Research Article

Neuroticism and BMI: The role of genetic tendency, behavior and environment on body weight

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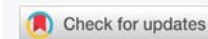
Abstract

Introduction: Recent research has explored the role that personality traits play in health and weight determination. This study extends current research by evaluating the extent to which behavior mediates the impact of neuroticism and body weight using polygenic risk as a measure of neurotic tendency.

Methods: Structural equation modelling disaggregates the effect of neurotic tendency on BMI into direct and indirect effects. Indirect effects-those transmitted through mediating health behaviors—allow for the simultaneous comparison of multiple behavioral mediators— exercise frequency, smoking intensity, sleep sufficiency and screen time.

Results: While health-related behavior-screen time, sleep, smoking and exercise-directly influence BMI, neurotic tendency showed no direct effect. The strong association between neurotic tendency and behavior, however, indicated that polygenic risk of neuroticism indirectly influenced BMI through two health related behaviors-screen time and smoking. Therefore, the relationship between neurotic disposition and BMI is transmitted through behavioral pathways rather than directly.

Conclusion: This research offers novel insight into the relationship between personality and health outcomes. If behavior manifests through personality disposition, then understanding the relationship between personality, behavior and BMI will help guide weight management interventions to focus on strategies to help manage responses to stress to elicit desired weight outcomes.

Introduction

Public health and medical researchers have dedicated ample resources to discovering the critical determinants of body weight. Studies have documented a variety of social, demographic, and genetic factors associated with body weight, but they may not explain all the observed heterogeneity. Recently, personality traits that describe individual disposition and behavior have received attention for the role they play in individual health and weight [1]. Increasing evidence suggests that personality traits substantially contribute to health and health behavior [2].

However, the relationship between personality traits and body weight is confounded by family fixed effects, individual behavior, and genetic backgrounds [3]. Among the "big five" personality traits, conscientiousness and neuroticism have shown the strongest association with body weight and garnered the most attention among social scientist [4-7].

However, studies have shown that neuroticism is associated with low BMI [8], high rates of obesity [9,10] and it has no relationship with body weight [11].

This study builds upon previous research by examining the association between neuroticism and weight using an objective measure of neurotic tendency-polygenic risk score (PGS)—calculated from individual genetic data. A structural equation framework evaluates the relationship controlling for genetic, family and individual effects. Mediation analysis test whether the neuroticism/weight relationship is mediated by behavior disaggregating the total effect into a direct effect of PGS on body mass index (BMI) and an indirect effect-as transmitted through exercise, smoking, screen time and sleep-accounting for the extent to which behavioral factors mediate this association. Results show that association between BMI and neuroticism is mediated by smoking and exercise frequency and may be modified by the context in which individuals live. In addition, the study examines whether the associations vary by ancestral background.

Neuroticism is defined as a long-term tendency to be in a negative or anxious emotional state. It is not a medical condition but a personality trait. People with neuroticism tend to have more depressed moods and suffer from feelings of guilt, envy, anger, and anxiety more frequently and more severely than other individuals [13]. Previous studies have shown evidence of robust associations between elevated scores of neuroticisms and obesity [4,5,13], suggesting a positive association between neuroticism and BMI. Neuroticism has been associated with both extremes of the BMI distribution-obese and underweight—and increased risk of unhealthy BMI [13-15]. In general, correlations were stronger for women and older individuals, and certain minority groups [16].

Much of the personality associations is likely due to the behavioral tendencies associated with these traits. Studies have reported that conscientious individuals high on are more physically active [17], less likely to overeat [18] and more like to report disordered eating [19]. Behavioral factors have been reported to account for as much as 50% of the association between personality and BMI [13]. Therefore, behaviors should be in investigations of personality and BMI as they could likely mediate any observed associations.

