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Genetic overlap between executive functions and BMI in childhood

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ABSTRACT

Background: Executive functions (EFs) comprise a group of cognitive processes that selectively control and regulate attention. Inverse relations have been reported between EFs and BMI. However, the mechanisms underlying this association are not well understood.

Objectives: We aimed to decompose the inverse relation between EFs and BMI into genetic and environmental components.

Methods: We employed a cross-sectional analysis of data from 869 twins aged 7–15 y from the Texas Twin Project, who completed a neuropsychological test battery measuring 4 EFs (switching, inhibitory control, working memory, and updating); academic achievement (reading and mathematics); and general cognitive abilities (general intelligence/intelligence quotient; crystallized and fluid intelligence; and processing speed). Participants also had their height and weight measured.

Results: After controlling for age, sex, and race/ethnicity, BMI was inversely associated with a general EF factor representing the capacity to control and regulate goal-oriented behaviors ($r = -0.125$; $P = 0.01$; $Q = 0.04$). This inverse BMI–EF association was due to a significant overlap in genetic factors contributing to each phenotype (genetic correlation, r_A, $= -0.15$; $P < 0.001$). Shared genetic influences accounted for 80% of the phenotypic association.

Conclusions: Children with higher general EF have lower BMIs, and this association is primarily attributable to shared genetic influences on both phenotypes. The results emphasize that higher weight associates not only with physical sequelae, but also with important cognitive attributes. This work adds to a growing body of research suggesting there are sets of genetic variants common across physical health and cognitive functioning. *Am J Clin Nutr* 2019;110:814–822.

Keywords: BMI, executive function, general cognitive ability, twin study, updating

Introduction

Obesity is associated with lower academic achievement, underscoring its association with cognitive health (1–4). Executive functions (EFs) are a set of heritable cognitive abilities foundational to complex reasoning and goal-directed behavior. EFs include the ability to initiate, monitor, and maintain goal-directed behaviors (5–7). An association between higher BMI and lower EFs has emerged in the literature. Inhibition has been the focus of much obesity-related research, with some (8–12), but not all (13–15) studies reporting small, inverse associations between inhibitory ability and weight status. Other EF domains

The Population Research Center is supported by NIH grant R24HD042849. Data collection for this research project was supported by NIH grants R01HD083613 and R21HD081437. LEE was supported by a National Science Foundation Graduate Research Fellowship. ACW is supported by a USDA grant (CRIS 309-5-001-058). This work is, in part, a publication of the US Department of Agriculture [USDA/Agricultural Research Service (ARS)] and ACW's role was funded in part by the USDA/ARS (Cooperative Agreement 6250–51000). The contents of this publication do not necessarily reflect the views or policies of the USDA, nor does mention of trade names, commercial products, or organizations imply endorsement from the US government. UV is supported by Personal Postdoctoral Research Funding project PUTJD654 and by a Fonds de Recherche du Québec–Santé (FRQS) foreign postdoctoral training award.

Supplemental Figure 1 and Supplemental Tables 1–4 are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/ajcn/.

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Abbreviations used: DZ, dizygotic; EF, executive function; FDR, false discovery rate; IQ, intelligence quotient; MZ, monozygotic; SSRT, stop signal reaction time; TTP, Texas Twin Project; WASI, Wechsler Abbreviated Scale of Intelligence; zBMI, standardized BMI.

Received August 28, 2018. Accepted for publication May 8, 2019.

First published online June 19, 2019; doi: https://doi.org/10.1093/ajcn/nqz109.

are less well studied, but differences between adolescents with and without obesity have also been reported for sustained attention, switching ability, and working memory (10, 11).

EF deficits are a potential contributor to obesity and are associated with poor psychosocial outcomes shared with obesity, such as academic achievement (1–4, 7). Although the EF–BMI relationship appears to be small (meta-analytic r across adults and children = 0.10–0.20) (16, 17), delineating its exact nature and understanding why it is observed could be important for obesity prediction, for ameliorating the known psychosocial consequences of obesity, or for augmenting existing prevention efforts (18, 19). The current understanding of the EF–BMI relationship is limited by: *1*) the prior use of modest sample sizes; *2*) the inclusion of only a single EF domain in individual studies disallowing analysis of whether BMI is associated with specific processes or a more general EF ability; and *3*) a failure to understand the etiology of any associations, with only 1 study suggesting that shared genetic influences underlie the association (13).

