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Untangling the relationship between BMI and academic achievement in the elementary years

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Abstract

Although the negative relationship between BMI and academic achievement (AA) is well documented, no prior studies have investigated the potential bi-directional relationship between BMI and AA in childhood. We investigated the longitudinal relationships between child BMI and AA across different school subjects (reading, math and science) and sexes. To do so, we employed the Early Childhood Longitudinal Study kindergarten cohort (2011), which is a nationally representative sample of American children who entered kindergarten in 2010–2011. We utilised the kindergarten–fifth grade longitudinal sample (*n* 17 480) and applied cross-lagged panel models with fixed effects to address unobserved heterogeneity. Our results showed significant but small reciprocal relationships between BMI and math/science achievement for girls (*n* 8540) (year-to-year effect sizes ranged from –0·01 to –0·04), but not for reading. In contrast, we did not find any evidence of reciprocal relationships between BMI and AA for boys (*n* 8940). Our results reveal that early weight status and academic performance may be jointly responsible for a vicious cycle of poor AA and unhealthy weight. Breaking the cycle from AA may complement existing obesity prevention strategies, particularly for girls in the science, technology, engineering and mathematics field.

Keywords: BMI: Academic performance: Bi-directional relationship: Cross-lagged panel models

The negative association between BMI and academic achievement (AA) is well documented, particularly for girls[1–3]. This association is believed to reflect a causal effect of BMI, partly due to internalisation of the social stigma associated with body weight[4–6] or to more direct physiological mechanisms including impaired brain development[7]. While previous studies have primarily focused on the unidirectional relationship from BMI to AA, this study is the first that investigates a potential *bi-directional* relationship between BMI and academic performance in childhood.

How might prior academic performance influence students' body weight? Although it has been rarely explored compared with studies on BMI effects on academic performance, it is plausible to hypothesise that student AA could affect body weight via several mechanisms. For example, Alatupa *et al.*[8] show that school performance in early and middle adolescence predicts adult obesity. Specifically, school-age children often suffer from several mental health problems caused by poor academic performance in the context of high stress school environments[9]. For example, meta-analyses reveal the significant effect of academic performance on depression[10] and subjective well-being[11]. At the same time, health researchers have identified a mutual relationship between mental health and body weight[12–14]. Thus, poor academic performance in school likely leads to reduced self-worth, emotional stress or even depression, in turn leading to unfavourable eating behaviours and effects on students' health[8]. Educational psychologists and sociologists describe these effects as problems of school adjustment, finding a strong link between academic and social experiences in school[15]. In this study, we focus on testing the basic reciprocal relationship between achievement and BMI across the span of elementary school, rather than examining specific mediating mechanisms.

These school-based processes may operate especially strongly for girls, who are more likely than boys to internalise problems in school as self-rejection and depression[16], which in turn affect weight gain[17]. Although girls perform well in school compared with boys overall, girls are still more susceptible to academic anxiety[18] and experience academic challenges in adjusting in particular to science, technology, engineering and

Abbreviations: AA, academic achievement; CFI, comparative fit index; CLPM, cross-lagged panel model; ECLS-K, Early Childhood Longitudinal Study kindergarten; FE-CLPM, cross-lagged model with fixed effect; RI-CLPM, random intercept cross-lagged panel model; RMSEA, root mean square error of approximation; TLI, Tucker–Lewis index.

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mathematics fields compared with boys[19,20]. Together, prior research points to the existence of a reciprocal relationship between BMI and academic performance through several mechanisms.

Reciprocal models provide a framework for researchers, health professionals and policymakers to identify the underlying causes of positive and negative changes in youth development[21,22]. To our knowledge, however, no prior research has investigated the potential reciprocal relationship between BMI and academic performance in childhood, with large-scale data. In this study, we argue that the relationship between BMI and achievement is indeed bi-directional and that the effect of achievement on BMI is an important part of this process, particularly for girls. If early weight status and academic performance are *jointly* responsible for a vicious cycle of poor AA and unhealthy weight, breaking the cycle from AA may complement existing obesity prevention strategies.

To test this hypothesis, we leverage the rich Early Childhood Longitudinal Study kindergarten (ECLS-K) cohort data that include high quality measures of BMI as well as reading, math and science test scores in the USA. We analyse these bi-directional relationships using the recently developed cross-lagged panel models (CLPM) framework, which can effectively address unobserved heterogeneity among students. Given the significant sex gaps in AA[23] and mental health[24], we further test whether the underlying reciprocal relationship between BMI and academic performance differs for girls and boys.

