scores (as opposed to raw scores), estimates of associations are likely to be less precise in these models, but statistically significant associations in these models nevertheless suggest that the association is not (entirely) accounted for by time-invariant factors. Equation 7 describes these models of within-person correlations.

$$\begin{aligned}\mathrm{BMI}_{ti} - \overline{\mathrm{BMI}}_i = {} & \beta_{1i}\left(\text{personality trait}_{ti} - \overline{\text{personality trait}}_i\right) \\ & + \beta_{2i}\left(\text{age}_{ti} - \overline{\text{age}}_i\right) + \beta_{3i}\left(\text{education}_{ti} - \overline{\text{education}}_i\right) \\ & + \beta_5(\mathrm{wave})_t + \left(\alpha_{ti} - \overline{\alpha}_i\right) + \left(e_{ti} - \overline{e}_i\right)\end{aligned} \quad (7)$$

To summarize: The bidirectional models reveal the predominant direction of the longitudinal associations, but cannot fully disaggregate within- and between-person effects. However, if within-person correlations are found in the separate within-person models, this will provide additional support for causality in the associations.

Attrition was assessed by comparing baseline values of BMI and personality domains of the participants for whom only one BMI and/or personality trait assessment was available to those for whom two or three assessments on the variables were available. People who only provided the data on one occasion were, on average, less conscientious, agreeable, and extraverted than those who provided two or more measurements of the respective variables (Table S2). No differences were found between the groups in BMI, Neuroticism, or Openness.

All analyses were done with R version 3.6.3. The package *glmnet* (version 4.1; Friedman et al., 2010) was used for elastic net models; *nlme* (version 3.1; Pinheiro et al., 2022) was used for MLMs. The full sample was used in all analyses, but due to the different principles of sampling between the graduate and sibling subsamples, all analyses were repeated with both subsamples separately (reported in the supplementary document). For elastic net models run on the full sample, we additionally ensured that related participants were always in the same partition to avoid inflation of the estimates. In each MLM in the full sample, the independent variable (BMI or personality trait) was first residualized for family structure. Continuous variables (BMI, personality traits, and age) were then standardized with the measurement at baseline as the reference so that each variable's mean at wave 1 was 0 (SD = 1). For each set of MLMs, we report the β_{1i} coefficients associated with the predictors of interest—either a personality trait or BMI. False discovery rate corrections were applied separately to the *p*-values of domains, selected items, and domains excluding the selected items, for each set of analyses, to minimize the risk of false positives.

2.4 | Transparency and openness

The current study was not preregistered. The data and materials used in this study are publicly available and can be retrieved from https://www.ssc.wisc.edu/wlsresearch/. The study follows the standards described at http://www.equator-network.org/ for reporting key aspects of the research design and data analysis. Principles of data exclusions and transformations are described in the Methods section. The code used for analysis is available at https://osf.io/jrsd7/.

3 | RESULTS

3.1 | Elastic net: Selecting items and predicting BMI

Four items—C3: Disorganized, C4: Lazy, E1: Talkative, and E3: Full of energy—had non-zero weights in the elastic net models predicting BMI in all waves and were included in further analyses. Thus, the Conscientiousness and Extraversion domains were also recalculated for further analyses based on the remaining items in each domain (excluding the selected items) to test if their associations with BMI depended solely on these items. The weights set to the items in the elastic net models are shown in Table S3; the items' weights in the graduate and sibling subsamples are reported in Tables S4 and S5.

As shown in Table 2, elastic net results indicated that the 29 personality items were collectively able to predict future BMI, but the five domains generally were not. Specifically, the items predicted BMI with accuracies of $r = 0.16 \ldots 0.25$, but the domains were only able to predict BMI (at $r = 0.04$) when the domains were assessed at wave 2 and BMI at wave 3. To compare, the cross-sectional associations were $r = 0.21$ for items and $r = 0.08$ for domains, suggesting that personality items associated with future BMI about as strongly as they did with concurrently measured BMI, but this was not the case for domains. Because the items outpredicted the five domains by a considerable margin, personality items appeared to have substantially more utility for prediction. Predictive accuracies in the graduate and sibling subsamples are reported in Tables S6 and S7.

Neither the five domains nor the 29 items were able to predict *change* in BMI between the waves (all predictors' weights were set to zero in all cases in the total sample as well as in the two subsamples).

3.2 | Cross-sectional associations

Cross-sectionally, BMI correlated with Conscientiousness and Agreeableness and had significant (although negligible) correlations with Openness and Extraversion (Table 3). Each of the selected individual items was associated with BMI and so were the domains to which they originally belonged, although the associations with the domains decreased slightly for Conscientiousness and increased for Extraversion. We also created, using elastic net, an aggregate score to summarize individuals' personality-based propensities for higher BMI, which we called the polypersonality score (PPS) and which consisted of 13 items with nonzero weights (shown in Table S8). The cross-sectional correlations were largely similar in the graduate and sibling subsamples tested separately (Tables S9 and S10).

3.3 | Bidirectional longitudinal associations

Model comparisons (reported in Tables S11 and S12) indicated that the random-coefficient models were appropriate to describe BMI's associations with personality traits. This also suggests that the within-person associations between BMI and the personality traits varied across people (although the comparisons also suggested that adding Extraversion or Neuroticism to the models did not improve prediction of BMI, and BMI did not improve the prediction of Extraversion after removing E1: Talkative and E3: Full of energy). Based on Nakagawa's conditional and marginal R^2, the proportion of within-person variance was lower than the proportion of between-person variance in models with BMI as the dependent variable whereas the proportion of within-person variance was similar to or exceeded between-person variance in most models with a personality trait as the dependent variable (Table S13).