To improve our understanding of the nature of the EF–BMI relationship, thereby contributing knowledge that might enable better prediction, intervention, and treatment opportunities, the aim of the current study was to conduct a large-scale examination of the inverse association between BMI and EF in a sample of 869 twin children, aged 7–15 y, who participated in the Texas Twin Project (TTP) (20). We characterized EF both in terms of its individual domains, and in terms of ability common across the domains. We further aimed to compare the specificity of EF–BMI relations relative to academic achievement, and to examine the relative contribution of genetic and environmental influences to any detected inverse associations between BMI and EF.

Methods

Participants

Families with twins or multiples were recruited from public school rosters to participate in an in-laboratory study as part of the TTP (20). Nine participants were excluded from the current analysis because their parents reported a medical disorder affecting growth (e.g., cerebral palsy). The present analyses are based on 869 children in grades 3 to 8 (age range: 7.80–15.25 y; mean: 10.91 ± 1.76 y), 51.6% of whom were female. Parents reported participants' race as 71.8% non-Hispanic white, 25.8% Hispanic, 8.5% African American, 6.6% Asian, and 1.4% another race or ethnicity. These percentages sum to more than 100% because 14.1% of the sample reported multiple races or ethnicities. Thirty-four percent of participating families reported having received means-tested public assistance, such as food stamps, at some point since the twins' birth. Participants were nested within 455 sibling pairs (404 twin pairs and 51 pairwise combinations from 17 triplet sets). All procedures were in accordance with the ethical standards of the University of Texas at Austin Institutional Review Board human subjects research.

Zygosity

Opposite-sex pairs are known to be dizygotic (DZ). For same-sex pairs, we used latent class analysis of experimenter and parent ratings of pairwise physical similarity to determine zygosity. When compared with classification by genotyping, latent class analysis of similarity ratings has been found to be >99% accurate (21). The current sample consisted of 153 (33.6%) monozygotic (MZ) pairs, 156 (34.2%) same-sex DZ pairs, and 146 (32.0%) opposite-sex DZ pairs.

Procedure

Children participated in an in-laboratory protocol that lasted approximately 4 h. The protocol consisted of a physical assessment, during which height and weight were measured; a self-report survey (~45 min); cognitive ability testing (~1 h); EF testing (~1 h); and academic achievement testing (~30 min). Participants were allowed breaks between each phase of the study. A trained research assistant worked independently with each twin to administer all of the tasks. Further details of the protocol and measures are available elsewhere (6, 22).

EFs

EFs were measured using a comprehensive battery of neuropsychological tasks. Aggregating data across EF measures—which are correlated at the genetic and phenotypic levels (6, 23–25)—into a general EF factor leads to a reduction in error variance, which can increase power to detect associations with other phenotypes, including BMI (13, 23, 24). Therefore, we focused the behavioral genetic analyses on the association between BMI and a latent factor representing the variance common to all EF domains (**Figure 1**, **Supplemental Figure 1**). The latent general EF factor is thought to represent an individual's overall capacity to control and regulate goal-oriented behaviors selectively. Although we focus on the biometric genetic models in the current analyses, we do present the correlations with BMI at the phenotypic level, broken down into 4 EF subdomains, which were themselves measured as latent factors of the following tasks within each domain.

Inhibition.

This is the ability to prevent oneself from executing a prepotent or practiced behavior. To assess inhibition, we used Animal Stroop (27), Stop Signal (28, 29), and Mickey (an antisaccade paradigm) (30). The Stroop and Mickey tasks contained inhibit and noninhibit trials, and the difference in response times between trial types was used to estimate an inhibition cost. The Stop Signal task produced a stop signal reaction time (SSRT) indexing the efficiency of inhibiting a prepotent motor response following a cue (i.e., the stop signal). After excluding scores on the basis of consistent stop failures, misidentification of arrow direction, failure to respond to go trials, and low SSRTs, remaining block scores were averaged to create a final SSRT measure (31).

Switching.

This is shifting attention across stimulus features or task rules. Trail Making (32), Local-Global (33), and Plus-Minus (33) tasks each contained a nonswitch condition (e.g., connecting letters alphabetically in Trail Making) and a switch condition (e.g., connecting letters and numbers in an alternating fashion).