Methods

Data source

The ECLS-K cohort is a nationally representative sample of American children who entered kindergarten in 2010–2011. ECLS-K followed this cohort until the 2015–2016 school year, providing a comprehensive picture of children's educational development through secondary school[25]. Approximately 18 170 kindergarteners from 1310 schools were sampled in the baseline year. This study utilised the kindergarten (mean age of 6·12 in spring)–fifth grade (mean age of 11·08 in spring) longitudinal sample. Final sample sizes (n 17 480) were rounded to the nearest 10 in accordance with US National Center for Education Statistics secure data requirements.

Measures

BMI. To obtain accurate measurements, each child's height (lower limit was 35 inches and upper limit was 80 inches) and weight (lower limit was 30 pounds and upper limit was 300 pounds) were measured twice at each data collection round in the ECLS-K. Child height was measured with a Shorr board, while weight was measured on a digital scale (for more information on the process, see Tourangeau *et al.*[25]). Child BMI (weight/height^2) was then calculated by averaging the ratios of weight and height (labelled 'composite BMI' in the ECLS-K data files)[26,27].

Academic achievement. AA measures include the reading, math and science item response theory scores widely used in previous studies[28,29]. Item response theory scoring facilitates longitudinal tracking of achievement gain, irrespective of the variation in assessments given to a child. The ECLS-K achievement measures have generally high reliability at each grade level[25]. We used standardised BMI and item response theory scores to compare bi-directional effects in a common metric. Descriptive statistics and correlation matrices of the variables are reported in online Appendix S1–3.

Analytic strategy

To investigate the reciprocal relationships between BMI and AA, we employed a cross-lagged model with fixed effects (FE-CLPM)[30,31] relying on information at six time points (kindergarten through grade 5). Kindergarten data were utilised to control for lagged effects of BMI and AA in children transitioning to elementary school and to examine changes in these relationships. The basic model can be written in two equations (estimated simultaneously) as follows:

$$BMI_{it} = \partial_t + \beta_1 BMI_{it-1} + \beta_2 AA_{it-1} + \alpha_i + v_{it}$$

$$AA_{it} = \tau_t + \beta_3 AA_{it-1} + \beta_4 BMI_{it-1} + \eta_i + u_{it},$$

where ∂_t and τ_t are intercepts that vary with time, and β_1 and β_3 are autoregressive coefficients, β_2 and β_4 are the cross-lagged coefficients of primary interest in this study and v_{it} and u_{it} are random disturbances. The residuals are assumed to be independent of each other and normally distributed with means of zero and constant variance. What differentiates these two equations from the conventional CLPM is that unobserved stable individual-specific or unit effects (α_i and η_i) are specified. These fixed effects capture unmeasured stable child, family, school and community/district characteristics that may confound the relationships between BMI and AA[32,33]. Thus, in the above equation the cross-lagged and autoregressive coefficients represent within-student estimates removing all between-student variation (including the effects of various student-level covariates related to family background, age at school entry, etc.). Within-student estimates of BMI and AA should be less biased than those from conventional covariate-adjustment models including conventional CLPM estimates[21,34].

Figure 1 represents the FE-CLPM framework, which is an expansion of the above equations. It is important to emphasise that the stable unit effects (η_i and α_i) are latent variables (identified with the availability of multiple time points) and are fixed at one to all endogenous variables as in the equations (for a general overview of SEM-based panel models see Bollen and Brand[35]). The FE-CLPM approach is similar to a random intercept cross-lagged panel model (RI-CLPM) in that within-person effects are separated from between-person effects[34]. We prefer the FE-CLPM over RI-CLPM, as recent studies highlight potential pitfalls of RI-CLPM in estimating the effects of repeated within-person measures, which are our key variables of interest here[36,37]. Yet, we confirmed that FE-CLPM results are very similar to the RI-CLPM specification (results from RI-CLPM are available in online Appendix S4–6, and applied syntax for FE- and RI-CLPM is provided in online Appendix S8).