None of the five domains predicted change in BMI (Table 4). Of items, only E1: Talkativeness predicted slightly higher BMI, but the effect was negligible ($b^* = 0.01$). In contrast, higher BMI did predict lower Agreeableness and Conscientiousness, as well as higher scores on E1: Talkativeness, lower scores on the three remaining items, and lower scores on Conscientiousness

TABLE 2 Predictive accuracies of personality variables in predicting BMI.

Personality measured	BMI measured	Domains			Items		
		r	95% CI	*p*	*r*	95% CI	*p*
Wave 1	Wave 1	0.08	0.06; 0.10	<.001	0.21	0.19; 0.23	<.001
Wave 1	Wave 2	N/A (all weights = 0)			0.19	0.16; 0.21	<.001
Wave 1	Wave 3	N/A (all weights = 0)			0.16	0.13; 0.18	<.001
Wave 2	Wave 3	0.04	0.02; 0.07	<.001	0.25	0.22; 0.27	<.001

Note: Personality domains and items were residualized for age, age^2, sex, and highest level of education. All *p*-values have been corrected for false discovery rate. Results for models predicting *change* in BMI are not depicted: All models were unable to predict change in BMI (weights were zero for all predictors).

TABLE 3 Personality traits' cross-sectional associations with BMI.

Personality trait	*b** (SE)	*t* (*df*)	*p*
Domains			
Agreeableness	−0.04 (0.01)	−6.57 (14,389)	<.001
Conscientiousness	−0.06 (0.01)	−11.28 (14,390)	<.001
Extraversion	−0.01 (0.01)	−2.27 (14,394)	.029
Neuroticism	0.00 (0.01)	−0.46 (14,360)	.645
Openness	−0.02 (0.01)	−2.50 (14,366)	.021
Selected items			
C3: Disorganized (R)	−0.04 (0.00)	−7.25 (14,010)	<.001
C4: Lazy (R)	−0.05 (0.00)	−10.43 (14,102)	<.001
E1: Talkative	0.02 (0.01)	4.34 (14,278)	<.001
E3: Full of energy	−0.11 (0.01)	−20.96 (14,104)	<.001
Domains excluding selected items			
Conscientiousness (excl. C3, C4)	−0.03 (0.01)	−6.43 (14,384)	<.001
Extraversion (excl. E1, E3)	0.02 (0.01)	2.87 (14,346)	.004
PPS	0.06 (0.00)	17.74 (10,958)	<.001

Note: Random-coefficients models accounting for age, sex, highest level of education, and family structure. Items are keyed in the direction implied by their domain; the items that were reversed to match their domains are marked with (R). Item labels indicate the content of the item but are not the items themselves.

Abbreviations: *b**, standardized estimate; PPS, polypersonality score.

after excluding the selected items (Table 5). Therefore, BMI also predicted Conscientiousness more broadly, not just the individual items. The weak, but statistically significant association with Extraversion became statistically nonsignificant after excluding E1: Talkativeness and E3: Full of energy.

The PPS did not predict change in BMI—so, just like personality traits could not predict change in BMI collectively in elastic net models, they did not predict change in BMI in MLMs. However, BMI predicted change in the PPS, suggesting that the direction of the associations is from BMI to personality traits.

Again, results were broadly similar in the graduate and sibling subsamples (Tables S14 and S15). As a difference, Agreeableness, Extraversion, and Neuroticism were also able to predict BMI in the graduate subsample, but the effects were only borderline statistically significant at $|b^*| = 0.01$.

3.4 | Within-person correlations: Associations accounting for time-invariant factors

Within-person correlations were found between BMI on one hand and Agreeableness, Conscientiousness, and Extraversion on the other hand (Table 5); this suggests correlated development in BMI and these traits that is

TABLE 4 Bidirectional longitudinal associations between BMI and personality traits.

	BMI (DV)			Personality trait (DV)		
Personality trait	*b** (SE)	*t* (*df*)	*p*	*b** (SE)	*t* (*df*)	*p*
Domains						
Agreeableness	0.01 (0.01)	2.15 (5518)	.078	−0.03 (0.01)	−5.59 (5561)	<.001
Conscientiousness	0.00 (0.01)	−0.01 (5516)	.989	−0.05 (0.01)	−9.15 (5559)	<.001
Extraversion	0.01 (0.01)	2.18 (5517)	.078	−0.01 (0.00)	−2.21 (5563)	.027
Neuroticism	−0.01 (0.01)	−1.77 (5507)	.128	0.00 (0.01)	−0.54 (5546)	.592
Openness	0.00 (0.01)	0.35 (5509)	.913	−0.01 (0.00)	−1.65 (5546)	.099
Selected items						
C3: Disorganized (R)	0.00 (0.01)	−0.78 (5383)	.581	−0.05 (0.01)	−8.31 (5303)	<.001
C4: Lazy (R)	−0.01 (0.01)	−0.98 (5419)	.581	−0.07 (0.01)	−10.06 (5371)	<.001
E1: Talkative	0.01 (0.00)	2.81 (5484)	.020	0.03 (0.01)	4.11 (5481)	<.001
E3: Full of energy	0.00 (0.01)	−0.08 (5425)	.935	−0.08 (0.01)	−12.80 (5389)	<.001
Domains excluding selected items						
Conscientiousness (excl. C3, C4)	0.01 (0.01)	1.22 (5516)	.222	−0.04 (0.01)	−6.85 (5557)	<.001
Extraversion (excl. E1, E3)	0.01 (0.01)	2.07 (5502)	.077	0.00 (0.00)	−0.85 (5534)	.397
PPS	0.01 (0.00)	1.68 (4291)	.092	0.19 (0.01)	14.33 (3361)	<.001

Note: Random-effects models with age, sex, highest level of education, family structure, and earlier measurements of the dependent variable accounted for. Item labels indicate the content of the item but are not the items themselves. Items are keyed in the direction implied by their domain; the items that were reversed to match their domains are marked with (R).