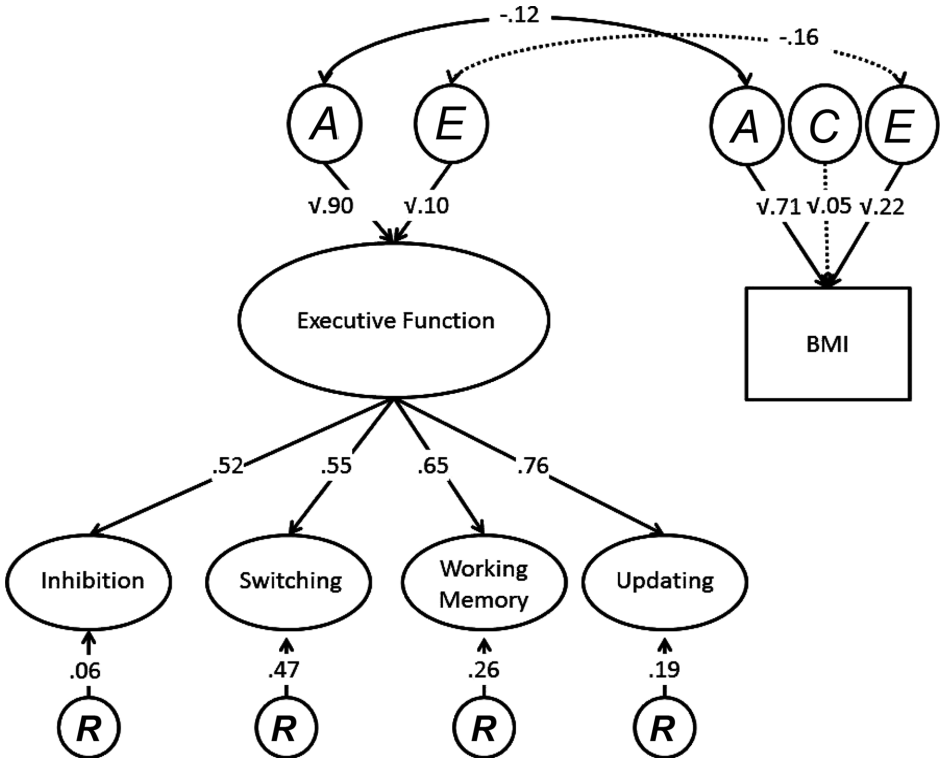

FIGURE 1 Standardized parameter estimates from biometric model of executive function (EF)–BMI relations. The observed (measured) variable, BMI, is represented by a square, and unobserved (latent) variables are represented by spheres following McArdle (26). Estimates come from the full biometric (genetically informed) multilevel structural equation model between EF and BMI, with associations between influences on EF and BMI modeled as correlated factors. Task scores and winsorized BMI were residualized for the effects of sex and race prior to analysis. Significant parameters ($P < 0.05$) are represented by solid arrows. The significance of parameters was tested using chi-square goodness-of-fit tests. The model included age covariation of the first-order EF factors (not depicted). Unsquared estimates, factor loadings for the specific tasks, as well as residual *A* and *E* influences on the tasks, are omitted for clarity but can be found in Table 3 or Supplemental Figure 1. $n = 869$. *A*, additive genetic influences; *C*, common environmental influences; *E*, nonshared environmental influences; *R*, residual variance representing *A* and *E* contributions specific to each domain.

Response-time differences for switch conditions relative to nonswitch conditions were used as the measure of switching costs.

Working memory.

This is the simultaneous processing and storage of information. Digit Span Backward (34), Symmetry Span (35), and Listening Recall (36) required storing and manipulating numerical, spatial, and verbal information, respectively. Performance was calculated as the number of items correctly recalled.

Updating.

This is the ability to monitor incoming stimuli and replace old information with new information. 2-Back (37), Keeping Track (33), and Running Memory for Letters (38) required participants to maintain in working memory the most recent stimuli from 1 or more specified sets while stimulus presentation was ongoing. For the latter 2 tasks, performance was assessed as the number of items correctly recalled. For 2-Back, performance was assessed as the number of true matches minus false alarms (i.e., incorrectly identifying nonmatches).

General cognitive abilities and academic achievement

General EF factors have shown high phenotypic and genetic correlations with general intelligence [intelligence quotient (IQ)] and with measures of general cognitive abilities such as processing speed (22). Because BMI is inversely associated with IQ (4), it remains an open question whether any EF–BMI association is independent of these correlates. To probe the specificity of EF–BMI relations relative to general cognitive abilities and academic achievement, we included measures of these constructs at the phenotypic analysis stage.

General cognitive ability.

The Wechsler Abbreviated Scale of Intelligence (WASI)-II (39) consists of 4 standardized tests: Vocabulary, Similarities, Block Design, and Matrix Reasoning. The first 2 tests measure verbal comprehension, and the latter 2 tests measure perceptual reasoning.

Fluid intelligence.