To parsimoniously capture the overall effects of BMI on AA, and AA on BMI across each set of time points, we first report

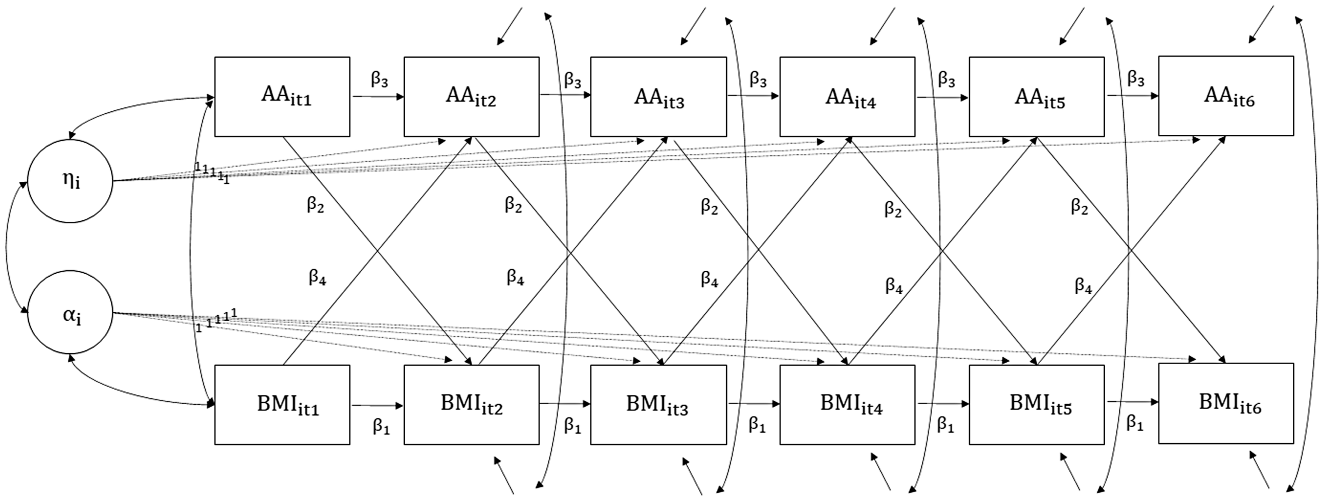

Fig. 1. Diagram of cross-lagged model with fixed effects with six time points. Note: potential time-varying confounders (family income, child learning disabilities and health conditions) were controlled for in extended models.

models where those key effects are constrained to be the same across each transition, essentially reporting the average effects (as shown in Fig. 1: β_1 to β_4 are not time point specific). Models that allow the effects to vary across each transition were then evaluated. Missing cases were imputed with full information maximum likelihood. We report results from unweighted analyses, which include standard ECLS-K design parameters[29,38]. We employed a maximum likelihood estimator with robust standard errors in Mplus 8.0 to carry out our analyses.

Results

Prior to the main analyses, we briefly explore the raw correlations between key variables, identifying basic associations and changes in AA and BMI for boys and girls over the study period. We then investigate the reciprocal relationship between BMI and AA with robustness checks on our findings.

Descriptive statistics

In the ECLS-K, 49% of the participants were girls, 13% were Black, 25% were Hispanic, 9 % were Asian and 47% were White (for more information on the data, see Tourangeau *et al.*[25] or visit https://nces.ed.gov/ecls/kindergarten2011.asp). Correlations between BMI and achievement in each school subject (along with means and SD) are reported separately for girls and boys in online Appendix S1–2. Capturing the basic stability of BMI and achievement, there were strong but not unitary correlations across time for each repeated measure (e.g. adjacent year-to-year correlations in BMI were 0·90–92 for girls). The repeated measure correlations for achievement were somewhat lower (e.g. 0·76–0·84 for girls in science). Considering the K-5th grade span, even this relatively small amount of year-to-year instability results in far from perfect intra-item correlations over this period. For example, Kindergarten BMI is correlated 0·75 with grade 5 BMI while achievement correlations range from 0·59 to 0·72 for boys.

Inter-item correlations between BMI and achievement were negative and became slightly stronger in later grades, particularly for girls (see bolded values); the test of correlation coefficients equality revealed significant differences in reading and science between sexes at grade 5. We also observed slightly higher correlations of BMI and math achievement than other subjects both for boys and girls. These relationships occurred within the context of rising mean scores for both BMI and academic performance. As in previous studies[39], girls showed slightly higher reading achievement than boys, while boys outperformed girls in math and science in tested achievement.

The reciprocal relationships between BMI and academic achievement

Table 1 reports results for the bi-directional relationships between BMI and achievement in each academic domain across sexes, beginning with the simplifying assumption of constant effects at each time point (i.e. average effects over time as in the traditional regression framework). Despite their simplicity, these models have excellent fit in terms of standard statistical fit indices including root mean square error of approximation (RMSEA), comparative fit index (CFI) and Tucker–Lewis index (TLI).