Abbreviations: *b**, standardized estimate; PPS, polypersonality score.

TABLE 5 Within-person correlations between BMI and personality traits.

Personality trait	*b** (*SE*)	*t* (*df*)	*p*
Domains			
Agreeableness	−0.03 (0.01)	−4.79 (14,258)	<.001
Conscientiousness	−0.03 (0.01)	−4.68 (14,259)	<.001
Extraversion	−0.02 (0.01)	−3.58 (14,263)	.001
Neuroticism	−0.01 (0.01)	−2.07 (14,229)	.048
Openness	0.01 (0.01)	1.49 (14,235)	.137
Selected items			
C3: Disorganized (R)	−0.01 (0.01)	−1.80 (13,883)	.072
C4: Lazy (R)	−0.03 (0.01)	−4.86 (13,977)	<.001
E1: Talkative	0.02 (0.01)	2.64 (14,148)	.011
E3: Full of energy	−0.09 (0.01)	−13.91 (13,976)	<.001
Domains excluding selected items			
Conscientiousness (excl. C3, C4)	−0.02 (0.01)	−2.65 (14,253)	.016
Extraversion (excl. E1, E3)	0.00 (0.01)	0.43 (14,215)	.666
PPS	0.07 (0.01)	11.58 (10,865)	<.001

Note: Fixed-coefficients multilevel models accounting for changes in age and highest level of education as well as family structure. Items are keyed in the direction implied by their domain; the items that were reversed to match their domains are marked with (R). Item labels indicate the content of the item but are not the items themselves.

Abbreviations: *b**, standardized estimate; PPS, polypersonality score.

independent of time-invariant factors like genetics or early-life experiences. A within-person association with Neuroticism was similarly found, but this link was only borderline statistically significant. Within-person associations with Conscientiousness remained significant even after excluding its items most strongly associated with BMI, suggesting that BMI was associated with this trait as a domain rather than only relating to certain narrower traits within it. Within-person associations were also found with C4: Lazy, but not C3: Disorganized. In the case of Extraversion, BMI had within-person associations with both E1: Talkative and E3: Full of energy, but not with the domain excluding these items. Lastly, BMI also had a within-person correlation with PPS. The results were broadly similar in the two subsamples (Tables S16 and S17).

All in all, because BMI had within-person correlations with Agreeableness, Conscientiousness and the items C4: Lazy and E3: Full of Energy, and because change in BMI predicted changes in the same traits in the longitudinal models, the results are consistent with influences of BMI on these traits. The results of the bidirectional and within-person models are summarized in Figure 1.

4 | DISCUSSION

Understanding the associations between personality and body weight has theoretical and practical implications, possibly informing what types of processes contribute to their development and clarifying whether personality trait measurements could be used in weight-management programs. We tested the bidirectional associations between personality traits and BMI in a large sample of adults to understand whether traits can predict future BMI and vice versa, and whether the associations were consistent with causal influences between them in either direction. Personality traits predicted future BMI in elastic net models (r = 0.16 ... 0.25) but did not predict change in BMI. BMI, on the other hand, did predict subsequent changes in Conscientiousness, Agreeableness, and several narrower personality traits represented by individual items ($|b^*|$ = 0.03 ... 0.08). Within-person correlations between these personality traits and BMI support influences of BMI on these traits as these associations are free from confounding by time-invariant factors, suggesting that BMI can contribute to personality trait development. In contrast to what may have been expected, causality in the opposite direction was not supported.

4.1 | Personality traits and future BMI

In elastic net models, personality items predicted BMI with substantially greater accuracy than domains did—in most cases, personality domains were unable to predict future BMI, depending on the particular study waves included in the analysis. These results are consistent with those reported by Seeboth and Mõttus (2018) who predicted BMI 5 years later using a similar procedure and similarly found item-based models to be substantially more useful than domain-based models. Considering that the three waves of the study covered a span of approximately 18 years, it is evident that personality items contain information that can be used to predict BMI over long periods. Moreover, considering that only 29 items were used in the models, the predictive accuracy was relatively strong at r = 0.16 ... 0.25; in comparison, previous studies have found personality items' collective association with BMI to be r = 0.12 (cross-sectionally, using 238 items of the NEO-PI-3; Arumäe et al., 2021) or 0.19 (5 years into the future, using 50 items of the International Personality Item Pool; Seeboth & Mõttus, 2018). Perhaps the specific items included in the BFI captured relevant variance in personality at least as well as the more numerous items in the previous studies or perhaps the relatively high predictive accuracy is due to greater variance in the current sample in particular. But either way, the results suggest