This is the ability to reason abstractly and solve novel problems. For finer grained analyses of associations specifically involving fluid intelligence, we used Block Design and Matrix

Reasoning from the WASI-II, in conjunction with Spatial Relations from the Woodcock–Johnson-III (40). Spatial Relations required participants to select, from a set of shapes, the shapes necessary to form a target conglomerate shape.

Crystallized intelligence.

This is accumulated knowledge and skills gained through learning. For finer grained analyses of associations specifically involving crystallized intelligence, we used Vocabulary and Similarities from the WASI-II.

Academic achievement.

Woodcock–Johnson-III Calculations and Passage Comprehension tests (40) assessed the participants' mathematics and reading abilities, respectively.

Processing speed

In each of the Letter Comparison (41), Pattern Comparison (41), and Symbol Search (34) tasks, participants completed as many lexical or symbolic comparisons as possible, within time limits, while maintaining accuracy.

BMI

Heights and weights were measured by trained study personnel using a mechanical height rod (model DS1100; Doran Scales, Inc.) and a Health O Meter digital scale (model 349KLX; Sunbeam Products, Inc.), or by using a two-in-one Seca measuring station (model 220). BMI was calculated as the square of a child's weight in kilograms divided by their height in meters. BMIs were converted to *z*-scores (zBMI) based on growth charts developed by the CDC (42).

Analyses

All analyses were conducted in Mplus Version 7.11 (43). As necessary, tasks were reverse scored so that higher scores represented better task performance. To approximate normal distributions, Trail Making and Local-Global scores were log transformed, and 2-Back and Listening Recall scores square-root transformed prior to analysis. zBMI and Plus-Minus scores >3 SD from the mean were winsorized to the next least extreme value. Winsorizing was applied to 11 BMIs (1% of total available) and 15 Plus-Minus scores (3% of total available).

All analyses of psychological constructs were based on confirmatory factor models in which the specific measures served as indicators of a latent factor (e.g., the tasks listed for processing speed were loaded onto a latent Speed factor), except when examining effects of math and reading achievement separately. Individual factor loadings for EF tasks onto specific EFs, and for specific EFs onto higher-order general EFs, are available in **Supplemental Table 1**. Loadings of non-EF tasks onto their respective latent factors are available in **Supplemental Table 2**.

Phenotypic analyses.

Correlations were computed based on the full sample, implementing the Complex Survey option in Mplus to correct for the nonindependence of data drawn from individuals in the same family. Pairs with incomplete data were included in analyses, and under the assumption that data were missing at random (MAR) or missing completely at random (MCAR), SEs for the parameter estimates were computed using the observed rather than the expected information matrix (44). We were not powered to conduct age-stratified analyses; however, previous work by us and others has indicated that the underlying structures of the genetic and environmental components for EF (6, 22) and BMI (45) do not differ greatly by age. We ran partial correlations between BMI and general EF, controlling for *1*) age only; *2*) age and sex; and *3*) age, sex, and race. Each set of models was corrected for multiple testing separately (i.e., we corrected first within the sex-controlled models, then separately within the sex- and race/ethnicity-controlled models). The series of partial correlation analyses was repeated to investigate associations between BMI and each of the following outcomes: inhibition, switching, working memory, updating, fluid intelligence, crystallized intelligence, processing speed, reading, mathematics, and combined achievement/crystallized intelligence. To guard against inflated false-positive rates that result from conducting multiple significance tests, we used a false discovery rate (FDR) correction and present *Q* values (FDR-corrected *P* values) in addition to *P* values for comparability across past and future studies (46).

Behavior genetic analyses of EF and BMI.

Structural equation models were fitted using full-information maximum likelihood estimation to compute parameter estimates using all available data. Each triplet set contributed 3 pair-wise combinations, with each individual represented in 2 of the 3 pairs. To correct SEs for this dependence, we implemented the Complex Survey option for nesting within families, and we used the Weighting option to downweight data from triplet pairs by 50%. Genetic models were specified according to the following assumptions: To the extent that multiples raised in the same family are similar on an outcome of interest, similarities are due to shared genetic influences (additive genetics, or *A*) and to being raised in the same environment (*C*). Estimation of these parameters relies on knowledge that MZ pairs share 100% of their segregating alleles, and DZ pairs share 50% of their segregating alleles, on average. Because individuals in any given pair are 100% concordant for shared environmental influences, greater similarity on an outcome for MZ pairs relative to DZ pairs implicates genetic factors. Finally, to the extent that multiples raised in the same family differ on an outcome, these differences are due to environments or experiences not shared by the pair or to measurement error (subsumed under the nonshared environment, or *E*). To avoid artificially biasing estimates of *A* and *C*, scores residualized for sex and race/ethnicity were entered into the biometric models. Further details on twin modeling and its assumptions can be found in the article by Rijsdijk and Sham (47).