Neuroticism, depression, and well-being are, to some extent, heritable [20-23], similar to biological and personal characteristics [24,25]. Research has found robust associations between neuroticism and cardiovascular disease, type 2 diabetes, BMI, weight gain and a variety of psychiatric symptoms [14,15,26,27]. However, it is unclear how these personality traits relate to health outcomes. Some hypothesize that behavioral differences, such as alcohol and tobacco use, sex or exercise, could account for the effect of personality on physical health [28-31]. Neurotic individuals could be more focused on weight leading to higher levels of exercise and more controlled dietary habits [18,32-35].

Demographic characteristics such as gender, age and race/ethnicity, rather than behavior, could moderate the association between personality and BMI [9,13,36-38], as different cohorts have shown different levels of association between personality traits and physical outcomes [8,37-41].

The present study examines the relationship between genetic risk of neuroticism and BMI evaluating the extent to which behavior and demographic factors mediate the observed impact. Extending beyond previous analyses which used surveys, questionnaires or self-assessments of personality as indicators of personality, this analysis uses polygenic risk score (PGR) as a measure of neurotic tendency [42]. PGS provides a measure of the cumulative additive genetic influences on neuroticism which is standard across individuals [43,44]. It is important to note that PGS measures risk of neuroticism, rather than current individual level of neurotic tendency. Many of the current studies are based on cross-sectional data, this paper uses a longitudinal panel capturing health status and behavior at various points in time. While the concept of linking personality traits and health outcomes is not unique, examining the association between genetic tendencies toward a personality traits and BMI while assessing the degree to behavior mediates the observed effect is novel to this work.

Materials and Methods

Data

Analysis utilizes the first three waves of data from the National Longitudinal Study of Adolescent to Adult Health (Add Health)-a longitudinal study of adolescents in grades 7-12 during the 1994-95 school year followed into young adulthood with in-home interviews. Waves I, II, and III were conducted in September 1994-December 1995, April 1996-August 1997 and August 2001-April 2002, respectively and contain consistent elements allowing longitudinal assessment of environmental, behavioral, and demographic controls. Mean values for all covariates are provided in table 1.

Genetic covariates

Identifying the biological pathways and genes associated with neuroticism has the potential to facilitate understanding of the physiological components [45]. As with other complex disorders, neuroticism appears to be a multifactorial, polygenic trait, influenced by multiple environmental factors and genetic loci whose individual effects are small [46]. Since individual effects are small, one way to identify causal variants is to consider the cumulative associations of multiple single nucleotide polymorphisms (SNPs) simultaneously [47].

One way to examine the aggregate influence of multiple genetic markers is by generating a polygenic risk score (PGS) based on results from a genome-wide association studies (GWAS). A PGS can be thought of as a measure of 'genetic burden' associated with a phenotype [48]. PGSs are generated by running a GWAS on a discovery sample, selecting SNPs on the basis of their association with the phenotype, and creating a sum of their phenotype-associated alleles (often weighted by the SNP-specific coefficients from the GWAS), that can be evaluated in a separate replication sample [44,49,50]. PGS serves as the best prediction for the trait that can be made when considering variation in multiple genetic variants. A PGS explains at least a few percent of a phenotype's variance and can therefore be assumed to effectively incorporate a significant fraction of the genetic variants affecting the phenotype. PGS represent a weighted sum of the associations between allele frequencies and the associated phenotype resulting in a free measure of the cumulative additive genetic influences on the phenotype being studied. This allows researchers to capture the broad influence of genetics in various analyses [44,50].

Approximately 80% of Add Health respondents provided saliva samples enabling calculation of genotyped data for four

genetic ancestry groups of Add Health respondents-European ancestry, African ancestry, Hispanic ancestry, and East Asian ancestry. Since results comparing PGSs for individuals of different ancestry groups may be less predictive and PGSs are standardized within ancestry groups to account for between-group population stratification, ancestral groups are analyzed separately [51,52].

To further control for within-group population stratification, principal components (PCs) of the genome-wide data are included in analyses [53,54]. In a structural equation framework, estimation would not allow for the inclusion of all PCs due to problems of multicollinearity. Therefore, this study calculated a weighted linear combination of the PCs where each item's weight is its factor loading representing its contribution. This index measure accounts for the within group variation and stratification of genetic structure using a single, weight component.