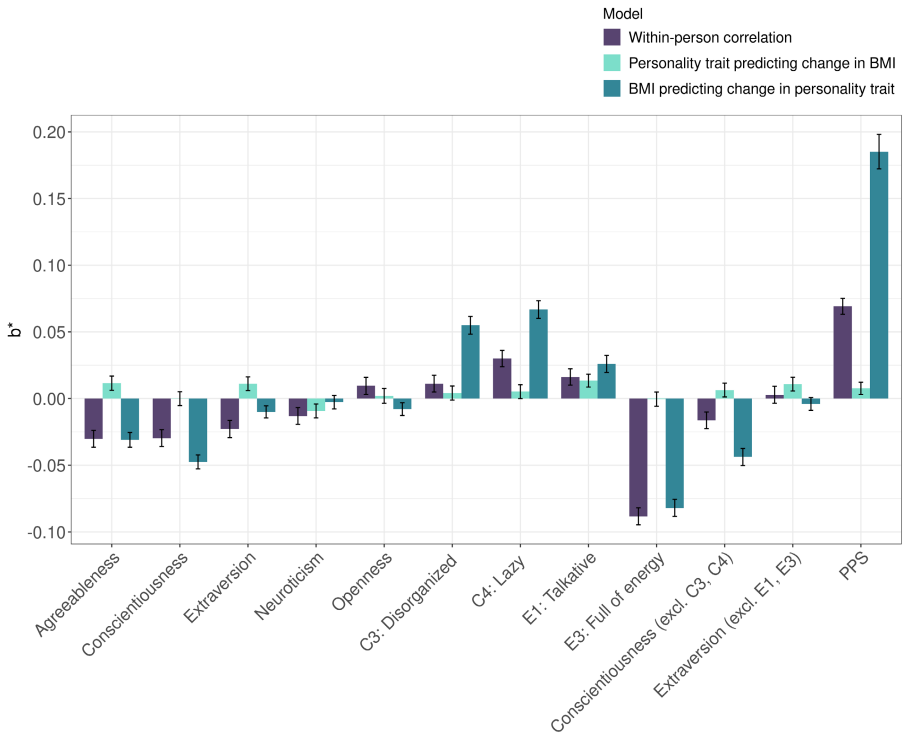

FIGURE 1 Associations between BMI and personality traits in bidirectional and within-person nodels. Error bars show standard errors. Items are keyed in their original direction. *b**, standardized estimate; PPS, polypersonality score.

that personality items can be useful in predicting future BMI while the utility of domains for this purpose is questionable.

However, the personality items did not predict subsequent *change* in BMI which is more telling in terms of possible causal associations: If personality traits influence body weight, then they would be expected to predict change in it. Trait-level analyses similarly indicated that individual personality traits did not predict change in BMI. Of the FFM domains, Neuroticism and Openness had no longitudinal associations with BMI, Extraversion was mainly related to BMI through its item reflecting energy levels and talkativeness, and Conscientiousness and Agreeableness were predicted by BMI but did not predict it in turn. Moreover, the fact that even single items (which generally have stronger relations with BMI than domains; Arumäe, Vainik, et al., 2022) did not predict change in BMI further casts doubt on personality traits having meaningful influences on body mass.

Considering the widespread expectation that personality traits influence body weight or health in general (Bogg & Roberts, 2004; Friedman, 2008; Sutin & Terracciano, 2017) as well as the empirical findings supporting such relations (Jokela et al., 2013; Sutin et al., 2011), these results are unexpected. This is especially true for Conscientiousness which can predict various other health outcomes (Friedman et al., 2014; Hampson et al., 2015; Roberts et al., 2005). The results also counter the stereotype that high body weight is a result of laziness, which could lead to people with obesity being blamed for their obesity (Schwartz et al., 2003), suggesting that (self-reported) laziness follows higher body weight rather than causing it. However, although no effect of personality traits on subsequent body weight was found, the results did indicate that the longitudinal associations between personality traits and BMI differed between people, suggesting that personality traits may still be relevant in shaping body weight in some individuals, even if such effects do not pertain to most people. Besides psychological traits, weight gain is influenced by factors as diverse as obesogenic food environments, government policies, sedentary lifestyles, some types of infections, certain medications, and sleep deprivation (Wright & Aronne, 2012). Given the diversity of factors that contribute to body weight, the relevance of each of those factors should also be expected to vary across people—and that includes personality traits. For instance, low self-control, a trait that has been linked to BMI (Gerlach et al., 2015), could contribute to excessive eating and thus weight gain in someone who lives in a household where unhealthy snacks are constantly available but be less of a problem for someone living in a household where the food environment is more strictly regulated. The same could apply to any other personality trait. Although the associations say little about whether deliberate change in

personality traits could lead to weight change, to the extent that it does, considering personality traits in weight-management programs may then benefit some and make no difference for others.

4.2 | BMI and future personality traits

In contrast, higher BMI predicted lower scores on Agreeableness, Conscientiousness, and the items E3: Full of energy and higher scores on the items E1: Talkative, C3: Disorganized, and C4: Lazy. Although BMI predicted a tendency to be disorganized longitudinally, third factors likely accounted for this association as no within-person correlation was found between BMI and this trait. However, because there were within-person correlations between BMI and each of the other traits in addition to them having longitudinal relations, the results are consistent with BMI having influences on these traits. In line with previous findings from genetic analyses across a wide range of ages (Arumäe et al., 2021), the current results suggest BMI contributes to personality trait development; health-related variables may thus be potential sources of differences in or development of personality traits. Associations with the PPS, an aggregate of personality traits weighted by their correlations with BMI, further support the conclusion that influences flow from BMI to personality traits unidirectionally. However, because these associations also differed between people, the relevance of BMI to subsequent changes in personality traits seems to be idiosyncratic. And yet, in the case of the aforementioned traits, the links were prominent enough to produce sample-level associations.