Our primary outcomes were the phenotypic, genetic, and environmental overlaps between EF and BMI. Additionally,

multivariate twin models also included the variance components (*A*, *C*, and *E*) of EF and BMI. Previous work with TTP data has reported results from genetic and environmental decompositions of EF (6, 22). Our model specifications were based on previous results from these studies, which indicated no *C* variance in EFs and no sex differences in the biometric structure of EFs (6, 22). Additionally, past meta-analytic work (to which TTP data contributed) (44) indicated *A, C,* and *E* variance components for BMI, and an opposite-sex genetic correlation of ~0.35. We therefore freely estimated the cross-twin *A* correlation for BMI for opposite-sex twin pairs (genetic correlation, r_A, = 0.38; SE = 0.18). This model specification allows the *ACE* estimates to be interpreted as unbiased estimates of the average parameters across sexes.

To investigate overlap in the genetic and environmental factors contributing to EF and BMI, we fitted a Cholesky model that estimated *a* and *e* cross-paths from genetic and nonshared environmental factors for EF to BMI (Figure 1). Next, we tested the fit of nested models that sequentially dropped the *a* and *e* cross-paths. Model fit was assessed using chi-square goodness-of-fit tests, as well as Akaike and Bayesian information criteria. We primarily interpret parameter estimates from the full model (Figure 1), as this model does not artificially inflate the genetic or environmental pathway due to constraining the alternative pathways to zero. In addition to *a* and *e* cross-paths, which are standardized regression coefficients, we also report genetic (r_A) and environmental (r_E) correlations obtained by transforming parameter estimates from the Cholesky decomposition into those from a mathematically equivalent correlated factors model.

Results

Descriptive statistics

Descriptive statistics for all measures are summarized in **Table 1**. The mean IQ of participants in our sample was 103.82, with an SD of 14.08, differing little from the normed values for the US population (mean: 100 ± 15). The mean standardized BMI was 0.11 ± 1.29 with an interquartile range of −0.661 to 1.031.

Phenotypic associations between EFs, psychometric cognitive abilities, achievement, and BMI

Full correlations between manifest variables are reported in **Supplemental Table 3.** When controlling for age and sex, BMI had negative associations with most EF domains, as well as general cognitive ability and academic achievement, but not with processing speed or inhibition (**Table 2**). However, when additionally controlling for race, many of the partial correlations dropped to nonsignificant levels, with only factors representing general EF and updating (tested in separate models) remaining significantly inversely related to BMI (for both models, $r = -0.13$; $Q < 0.05$; Table 2). To probe for sex differences in the EF–BMI association, we allowed for an interaction between sex and latent EF in predicting BMI. This was not significant ($P = 0.65$).

Biometric genetic associations between EF and BMI

Based on age, sex, and race-controlled phenotypic results, as well as previous research suggesting increased power when using higher-order EF factors (13, 23, 24), we included general EF only in the biometric genetic models. Scores residualized for race/ethnicity and sex were entered into these models (**Table 3**, **Supplemental Table 4**), and age was included as a covariate of the first-order EFs and BMI (Supplemental Figure 1). Intraclass correlations between all manifest variables are reported in Supplemental Table 3.

The full model indicated a small but highly significant negative phenotypic association between general EF and BMI ($r = -0.13$; $P < 0.001$). The magnitudes of the genetic and environmental regression coefficients from the Cholesky decomposition were −0.10 and −0.08 (both $P < 0.05$), respectively. Although the genetic correlation was significant ($r_A = -0.12$; $P < 0.001$), the environmental correlation was not ($r_E = -0.16$; $P > 0.05$). Similarly, models in which the *a* cross-path between EF and BMI was dropped fitted significantly worse than those in which it was estimated ($P < 0.001$; Supplemental Table 4). At the same time, the *e* cross-path could be dropped without significant loss of model fit ($P = 0.24$; Supplemental Table 4). This indicates that the genetic association between EF and BMI was significant, but the environmental correlation was not. Because both general EF and BMI were highly heritable (Table 3), the observed phenotypic association was primarily due to a genetic pathway (80%) rather than an environmental pathway (20%).