Other covariates

Age, gender, school enrollment, residence in the south and general health perception were included as demographic conditions given their association with BMI and behavior. Age was measured continuously while school enrollment, southern residence and gender were modeled dichotomously. General health captures respondents' categorical classifications of overall health: 1-excellent, 2-very good, 3-good, 4-fair and 5-poor.

Dependent variable

Self-reported weight and height are used to construct measurement-error adjusted BMI (weight in kilograms divided by height in meters squared) for individuals by wave. For ease of statistical inference, the logarithm of BMI is used as the dependent variable.

Potential mediators

Exercise frequency, smoking intensity, sleep sufficiency and screen time were tested as potential behavioral mediators. Exercise, ranging from zero to 20, captures how many times in the past week respondents exercised or went to a fitness center to workout. Cigarette smoking includes the number of days in the last month that respondents smoked cigarettes and ranges from zero to 30. Screen time includes the number of hours, from zero to 160, the respondent watched television or video, played video games or viewed electronic devices in the past week. Sleep sufficiency is given a value of one is the respondents reports getting enough sleep at night and zero otherwise.

Mediation analyses

This uses mediation analysis to explore the underlying mechanism by which neuroticism affects BMI. Mediation analysis, as popularized in psychology and the social sciences by Judd and Kenny and Baron and Kenny [55,56], enables the

decomposition of total causal effects into an indirect effect and direct effect. Mediation refers to the transmission of the effect of an independent variable on a dependent variable through one or more other variables-referred to as mediators. Mediation analysis allows the total effect of PGS on BMI to be decomposed into an indirect and direct effect. The direct effect measures the extent to which the BMI changes when the PGS increases by one unit and the mediator variables (behaviors) remain unaltered. In figure 1, the direct is represented by c or c' when the mediators are included. The indirect effect measures the change in the in BMI when PGS is fixed and the mediator variables change. In figure I, the indirect effect is represented by ab. The total effect is equal to the sum of the direct and indirect effects ($c' + ab$).

Analyses uses structural equation modeling (SEM). SEM can capture complex, dynamic relationships by incorporating the path model presented in figure I through a system of linked regression-style equations [57-59]. This application of SEM allows the indirect effect of multiple mediators to be separated and their relative mediation effects compared [59]. The model is estimated using the R package lavaan, which is available from the Comprehensive R Archive Network (CRAN) at https://cran.r-project.org/web/packages/lavaan/index.html. Regression analysis uses log of BMI is the dependent variable and includes controls for gender, age, school enrollment, residence in the south and principle component effects. Pathway estimation uses the bootstraps method to measure uncertainty in estimating the mediation effects. A vector of weights is used since the observations in the Add Health are not treated equally in the analysis. The weights account for longitudinal sampling variation in sampling and response patterns.

Results

Descriptive

Table I presents participant characteristics. The sample includes 4,501 individuals. Nearly half, 47%, are female and 37% reside in the south. Age ranges from 12–24 years. Average BMI was 24-considered normal weight. PGS varies
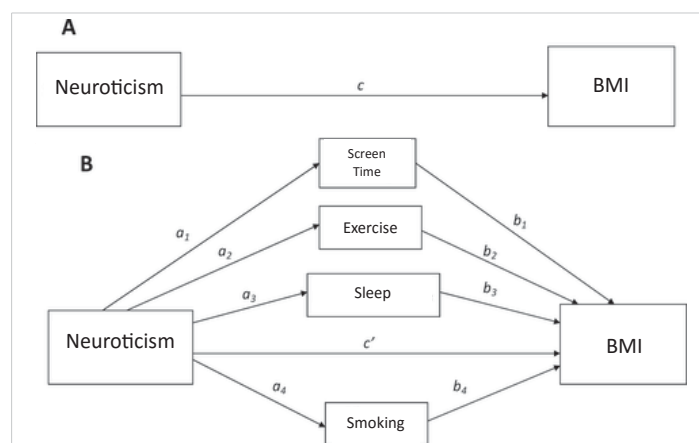