In general, BMI predicted changes in the same traits it had cross-sectional associations with, although it did not predict changes in the Extraversion domain independently of its items E1: Talkative and E3: Full of energy. Thus, the BMI–Extraversion association may have arisen due to confounding rather than causality. The longitudinal associations were also comparable in size to the cross-sectional ones. As an exception, the longitudinal association between BMI and the PPS, which included all 29 items, was appreciably larger ($b^* = 0.19$) than their cross-sectional correlation ($b^* = 0.06$). Assuming a causal effect of body weight on personality traits, this make sense: As more time is available for body weight to exert its effect on the personality traits, the correlation between BMI (measured at one time point) and the relevant personality traits (measured at various intervals from the measurement of BMI) could be reasonably expected to get stronger. Yet, there were no stark differences between the cross-sectional and longitudinal associations among the traits analyzed individually, suggesting that some of the other processes that contribute to either body weight or personality may have canceled out any increases that would have otherwise been seen in their longitudinal correlations.

Because BMI is not only a measure of body weight but also an index of various health concerns (Nuttall, 2015), the longitudinal and within-person associations can be interpreted as either health status in general or body mass in specific having influences on personality traits. Deteriorating health, which tends to be associated with increasing age, could influence personality traits through the onset of chronic diseases (Goodman et al., 2013). For instance, various diseases are accompanied by feelings of fatigue and lower energy levels (de Ridder et al., 2008) which is in line with higher BMI predicting lower energy levels and higher reported laziness. Lower energy levels can in turn decrease a person's ability to complete everyday tasks with their usual efficiency and thoroughness, potentially leading to lower reported Conscientiousness. Lower levels of Agreeableness could similarly be explained by the effects of physical illness: For example, physical discomfort or the increased need for support could potentially decrease concern for or patience toward others (Jokela et al., 2014; Stanton et al., 2007).

But previous studies provide only partial support for disease status having influences on these traits. In assessing whether chronic diseases predict changes in personality traits, Jokela et al. (2014) found chronic disease to predict decreases in Conscientiousness, but the two were unrelated in another study by Sutin, Zonderman, et al. (2013); neither of the studies found chronic illnesses to predict changes in Agreeableness. Because the associations of disease and BMI with changes in personality traits are inconsistent across studies, it is unclear whether (or to what extent) BMI is associated with personality traits because it indexes physical health generally. Of course, the differences may be due to different studies having measured the same domains using different personality items, but it is impossible to tell whether or not this is the case based on domain-level associations alone.

Personality traits may also be influenced by body mass specifically rather than health in general. Similar to what we found in the current study, Lahti et al. (2013) reported slower growth in BMI and body weight from childhood to adulthood to be associated with higher Agreeableness and Conscientiousness. In light of their results as well as those of the current study, the processes that link body weight to Agreeableness and Conscientiousness seem to operate throughout life rather than being specific to certain developmental periods. Such lifelong associations speak against the association being driven by illnesses and suggest that body weight is the driving factor behind the associations. As for possible mechanisms, lower Agreeableness could be the result of the stigma and discrimination faced by

people with high body weight (Puhl & King, 2013): If people are treated differently based on their body weight, the social feedback they receive could affect their behavior accordingly. Higher body weight could also have effects similar to those of chronic disease in that it could limit physical functioning (Woo et al., 2007) and, therefore, energy levels and energy-requiring activities including many daily tasks, also leading to lower self-reports of Conscientiousness. Of course, one pathway of influence does not preclude another; multiple causal pathways are likely to be involved in the associations between personality and health variables (Friedman, 2008) and changes in personality traits may result from change in body weight as well as the other aspects of health that BMI indexes.

Whatever the mechanisms, however, the results support BMI as a contributor to personality differences or their development. Despite the hypothesis that personality traits are largely rooted in biology (McCrae & Sutin, 2018), little is known about the specific biological factors that contribute to their development and doubt has been expressed concerning the possibility of identifying such factors (Turkheimer et al., 2014). Attempts to identify life experiences that contribute to personality change have been similarly inconclusive (Bleidorn et al., 2020). The correlates of personality trait change, biological (like health variables) or otherwise, have thus remained elusive. However, the current results combined with evidence from previous twin-based and molecular genetic analyses (Arumäe et al., 2021) indicate that body weight may well be one of the first consistent correlates of trait change that has been identified. Given the relevance of personality traits in mental health as well as quality of life more generally (Lamers et al., 2012; Wrosch & Scheier, 2003), body weight could ultimately contribute to an individual's well-being through its effects on psychological traits. Whether deliberate weight change results in changes in personality traits remains unclear, but deserves attention in future studies.

4.3 | Limitations

While the strengths of the study included a large sample and an analytic strategy that enabled controlling for a broad range of potential confounds, it also had several limitations. First, despite controlling for the effects of time-invariant factors as well as age and level of education which could all affect the links between BMI and personality traits, we could not rule out the possible effects of unmeasured time-varying factors in testing whether personality traits' associations with BMI were consistent with causality. Therefore, unknown third variables could still have given rise to the associations instead of causal processes. An additional caveat is that although the results of the longitudinal and within-person MLMs seemed to align with each other, the longitudinal associations should not be interpreted as reflecting only within-person associations because between-person effects additionally contributed to them. Yet, we did observe that within-person effects often accounted for a larger proportion of the variance than between-person effects in the longitudinal models with personality traits as outcomes, suggesting that BMI and personality traits did not relate to each other solely due to stable individual differences (i.e., non-causal mechanisms).