Discussion

Previous studies have suggested that there is an inverse association between EF and BMI in adolescents, but only 1 previous study has examined the etiology of this relation, reporting that the inverse association was almost entirely due to genetic influences (13). We conducted a large-scale study into EF and BMI using 869 twins aged 7–15 y, and our results indicated that BMI shows a small negative association with general EF ability. Furthermore, ~80% of the inverse correlation between general EF and BMI was attributable to genetic influences shared between the phenotypes. This corroborates the previous report of a genetic basis for the EF–BMI association in middle childhood that used a more limited set of EF measures (13). The current findings provide evidence that this relation is also apparent among older children and early adolescents.

The inverse EF–BMI association documented here supplies more evidence that differences in weight status are associated with important cognitive differences. Given the importance of EF for academic achievement (7) and the role of cognitive function as a determinant of physical and psychosocial risk factors (49), our findings support the notion that individuals with obesity could benefit from aid improving cognitive as well as physical functioning. Although any generalization from BMI to obesity should be made with caution, these findings support the importance of identifying cognitive correlates of higher weight status. The current results suggest that a reduced capacity to control and regulate attention selectively co-occurs with excess adiposity. In clinical settings, there could be benefits in tailoring weight loss interventions so that lower EF ability is acknowledged (18, 19).

TABLE 1 Descriptive statistics for BMI, executive function, general cognitive abilities, and processing speed tasks[1]

Domain/task	Dependent variable	*n*	Mean	SD	Skewness	Kurtosis	Reliability estimate (α)
BMI	Weight (kg) divided by height (m) squared, standardized relative to CDC age- and sex-specific norms	866	18.70	4.05	1.28	2.26	—
Inhibition							
Animal Stroop	Mean RT cost for incongruent conditions relative to congruent and neutral conditions	867	232.07	227.75	3.02	19.27	0.85[2]
Mickey	Mean RT cost for incongruent trials relative to congruent and neutral trials	769	35.73	71.15	0.10	2.29	0.47[3]
Stop Signal Auditory	Mean RT cost for go trials relative to stop signal delay (time between arrow and stop signal presentation)	514	326.75	80.88	0.47	1.80	0.40[3]
Switching							
Trail Making	Mean RT cost for alternating conditions relative to simple conditions	837	1286.18	1056.70	4.46	30.84	0.85[2]
Local-Global	Mean RT cost for alternating conditions relative to simple conditions	854	1415.33	762.72	3.62	23.28	0.73[2]
Plus-Minus	Mean RT cost for alternating conditions relative to simple conditions	585	721.11	1826.95	4.86	49.69	0.69[2]
Working memory							
Digit Span Backward	Total number of trials correctly recalled	842	7.02	1.82	0.37	0.54	0.60[4]
Symmetry Span	Total number of visually presented squares correctly recalled	857	20.25	8.77	−0.17	−0.37	0.78[4]
Listening Recall	Total number of auditorily presented letters correctly recalled	844	23.48	8.03	0.12	−0.43	0.79[4]
Updating							
Keeping Track	Total number of verbally presented words correctly recalled	854	6.62	2.36	−0.13	−0.46	0.52[4]
Running Memory for Letters	Total number of visually presented letters correctly recalled	810	18.86	8.33	−0.07	−0.68	0.74[4]
2-Back	Total number of hits (correct matches) minus false alarms (nonmatches indicated)	593	2.64	8.06	0.12	−0.22	0.83[3]
General cognitive abilities							
Block Design	Points awarded for recreating block designs	863	27.02	13.16	0.38	−0.56	0.84[4]
Matrix Reasoning	Number of items correctly identified as following spatial pattern	863	18.18	4.60	−0.90	0.65	0.87[4]
Spatial Relations	Number of items for which correct constituent pieces were selected	837	14.14	3.43	0.28	0.69	0.73[4]
Vocabulary	Points awarded for defining words	864	29.73	6.84	−0.37	−0.22	0.86[4]
Similarities	Points awarded for determining similarities between 2 concepts	865	24.32	5.72	−0.15	0.65	0.82[4]
Academic achievement							
Passage Comprehension (reading)	Number of sentences for which a missing word was correctly supplied	826	30.50	4.89	−0.70	0.84	0.86[4]
Calculation (math)	Number of problems correctly solved	806	20.63	5.94	0.09	−0.41	0.91[4]
Processing speed							
Letter Comparison	Total number of pairs of letter strings identified as matches or rejected as mismatches	867	14.01	4.97	0.63	0.53	0.85[3]
Pattern Comparison	Total number of pairs of symbols identified as matches or rejected as mismatches	866	27.60	7.24	0.30	0.56	0.85[4]
Symbol Search	Total number of symbols identified as matches or rejected as mismatches	866	23.61	7.04	−0.01	0.12	0.79[5]

[1] Adapted from reference (48) with permission. Reliability estimates in righthand column were derived from Cronbach α. RT, reaction time.
[2] Reliability estimates were calculated based on difference scores formed by subtracting reaction time on nonswitch (or noninhibit) blocks from reaction time on switch (or inhibit) blocks, for each possible pair of switch (inhibit) and nonswitch (noninhibit) blocks.
[3] Reliability estimates were calculated across blocks.
[4] Reliability estimates were calculated across trials.
[5] Short-term test-retest stability for Symbol Search came from the WISC-IV technical manual (34).