Figure 1:

Table 1:

Demographic Characteristics Means and Frequency by Ancestral Group										
			European Ancestry		African Ancestry		Asian Ancestry		Hispanic Ancestry	
			N =	22516	N =	7644	N =	1732	N =	3816
Variable	Min	Max	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Female	0	1	0.4717	0.0090	0.4427	0.0117	0.5543	0.0200	0.5147	0.0164
General Health	1	5	2.1433	0.0153	2.1674	0.0232	2.2304	0.0825	2.2275	0.0276
Screen Time	0	100	13.1440	0.2229	17.6101	0.3813	13.9693	0.6911	14.2642	0.3610
Smoking	0	30	13.5150	0.3312	7.6801	0.3941	9.3829	0.7075	9.2120	0.7858
BMI	2	91	24.9322	0.1118	26.3859	0.1705	24.5398	0.7420	25.8943	0.2692
Exercise	0	3	1.2048	0.0107	1.1919	0.0140	1.2083	0.0163	1.2139	0.0175
Body Perception	1	5	3.3519	0.0110	3.3054	0.0158	3.2776	0.0812	3.4268	0.0266
Sufficient Sleep	0	1	0.7359	0.0050	0.6921	0.0071	0.6609	0.0204	0.7113	0.0106
Age	12	34	21.2080	0.1276	21.2841	0.1956	21.7825	0.4572	21.5934	0.2426
School	0	1	0.5966	0.0065	0.6077	0.0087	0.6318	0.0171	0.5942	0.0078
Highest Grade	1	22	9.4456	0.0732	9.2024	0.1394	10.1895	0.1308	9.3846	0.1384
PC1- Parent Relationship to Adolescent	-0.779	0.170	0.0000	0.0002	0.0000	0.0005	0.0000	0.0034	-0.0001	0.0016
PC2 Bio Mother in HH	-0.613	0.161	0.0000	0.0002	0.0000	0.0006	0.0001	0.0094	0.0001	0.0015
PC3- Ever Lived with Bio Mother	-0.085	0.017	-0.0001	0.0005	-0.0001	0.0017	0.0001	0.0077	-0.0001	0.0045
PC4- Most Recent YR Lived with Bio Mother	-0.450	0.444	0.0000	0.0002	0.0000	0.0006	0.0000	0.0028	0.0000	0.0018
PC5- Monthly Support from Bio Mother	-0.070	0.186	0.0000	0.0005	0.0001	0.0005	0.0001	0.0094	-0.0004	0.0030
PC6- Bio Father in HH	-0.371	0.480	0.0000	0.0002	0.0002	0.0005	0.0000	0.0020	0.0001	0.0013
PC7- Ever Lived with Bio Father	-0.296	0.563	0.0001	0.0002	-0.0001	0.0006	-0.0001	0.0010	0.0001	0.0011
PC8- Most Recent Year Live with Bio Father	-0.328	0.218	0.0000	0.0003	0.0001	0.0010	0.0000	0.0030	0.0000	0.0010
PC9- Monthly Support from Bio Father	-0.510	0.462	0.0000	0.0002	0.0002	0.0005	0.0000	0.0029	-0.0002	0.0007
PC10- Best Friend in School	-0.516	0.246	0.0000	0.0002	0.0001	0.0006	0.0000	0.0022	-0.0002	0.0016

Estimates are weighted using longitudinal sampling weights. Data is clustered by school sampling unit and stratified by region.

between -14 and 34, with an average of eight. However, PGS cannot be interpreted in absolute terms. It can only explain relative risk for neuroticism. The data used for generating a polygenic risk score comes from a large-scale genomic study that finds genomic variants by comparing groups with a certain disease to a group without the disease. A polygenic risk score indicates how a person's risk compares to others with a different genetic constitution. However, polygenic scores do not provide a baseline or timeframe for the progression of a disease. Polygenic risk scores only show correlations, not causations. Respondents had an average of 14 hours of screen time each day, exercised 3 times each week and smoked 14 out of the last 30 days.