To begin, as anticipated by the descriptive correlations, we found strong autoregressive intra-item associations for both BMI and achievement among both boys and girls. Yet the observed associations were slightly stronger for boys, and the magnitudes of autoregressive associations were greater for BMI. Table 1 also presents initial findings on our central hypotheses concerning cross-lagged, inter-item relationships. We found significant relationships between prior-year test scores and current levels of BMI for girls in all school subjects, although estimated coefficients were small (–0·02 for reading/math and –0·01 for science). There were also significant associations between previous levels of BMI and current math (–0·02) and science (–0·04) test scores. Using the results from Table 1, a model-based summary of changes associated only with the cross-lagged relationships for girls with obesity throughout elementary school (2SD ≥ BMI) shows that obese girls are expected to have math scores 0·20 of an SD lower at grade 5 ((–0·02 × 2) × 5) than the

Table 1. Results from cross-lagged model with fixed effects: average lagged and cross-lagged effects

Models	Girls (*n* 8540)		Boys (*n* 8940)	
Paths	Standardised coefficients	Confidence interval	Standardised coefficients	Confidence interval
$Reading_{T-1}$->$Reading_T$	0·28***	0·27, 0·30	0·31***	0·30, 0·33
BMI_{T-1}->BMI_T	0·42***	0·38, 0·46	0·46***	0·42, 0·50
$Reading_{T-1}$->BMI_T	–0·02**	–0·03, –0·01	0·00	–0·01, 0·01
BMI_{T-1}->$Reading_T$	–0·01	–0·03, 0·01	0·01	–0·01, 0·02
Model fit indices for BMI and math	χ^2: 486·20 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·98		χ^2: 553·05 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·98	
$Math_{T-1}$->$Math_T$	0·29***	0·28, 0·31	0·37***	0·35, 0·38
BMI_{T-1}->BMI_T	0·42***	0·38, 0·46	0·46***	0·42, 0·50
$Math_{T-1}$->BMI_T	–0·02**	–0·03, –0·01	–0·01	–0·02, 0·003
BMI_{T-1}->$Math_T$	–0·02*	–0·04, –0·01	–0·01	–0·03, 0·003
Model fit indices for BMI and science	χ^2: 430·05 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·99		χ^2: 544·73 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·98	
$Science_{T-1}$->$Science_T$	0·27***	0·25, 0·29	0·29***	0·27, 0·31
BMI_{T-1}->BMI_T	0·42***	0·38, 0·46	0·46***	0·42, 0·50
$Science_{T-1}$->BMI_T	–0·01**	–0·02, –0·003	0·01	–0·01, 0·02
BMI_{T-1}->$Science_T$	–0·04***	–0·06, –0·02	–0·00	–0·02, 0·02
Model fit indices for BMI and reading	χ^2: 452·01 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·98		χ^2: 544·36 (53) RMSEA: 0·03; CFI: 0·99; TLI: 0·98	

T represents time.
* $P<0·05$.
** $P<0·01$.
*** $P<0·001$.

average. Isolating the cross-lagged 'effect' of math achievement, high-achieving girls (one SD above *vs*. the mean) are expected to have 0·10 of an SD lower BMI at grade 5 (–0·02 × 5). Overall, Table 1 reveals that the relationships between BMI and math/science subjects are indeed reciprocal rather than unidirectional. However, this finding is restricted to girls in mathematics and science.

The time-varying reciprocal relationships between BMI and academic achievement

In Tables 2 (for girls) and 3 (for boys), we relaxed the equality constraints on the autoregressive and cross-lagged parameters, as well as covariances of the residuals. These models capture the time-specific effects of BMI and AA, such that for example, achievement might have a stronger cross-lagged effect on BMI in later grades as self-conceptions of ability become more fully formed. Examining the auto-regressive, intra-item relationships between repeated measures for BMI and AA (e.g. $BMI_k \rightarrow BMI_{G1}$), they were similar on average to estimates from Table 1, but we now see additionally that the intra-item associations are relatively stable across grade levels. Regarding cross-lagged, inter-item relationships, consistent with the findings from Table 1, we found little or no relationships for boys (Table 3). In contrast, for girls we found significant reciprocal relationships of BMI with math and science achievement. With effects estimated for each year in Table 2, we now see that the observed cross-lagged relationships from math/science achievement to BMI for girls become more pronounced in later grades, while differences in the cross-lagged relationship from BMI to math/science achievement across grade levels are less consistent.