The sample was also relatively homogeneous in terms of age and cultural background and the results may therefore not generalize to different samples: Different associations may be found in other cultures or age groups. An additional limitation is one that this study shares with any other study that relies on BMI: This index of body weight reflects lean mass in addition to fat mass and can therefore conflate the two. Yet, BMI broadly relates to the same personality traits as skinfold thickness, waist circumference, and an estimate of fat mass based on waist circumference (Arumäe, Mõttus, et al., 2022; Sutin et al., 2011). But still, relying on self-reported height and weight data in two of the three study waves may have additionally suppressed BMI's associations with personality traits (see Roehling et al., 2008).

Further, focusing on individual personality items allowed us to test more specific associations than relying only on domains would have, but the 29-item personality inventory did not provide a comprehensive representation of all personality traits—there are many more items that can be mapped to the FFM domains (Mõttus et al., 2019). Attempts to clarify the associations between personality traits and BMI would benefit from a broader set of items. Additionally, internal consistencies of the personality domains (particularly Openness) were low, limiting the upper bound of the domains' associations with BMI—however, this does not affect item-level associations. Another limitation pertains to the small number of time points. Although three measurement waves are sufficient for parameter estimation in two-level MLMs, a larger number of time points would contribute to more precise estimates of the standard errors (West et al., 2011). And finally, the three waves of the study covered a time span of about 18 years. Although long time spans allow the possible influences between body weight and personality traits to exert themselves and are therefore likely well-suited to test their associations, it is unclear what the optimal time span would be: Considering that BMI and personality trait levels can fluctuate, the effects between them may wax and wane over time and might actually be reversed during long periods (Luhmann et al., 2014).

4.4 | Conclusion

In sum, we found that BMI had within-person correlations with Agreeableness, Conscientiousness, and several personality items and that it also predicted changes in the same traits in a large sample of adults over time intervals of about 7 to 11 years. The associations were consistent with causal influences of BMI on these personality traits, suggesting that either body weight or health status more generally may influence them. BMI may thus be among the currently poorly understood correlates of personality development. In contrast, although personality traits were collectively able to predict future BMI, no clear support was found for causal influences of personality traits on BMI.

FUNDING INFORMATION

This research uses data from the Wisconsin Longitudinal Study, funded by the National Institute on Aging (R01 AG009775; R01 AG033285; R01 AG060737), available at https://www.ssc.wisc.edu/wlsresearch/. Uku Vainik and Kadri Arumäe were funded by Estonian Research Council's grant PSG759.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION

KA, RM, UV: study conceptualization; KA: data preparation and analyses; KA: drafting the manuscript; KA, RM, UV: review and editing of the manuscript.

ETHICS STATEMENT

The present study uses publicly available data, ethical approval was not sought.

ORCID

Kadri Arumäe https://orcid.org/0000-0001-9950-904X
René Mõttus https://orcid.org/0000-0002-6403-5224
Uku Vainik https://orcid.org/0000-0002-9375-9520

ENDNOTE

[1] Although alternative approaches to modeling within-person associations exist within the structural equation modeling framework (see Bainter & Howard, 2016 for a comparison of various approaches), many have assumptions that most longitudinal datasets used by psychologists do not meet, like the assumption of equal time intervals between measurements. Thus, here we rely on the multilevel modeling framework.

REFERENCES

Anusic, I., & Schimmack, U. (2016). Stability and change of personality traits, self-esteem, and well-being: Introducing the meta-analytic stability and change model of retest correlations. *Journal of Personality and Social Psychology*, *110*(5), 766–781. https://doi.org/10.1037/pspp000006

Armon, G., Melamed, S., Shirom, A., Shapira, I., & Berliner, S. (2013). Personality traits and body weight measures: Concurrent and across-time associations. *European Journal of Personality*, *27*(4), 398–408. https://doi.org/10.1002/per.1902

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*, *45*(10), 2244–2251. https://doi.org/10.1038/s41366-021-00885-4

Arumäe, K., Mõttus, R., & Vainik, U. (2022). Beyond BMI: Personality traits' associations with adiposity and metabolic rate. *Physiology & Behavior*, *246*, 113703. doi:10.1016/j.physbeh.2022.113703

Arumäe, K., Vainik, U., & Mõttus, R. (2022). Body mass is linked with a broad range of personality nuances, but especially those with behavioral content: A multi-sample exploration. *Personality Science*, *3*, 1–26.

Bagnjuk, J., König, H.-H., & Hajek, A. (2019). Personality traits and obesity. *International Journal of Environmental Research and Public Health*, *16*(15), 2675. https://doi.org/10.3390/ijerph16152675

Bainter, S. A., & Howard, A. L. (2016). Comparing within-person effects from multivariate longitudinal models. *Developmental Psychology*, *52*(12), 1955–1968. https://doi.org/10.1037/dev0000215

Bleidorn, W., Hopwood, C. J., Back, M. D., Denissen, J. J. A., Hennecke, M., Jokela, M., Kandler, C., Lucas, R. E., Luhmann, M., Orth, U., Roberts, B. W., Wagner, J., Wrzus, C., & Zimmermann, J. (2020). Longitudinal experience-wide association studies—A framework for studying personality change. *European Journal of Personality*, *34*(3), 285–300. https://doi.org/10.1002/per.2247

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

Brummett, B. H., Babyak, M. A., Williams, R. B., Barefoot, J. C., Costa, P. T., & Siegler, I. C. (2006). NEO personality domains and gender predict levels and trends in body mass index over 14 years during midlife. *Journal of Research in Personality*, *40*(3), 222–236. https://doi.org/10.1016/j.jrp.2004.12.002

Charles, S. T., Gatz, M., Kato, K., & Pedersen, N. L. (2008). Physical health 25 years later: The predictive ability of neuroticism. *Health Psychology*, *27*(3), 369–378.