Mediation models

Mediation model results table 2 showed estimates of all relationships outlined in figure 1. The columns denote values of corresponding a, b and c estimates. Control variables assume the expect sign and significance. Females have lower BMI than males and age is positively correlated with weight. As baseline BMI increases, so does BMI in the observed wave. Those enrolled in school have lower comparative BMI due to higher education and healthy lifestyle effects. The mediation model framework allows for behaviors to have both direct effects (b) and indirect effects (a) transmitted through PGS on BMI. Estimates show no significant direct BMI effect from getting enough sleep. However, exercise, smoking and screen time direct effect BMI. Higher amounts of exercise and smoking have a negative direct effect, while higher amounts of screen time have a positive direct impact.

While genetic neurotic tendency has no direct effect on BMI (c in figure 1), it is significantly correlated with sleep, smoking and screen time. Neurotic tendency Is positively associated with receiving enough sleep and negatively associated with high amount of screen time and smoking. These results are not surprising given the significant relationships between neuroticism and sleep, sleep problems and sleep duration [60]. Neurotic individuals have also been shown to be more vulnerable to compulsive behaviors-like smoking and screen time-and more susceptible to addiction [61-63].

These correlations explain the estimated indirect effect (a*b). The indirect effect refers to the transmission of the PGS effect on BMI through sleep, screen time, exercise and smoking—the mediators. The magnitude of the indirect effect indicates the amount of mediation. Indirect effects are relatively small in magnitude (-0.00019 to 0.004). Exercise (0.001) and smoking have a positive indirect effect (0.004) while screen time (-0.003) and sleep (-0.00019) had a negative indirect effect. These indirect effects represent the impact that PGS has on BMI through its influence on behavior. For example, the positive correlation between neurotic tendency and smoking frequency results in a positive indirect effect on BMI.

The total indirect effect (0.001) is the sum of all indirect behavioral effects. Adding the total indirect effect to the direct effect results in the total effect of genetic tendency for neuroticism on BMI (0.015). The net positive influence is consistent with other studies which showed an elevated level of neuroticism among obese individuals. Obese and underweight individuals report more psychiatric symptoms

Table 2:

	SEM Mediation Model Estimates			
Dependent	Independent	Estimate	Std Error	Z Stat
BMI	Exercise (b1)	-0.009*	0.001086	-8.0228
BMI	Sleep (b2)	-0.001	0.002563	-0.5456
BMI	Smoking (b3)	-0.008*	0.001482	-5.28033
BMI	TV (b4)	0.007*	0.001259	5.601243
BMI	SPGSNEUG (c)	0.014	0.024707	0.549415
BMI	Baseline	0.885*	0.010191	86.8162
BMI	South	0.002	0.006013	0.375328
BMI	BIO_SEX	-0.007*	0.003399	-2.05013
BMI	School	-0.046*	0.005635	-8.09106
BMI	Age	0.011*	0.000384	27.891
BMI		0.121*	0.036835	3.286515
Exercise	SPGSNEUG (a1)	-0.088	0.155892	-0.56299
Sleep	SPGSNEUG (a2)	0.139*	0.061237	2.263638
Smoking	SPGSNEUG (a3)	-0.437*	0.156426	-2.79189
TV	SPGSNEUG (a4)	-0.485*	0.135283	-3.58229
Exercise Indirect Effect	a1*b1	0.001	0.001375	0.555872
Sleep Indirect Effect	a2*b2	0.000	0.000358	-0.54193
Smoking Indirect Effect	a3*b3	0.004*	0.001378	2.480624
TV Indirect Effect	a4*b4	-0.003*	0.001168	-2.92472
Total Indirect Effect	(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	0.001	0.002364	0.241831
Total Effect	c+(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	0.015	0.024629	0.57438

Dependent Variable: logBMI
*= Statically Significant at 95% Level
Estimates are weighted using longitudinal sampling weights. Data is clustered by school sampling unit and stratified by region.

than normal-weight individuals [14] suggesting a positive association between neuroticism and BMI [4,5,13]. To ensure that results were robust to gender differences, SEM models were re-estimated separately for males and females (Table 3). Results show no variation from the pooled model. Therefore, results are assumed to be robust to gender.