Our findings of shared genetic effects underlying BMI and EF are consistent with molecular genetic investigations: In a large meta-analytic study of obesity, 75% of newly identified genetic variants associated with BMI were expressed in the brain, suggesting they might manifest as cognitive-behavioral phenotypes (50). Genetic underpinnings of the inverse EF–BMI association could be more stable than environmental underpinnings, because stable genetic effects contribute to phenotypic continuity for both BMI and cognitive abilities (including EFs) in childhood (51–53).

We also provided, to our knowledge, the first report of a significant inverse association between BMI and the ability to monitor incoming stimuli and replace old information with new information (updating), with no evidence for an inverse

TABLE 2 Partial Pearson correlations between executive functions, psychometric cognitive abilities, academic achievement, and BMI[1]

	Parameter estimates, partialling age				Parameter estimates partialling age and sex				Parameter estimates partialling age, sex, and race			
	r	SE	*P*	*Q*	*r*	SE	*P*	*Q*	*r*	SE	*P*	*Q*
General factors												
General executive function higher order	−0.203	0.045	<.0005	<0.002	−0.203	0.045	<0.0005	<0.001	−0.125	0.045	0.006	0.04
General cognitive ability (4 indicators from WASI)	−0.169	0.049	0.001	<0.002	−0.169	0.049	0.001	0.001	−0.072	0.050	0.152	—
EF domains												
Inhibition factor	−0.320	0.311	0.303	—	—	—	—	—	—	—	—	—
Switching factor	−0.125	0.061	0.042	0.05	−0.125	0.061	0.041	0.041	−0.057	0.065	0.38	—
Working memory factor	−0.194	0.049	<0.0005	<0.002	−0.196	0.049	<0.0005	<0.001	−0.123	0.052	0.018	0.06
Updating factor	−0.210	0.049	<0.0005	<0.002	−0.211	0.049	<0.0005	<0.001	−0.134	0.051	0.008	0.04
Psychometric cognitive ability domains												
Fluid intelligence factor	−0.169	0.045	<0.0005	<0.002	−0.170	0.045	<0.0005	<0.001	−0.090	0.047	0.058	—
Crystallized intelligence factor	−0.113	0.045	0.013	0.02	−0.113	0.045	0.013	0.015	−0.041	0.046	0.371	—
Processing speed factor	−0.060	0.043	0.168	—	—	—	—	—	—	—	—	—
Academic achievement												
Reading variable	−0.136	0.041	0.001	0.002	−0.137	0.041	0.001	0.001	−0.070	0.041	0.088	—
Mathematics variable	−0.105	0.041	0.011	0.02	−0.105	0.041	0.011	0.01	−0.054	0.041	0.192	—
Combined achievement/ crystallized factor	−0.148	0.045	0.001	0.002	−0.109	0.034	0.001	0.001	0.07	0.045	0.121	—

[1] $n = 869$. EF, executive function; WASI, Wechsler Abbreviated Scale of Intelligence.

association between BMI and the other EF domains measured here, nor general cognitive ability or academic abilities. Although these data support the null findings reported in the largest study to date on inhibition and BMI ($n = 1312$) (13), whether there exists an inverse association between these constructs remains a topic of lively debate (8–14).

Twin studies operate on a number of assumptions, such as the assumption that shared environmental influences operate equally on twins raised together, regardless of their zygosity. An additional assumption is that there is no assortative mating for BMI and EF, that is, people with similar EF and BMI are not mating one another more frequently than would be expected under a random mating pattern (47). We were unable to directly test these assumptions in our study. In addition, our study had limited power to conduct age-, sex- and ethnicity-stratified analyses, or to detect differences in the magnitudes of associations, although previous work has not indicated that the underlying structure of the genetic and environmental components for EF and BMI differs by these demographic factors (6, 22, 45). Therefore, we were unable empirically to probe the specificity of EF–BMI associations in relation to other cognitive measures, or to fully explore the differences in the associations between single EF domains and lower BMI, compared with that of a general EF factor. We support more focused research to tease this relation apart.