Daly, M., McMinn, D., & Allan, J. L. (2015). A bidirectional relationship between physical activity and executive function in older adults. *Frontiers in Human Neuroscience*, *8*, 1044. https://doi.org/10.3389/fnhum.2014.01044

de Ridder, D., Geenen, R., Kuijer, R., & van Middendorp, H. (2008). Psychological adjustment to chronic disease. *The Lancet*, *372*(9634), 246–255. https://doi.org/10.1016/S0140-6736(08)61078-8

Friedman, H. S. (2008). The multiple linkages of personality and disease. *Brain, Behavior, and Immunity*, *22*(5), 668–675. https://doi.org/10.1016/j.bbi.2007.09.004

Friedman, H. S., Kern, M. L., Hampson, S. E., & Duckworth, A. L. (2014). A new life-span approach to conscientiousness and health: Combining the pieces of the causal puzzle. *Developmental Psychology*, *50*(5), 1377–1389. https://doi.org/10.1037/a0030373

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, *33*(1), 1–22. https://doi.org/10.18637/jss.v033.i01

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

Goodman, R. A., Posner, S. F., Huang, E. S., Parekh, A. K., & Koh, H. K. (2013). Defining and measuring chronic conditions: Imperatives for research, policy, program, and practice. *Preventing Chronic Disease*, *10*, E66. https://doi.org/10.5888/pcd10.120239

Hampson, S. E., Edmonds, G. W., Goldberg, L. R., Dubanoski, J. P., & Hillier, T. A. (2015). A life-span behavioral mechanism relating childhood conscientiousness to adult clinical health. *Health Psychology*, *34*(9), 887–895. https://doi.org/10.1037/hea0000209

Hauser, R. M., Sewell, W. H., & Herd, P. (2020). *Wisconsin longitudinal study (WLS) [graduates, siblings, and spouses]: 1957–2020 (version 13.07) [machine-readable data file]*. http://www.ssc.wisc.edu/wlsresearch/documentation/

Herd, P., Carr, D., & Roan, C. (2014). Cohort profile: Wisconsin longitudinal study (WLS). *International Journal of Epidemiology*, *43*(1), 34–41.

Herman, K. M., Craig, C. L., Gauvin, L., & Katzmarzyk, P. T. (2009). Tracking of obesity and physical activity from childhood to adulthood: The physical activity longitudinal study. *International Journal of Pediatric Obesity*, *4*(4), 281–288. https://doi.org/10.3109/17477160802596171

John, O. P., Donahue, E. M., & Kentle, R. L. (1991). Big Five inventory. *Journal of Personality and Social Psychology*, *60*, 348–361.

Jokela, M., Airaksinen, J., Kivimäki, M., & Hakulinen, C. (2018). Is within–individual variation in personality traits associated with changes in health behaviours? Analysis of seven longitudinal cohort studies. *European Journal of Personality*, *32*(6), 642–652. https://doi.org/10.1002/per.2173

Jokela, M., Hakulinen, C., Singh-Manoux, A., & Kivimäki, M. (2014). Personality change associated with chronic diseases: Pooled analysis of four prospective cohort studies. *Psychological Medicine*, *44*(12), 2629–2640. https://doi.org/10.1017/S0033291714000257

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

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

Lamers, S. M. A., Westerhof, G. J., Kovács, V., & Bohlmeijer, E. T. (2012). Differential relationships in the association of the big five personality traits with positive mental health and psychopathology. *Journal of Research in Personality*, *46*(5), 517–524. https://doi.org/10.1016/j.jrp.2012.05.012

Luhmann, M., Orth, U., Specht, J., Kandler, C., & Lucas, R. E. (2014). Studying changes in life circumstances and personality: It's about time. *European Journal of Personality*, *28*(3), 256–266. https://doi.org/10.1002/per.1951

Magee, C. A., Heaven, P. C., & Miller, L. M. (2013). Personality change predicts self-reported mental and physical health. *Journal of Personality*, *81*(3), 324–334.

Magee, C. A., & Heaven, P. C. L. (2011). Big-five personality factors, obesity and 2-year weight gain in Australian adults. *Journal of Research in Personality*, *45*(3), 332–335. https://doi.org/10.1016/j.jrp.2011.02.009

McCrae, R. R., & John, O. P. (1992). An introduction to the Five-Factor Model and its applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McCrae, R. R., & 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

Mõttus, R., Sinick, J., Terracciano, A., Hřebíčková, M., Kandler, C., Ando, J., Mortensen, E. L., Colodro-Conde, L., & Jang, K. L. (2019). Personality characteristics below facets: A replication and meta-analysis of cross-rater agreement, rank-order stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*, *117*, e35–e50. https://doi.org/10.1037/pspp0000202

Mõttus, R., Wood, D., Condon, D. M., Back, M. D., Baumert, A., Costantini, G., Epskamp, S., Greiff, S., Johnson, W., & Lukaszewski, A. (2020). Descriptive, predictive and explanatory personality research: Different goals, different approaches, but a shared need to move beyond the big few traits. *European Journal of Personality*, *34*(6), 1175–1201.