However, estimates of the total indirect effect, direct effect and the total effects are insignificant at the 95% level. Were statistically significant. Given that studies have shown strong relationships between neuroticism and body weight, these results are surprisingly. Three logical explanations explain lack of significance. First, this study used polygenic risk as a measure of neurotic tendency, while other analyses have employed binary or discrete ratings of neurotic tendencies. While undoubtedly related, these dependent variables assess different individual traits leading to different causal pathways. Second, genetic risk of neuroticism, as measured by additive genetic risk of the phenotype, could exert a primary diiect effect on health-related behavior. Rather than influencing body weight through direct and indirect pathways, the BMI effect could transmit exclusively through behavior. Finally, PGS of neuroticism could exert indirect effects through behavioral pathways not considered in this study. This association could manifest through health-related behaviors such as diet, alcohol consumption and drug use [15]. Future research exploring this topic should include additional behavioral mediators to explore alternative hypotheses of behavioral effects.

Discussion

Despite the observed complexities of the SEM framework

and estimated network of causal pathways, these results have important clinical implications for both those diagnosed with personality disorders but also for those with genetic pre-disposition to these disorders. Emotional eating, for example, could be indicative of neurotic individuals while also contributing to increase BMI. Emotional eating could be a protective response to naturally occurring stressors. If emotional eating manifests from genetic neurotic tendency, then understanding the relationship between PGS, health behavior and BMI will inform strategies designed to assist weight. Individuals with neurotic tendencies should be mindful of how their innate behavioral responses impact body weight and other health outcomes [64]. Weight management interventions should address new strategies to help them manage their responses to stress and negative stimuli to elicit desired weight outcomes.

Conclusion

This paper explored the role of genetic disposition to neuroticism in BMI determination through an explanatory mechanism of health-related behavior. Guided by previous literature, this paper tested a theoretical model suggesting that neuroticism was indirectly associated with BMI through smoking intensity, exercise frequency, sleep and screen time (Figure 1). The model was tested using a sample of individuals age 12 to 34. Using polygenic risk of neuroticism as an indicator of heritable neurotic tendency, analysis employed the SEM framework to estimate a mediation model of potential behavioral mediators.

Table 3:

Male: SEM Mediation Model Estimates				
Dependent	Independent	Estimate	Std Error	Z Stat
BMI	Exercise (b1)	-0.00864*	0.00164	-5.26883
BMI	Sleep (b2)	-0.00372	0.003746	-0.99252
BMI	Smoking (b3)	-0.00503*	0.002395	-2.10098
BMI	TV (b4)	0.009805*	0.002026	4.839968
BMI	SPGSNEUG (c)	0.030994	0.034029	0.910831
BMI	Baseline	0.936672*	0.011876	78.87257
BMI	South	0.0109	0.006783	1.60696
BMI	School	-0.04381*	0.007796	-5.61989
BMI	Age	0.010986*	0.000583	18.83627
BMI		0.143109*	0.041839	3.420449
Exercise	SPGSNEUG (a1)	-0.18448	0.172553	-1.06911
Sleep	SPGSNEUG (a2)	0.133954	0.09742	1.37502
Smoking	SPGSNEUG (a3)	-0.31085	0.246366	-1.26174
TV	SPGSNEUG (a4)	-0.65168*	0.264452	-2.46428
Exercise Indirect Effect	a1*b1	0.001594	0.001509	1.056207
Sleep Indirect Effect	a2*b2	-0.0005	0.000638	-0.78106
Smoking Indirect Effect	a3*b3	0.001564	0.001376	1.136914
TV Indirect Effect	a4*b4	-0.00639*	0.002759	-2.31596
Total Indirect Effect	(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	-0.00373	0.003736	-0.9984
Total Effect	c+(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	0.027265	0.034962	0.779841
Female: SEM Mediation Model Estimates				
Dependent	Independent	Estimate	Std Error	Z Stat
BMI	Exercise (b1)	-0.00851*	0.0016	-5.3198
BMI	Sleep (b2)	0.001331	0.003566	0.373119
BMI	Smoking (b3)	-0.01135*	0.002042	-5.56117
BMI	TV (b4)	0.003801*	0.00153	2.484358
BMI	SPGSNEUG (c)	-0.0025	0.035443	-0.07054
BMI	Baseline	0.825804*	0.012917	63.93144
BMI	South	-0.00512	0.006646	-0.77106
BMI	School	-0.04728*	0.006643	-7.11689
BMI	Age	0.010513*	0.0005	21.0251
BMI		0.020182	0.071144	0.283676
Exercise	SPGSNEUG (a1)	0.000338	0.244887	0.001381
Sleep	SPGSNEUG (a2)	0.156097*	0.080042	1.950183
Smoking	SPGSNEUG (a3)	-0.54336*	0.20062	-2.70838
TV	SPGSNEUG (a4)	-0.2956	0.207046	-1.4277
Exercise Indirect Effect	a1*b1	-2.9E-06	0.002085	-0.00138
Sleep Indirect Effect	a2*b2	0.000208	0.000574	0.361624
Smoking Indirect Effect	a3*b3	0.006169*	0.002783	2.216862
TV Indirect Effect	a4*b4	-0.00112	0.000892	-1.26016
Total Indirect Effect	(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	0.00525	0.003625	1.448144
Total Effect	c+(a1*b1)+(a2*b2)+(a3*b3)+(a4*b4)	0.00275	0.034344	0.080068
Dependent Variable: log BMI				
*= Statically Significant at 95% Level				
Estimates are weighted using longitudinal sampling weights. Data is clustered by school sampling unit and stratified by region.				

While previous studies showed correlations between neuroticism and weight outcomes, this paper, accounting for explicit behavioral pathways, showed no significant direct effect of PGS on BMI. Exercise, smoking and screen time did, however, show significant direct BMI effects. The direct behavioral effects combined with the significant association between PGS and sleep, smoking and screen time resulted in two robust indirect BMI associations-smoking and screen time. Therefore, the relationship between PGS and BMI was transmitted through behavioral pathways thus attenuating the direct effect. The BMI/PGS relationship is mediated by health-related behaviors suggesting that the increased risk of neurotic tendency effects BMI through the characteristic behaviors of these individuals.

However, our study is not without limitations. First, distinct genetic lineage among ancestral groups require separate analyses when genetic information is included. However, sample size restrictions precluded analysis of Africa, Asian and Hispanic ancestry groups. While robust, the model of European ancestral group cannot be generalized to other racial and ethnic groups that might present different pathways between neuroticism and BMI. Second, while analysis controlled for age, it did not control for all age-

related factors, such as more adaptive coping strategies, maturation and life changes and development of complex interpersonal relationships and social networks [65]. Third, BMI used self-reported height and weight which can lead to an underestimation and overestimation of weight and height, respectively [66]. Despite these shortcomings, studies find that BMI is an excellent approximation of actual body weight across populations [67,68]. Fourth, it is possible that health related behaviors other than those included in this study serve as prevalent mediators. Fast food consumption, hydration levels and meal habits could have stronger associations' neuroticism and BMI.

Despite these limitations, this research offers novel insight into the relationship between personality and health. Polygenic risk score—an object measure of neurotic tendency across all individuals—provided an alternative to survey-based measures of neuroticism. These findings represent an important step in reducing the reliance on survey-based personality assessments in mediation studies of health outcomes. The results of the present study suggest that personality is significantly associated with BMI indirectly via smoking and screen time. Generally, these associations with behavioral mediators were relatively weak, and the only behaviors that were significantly related to BMI were smoking and screen time after adjusting for gender, age and region. Future studies should consider the utilizing the polygenic scores to assess personality traits and include additional behaviors to test for indirect effects.

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