Our general EF factor was created from the loadings of 4 EF domains: inhibition, switching, working memory, and updating. Some controversy surrounds the use of a 4-domain model, which is highly similar to common 3-domain models—such as those described by Miyake et al. (54) and Engle (55)—with the addition of a working memory factor. Conceptually, the updating factor represents similar cognitive processes to our fourth factor, and

TABLE 3 Parameter estimates from biometric models of EF–BMI relations[1]

	A and *E* underlying EF		*ae* regression coefficients between BMI and higher-order EF		Residual *A*, and *E*, and total *C* unique to BMI			Genetic (r_A) and environmental (r_E) correlations	
Model	*A*	*E*	β_a	β_e	*A*	*C*	*E*	r_A	r_E
1: Full Cholesky	0.95 (0.03)*	0.31 (0.09)*	−0.100 (0.053)*	−0.078 (0.077)	0.84 (0.12)*	0.22 (0.39)	0.47 (0.06)*	−0.12 (0.06)*	−0.16 (0.16)
2a: Drop *A* cross-path	0.95 (0.03)*	0.31 (0.09)*	—	−0.149 (0.076)*	0.84 (0.11)*	0.25 (0.34)	0.46 (0.06)*	—	−0.31 (0.14)*
2b: Drop *E* cross-path	0.95 (0.03)*	0.31 (0.09)*	−0.124 (0.048)*	—	0.83 (0.12)*	0.24 (0.36)	0.48 (0.06)*	−0.12 (0.06)*	—
3: Drop *A* and *E* cross-paths	0.95 (0.029)*	0.30 (0.09)*	—	—	0.83 (0.12)*	0.28 (0.31)	0.48 (0.06)*	—	—

[1] All scores and BMI values were residualized for sex and race/ethnicity prior to being incorporated into the model. SEs are in parentheses. Biometric models were conducted as a multilevel structural equation model in MPlus, with associations between influences on EF and BMI modeled as correlated factors. $n = 869$. Significant parameters ($P < 0.05$) are denoted by an asterisk (*). The significance of parameters was tested using chi-square goodness-of-fit tests. *A*, additive genetic influences; *C*, common environmental influences; *E*, nonshared environmental influences; EF, executive function.

empirically these 2 factors are highly correlated. However, the 4-factor model provides better fit to the data in the current sample than does a 3-factor model (6). Our data include a set of indicators that are sufficiently diverse to distinguish between the 2 factors, and our previous work shows that the pattern of external correlates remains stable even after exclusion of the working memory (fourth) factor (22, 56). Therefore, it is unlikely that the use of a 4-factor model over that of a 3-factor model affected the results of this study. Nevertheless, our conclusions should be viewed in the light of our model specification and task selection, and generalizations to EF models with different numbers of factors or derived from different EF tasks should be made with caution.

With our cross-sectional design, we were also unable to determine the direction of effect between higher BMI and lower EF ability: lower EF could be either a cause or a consequence of higher BMI, or the EF–BMI relationship could be bidirectional. Longitudinal designs will help disentangle the directionality of the inverse association. Finally, BMI is a crude proxy for metabolic health; future studies that focus on supplemental adiposity-related measures, such as eating behaviors, fat percentage, or blood pressure, will deepen our understanding of the mechanisms of the EF–BMI association.

As one of the largest investigations into the inverse relationship between EF and BMI to date, our study contributes to a growing body of research suggesting an association between higher weight status and lower EF abilities. Given the importance of both childhood EF and BMI to subsequent academic functioning (7, 57–59), our research emphasizes the need to consider these cognitive differences when treating obesity. Replicating these results is a key future direction, and we would encourage research using both quantitative (twin) and molecular (measured DNA variant) approaches. Pursuing such studies using adequately powered, carefully designed investigations promises to improve outcomes for children with a high weight status.

We thank the families who participated in the Texas Twin Project, without whom this research would not be possible.

The authors' contributions were as follows—ACW, UV, JAC, KPH, and EMT-D: designed the research project; DAB, LEE, and EMT-D: analyzed data; ADG, DAB, and LEE: contributed to data collection; ACW and UV: wrote the paper; ACW, KPH, and EMT-D: had primary responsibility for final content; and all authors: read and approved the final manuscript.KPH and EMT-D are directors of the Texas Twin Project. ACW, UV, LEE, DAB, ADG, JAC, KPH, and EMT-D had no conflicts of interest.

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