Mueller, S., Wagner, J., Smith, J., Voelkle, M. C., & Gerstorf, D. (2018). The interplay of personality and functional health in old and very old age: Dynamic within-person interrelations across up to 13 years. *Journal of Personality and Social Psychology*, *115*(6), 1127–1147. https://doi.org/10.1037/pspp0000173

Nakagawa, S., Johnson, P. C. D., & Schielzeth, H. (2017). The coefficient of determination R^2 and intra-class correlation coefficient from generalized linear mixed-effects models revisited and expanded. *Journal of the Royal Society Interface*, *14*(134), 20170213. https://doi.org/10.1098/rsif.2017.0213

Nuttall, F. Q. (2015). Body mass index: Obesity, BMI, and health: A critical review. *Nutrition Today*, *50*(3), 117–128. https://doi.org/10.1097/NT.0000000000000092

Pinheiro, J., Bates, D., & R Core Team (2022). *nlme: Linear and nonlinear mixed effects models*. R package version 3.1-159. https://CRAN.R-project.org/package=nlme

Puhl, R. M., & King, K. M. (2013). Weight discrimination and bullying. *Best Practice & Research Clinical Endocrinology & Metabolism*, *27*(2), 117–127. https://doi.org/10.1016/j.beem.2012.12.002

Roberts, B. W., Walton, K. E., & Bogg, T. (2005). Conscientiousness and health across the life course. *Review of General Psychology*, *9*(2), 156–168. https://doi.org/10.1037/1089-2680.9.2.156

Roehling, M. V., Roehling, P. V., & Odland, L. M. (2008). Investigating the validity of stereotypes about overweight employees: The relationship between body weight and normal personality traits. *Group & Organization Management*, *33*(4), 392–424. https://doi.org/10.1177/1059601108321518

Rohrer, J. M., & Murayama, K. (2021). These are not the effects you are looking for: Causality and the within−/between-person

distinction in longitudinal data analysis. *PsyArXiv*. https://doi.org/10.31234/osf.io/tg4vj

Schwartz, M. B., Chambliss, H. O., Brownell, K. D., Blair, S. N., & Billington, C. (2003). Weight bias among health professionals specializing in obesity. *Obesity Research*, *11*(9), 1033–1039. https://doi.org/10.1038/oby.2003.142

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

Stanton, A. L., Revenson, T. A., & Tennen, H. (2007). Health psychology: Psychological adjustment to chronic disease. *Annual Review of Psychology*, *58*(1), 565–592. https://doi.org/10.1146/annurev.psych.58.110405.085615

Stephan, Y., Sutin, A. R., & Terracciano, A. (2019). Change in weight and personality in middle-aged and older adults. *Psychology & Health*, *15*, 872–886. https://doi.org/10.1080/08870446.2019.1679372

Sutin, A. 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.

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., Rogers, D. L., Mercado, A., Weimer, A., Rodriguez, C. C., Gonzalez, M., Robins, R. W., Schwartz, S. J., & Terracciano, A. (2015). The association between personality traits and body mass index varies with nativity among individuals of Mexican origin. *Appetite*, *90*, 74–79.

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

Sutin, A. R., Zonderman, A. B., Ferrucci, L., & Terracciano, A. (2013). Personality traits and chronic disease: Implications for adult personality development. *The Journals of Gerontology: Series B*, *68*(6), 912–920. https://doi.org/10.1093/geronb/gbt036

Turiano, N. A., Pitzer, L., Armour, C., Karlamangla, A., Ryff, C. D., & Mroczek, D. K. (2012). Personality trait level and change as predictors of health outcomes: Findings from a national study of americans (MIDUS). *The Journals of Gerontology: Series B*, *67B*(1), 4–12. https://doi.org/10.1093/geronb/gbr072

Turkheimer, E., Pettersson, E., & Horn, E. E. (2014). A phenotypic null hypothesis for the genetics of personality. *Annual Review of Psychology*, *65*(1), 515–540. https://doi.org/10.1146/annurev-psych-113011-143752

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

West, S. G., Ryu, E., Kwok, O.-M., & Cham, H. (2011). Multilevel modeling: Current and future applications in personality research. *Journal of Personality*, *79*(1), 2–50. https://doi.org/10.1111/j.1467-6494.2010.00681.x

Weston, S. J., Hill, P. L., & Jackson, J. J. (2015). Personality traits predict the onset of disease. *Social Psychological and Personality Science*, *6*(3), 309–317. https://doi.org/10.1177/1948550614553248

Woo, J., Leung, J., & Kwok, T. (2007). BMI, body composition, and physical functioning in older adults. *Obesity*, *15*(7), 1886–1894. https://doi.org/10.1038/oby.2007.223

Wright, A. J., Weston, S. J., Norton, S., Voss, M., Bogdan, R., Oltmanns, T. F., & Jackson, J. J. (2022). Prospective self- and informant-personality associations with inflammation, health behaviors, and health indicators. *Health Psychology*, *41*(2), 121–133. https://doi.org/10.1037/hea0001162

Wright, S. M., & Aronne, L. J. (2012). Causes of obesity. *Abdominal Radiology*, *37*(5), 730–732. https://doi.org/10.1007/s00261-012-9862-x

Wrosch, C., & Scheier, M. F. (2003). Personality and quality of life: The importance of optimism and goal adjustment. *Quality of Life Research*, *12*(1), 59–72. https://doi.org/10.1023/A:1023529606137

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

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *67*(2), 301–320. https://doi.org/10.1111/j.1467-9868.2005.00503.x

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Arumäe, K., Mõttus, R., & Vainik, U. (2023). Body mass predicts personality development across 18 years in middle to older adulthood. *Journal of Personality*, *00*, 1–15. https://doi.org/10.1111/jopy.12816