Robustness checks

We checked the robustness of our findings with supplemental models as follows: First, we reassessed our findings with RI-CLPM. The results illustrated in online Appendix S4–6 show very similar patterns, particularly for cross-lagged relationships. Second, although FE- and RI-CLPM can effectively address unobserved stable characteristics, they are still susceptible to time-varying confounding. To address this concern, we controlled for several observed time-varying confounders: family income, as well as parent reports of child learning disabilities and health conditions. Further, we allowed the *effects* of unobserved time-invariant factors for each unit (α_i and η_i in Fig. 1) to vary over time. This may be a more realistic model, in that even as the variables themselves do not change, the effects of stable unobservables may change over time. The models with time-varying unit effects should address some portion of the unobserved time-varying confounding[30]. The results presented in online Appendix S7 also show similar patterns, providing a degree of confidence in our findings.

Discussion

In the present study, we argue that the relationship between BMI and AA may be reciprocal rather than unidirectional. To test our claim, we employed CLPM with fixed effects to account for unobserved individual and environmental factors affecting BMI and AA. To our knowledge, this study is the first that provides empirical evidence on this relationship longitudinally, with large-scale data. We found significant bi-directional relationships between BMI and math/science achievement for girls, but not for reading. The observed year-to-year effect sizes (between –0·01 and –0·04) represent relatively small effects[40], although when accumulated over the elementary years the relationships are more substantial. In contrast, we did not find any evidence of reciprocal relationships between BMI and AA for boys.

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Table 2. Results for girls: cross-lagged model with fixed effects without equality constraints

Models	Reading		Math		Science	
Paths	Standardised coefficients	Confidence interval	Standardised coefficients	Confidence interval	Standardised coefficients	Confidence interval
AA_K->AA_{G1}	0·31***	0·29, 0·32	0·29***	0·27, 0·31	0·28***	0·26, 0·30
AA_{G1}->AA_{G2}	0·28***	0·26, 0·30	0·29***	0·27, 0·31	0·27***	0·25, 0·29
AA_{G2}->AA_{G3}	0·24***	0·22, 0·26	0·29***	0·27, 0·31	0·26***	0·24, 0·28
AA_{G3}->AA_{G4}	0·26***	0·25, 0·28	0·30***	0·28, 0·32	0·25***	0·23, 0·27
AA_{G4}->AA_{G5}	0·26***	0·24, 0·28	0·31***	0·29, 0·33	0·26***	0·24, 0·29
BMI_K->BMI_{G1}	0·43***	0·39, 0·47	0·43***	0·39, 0·47	0·43***	0·39, 0·47
BMI_{G1}->BMI_{G2}	0·40***	0·36, 0·44	0·40***	0·36, 0·44	0·40***	0·36, 0·44
BMI_{G2}->BMI_{G3}	0·41***	0·37, 0·44	0·40***	0·37, 0·44	0·41***	0·37, 0·45
BMI_{G3}->BMI_{G4}	0·41***	0·37, 0·44	0·40***	0·37, 0·44	0·41***	0·37, 0·45
BMI_{G4}->BMI_{G5}	0·40***	0·37, 0·44	0·40***	0·37, 0·44	0·40***	0·37, 0·44
AA_K->BMI_{G1}	−0·01	−0·02, 0·003	−0·01	−0·02, 0·003	−0·01	−0·02, 0·001
AA_{G1}->BMI_{G2}	−0·01	−0·02, 0·004	−0·01	−0·02, 0·007	−0·00	−0·02, 0·01
AA_{G2}->BMI_{G3}	−0·02**	−0·03, −0·01	−0·02**	−0·04, −0·01	−0·02*	−0·03, −0·003
AA_{G3}->BMI_{G4}	−0·02**	−0·04, −0·01	−0·03***	−0·04, −0·01	−0·02*	−0·03, −0·003
AA_{G4}->BMI_{G5}	−0·04***	−0·06, −0·02	−0·04***	−0·06, −0·02	−0·03**	−0·04, −0·01
BMI_K->AA_{G1}	−0·01	−0·04, 0·01	−0·02	−0·04, 0·002	−0·03*	−0·05, −0·01
BMI_{G1}->AA_{G2}	−0·01	−0·03, 0·01	−0·04***	−0·06, −0·02	−0·04***	−0·07, −0·02
BMI_{G2}->AA_{G3}	−0·02	−0·04, 0·01	−0·04***	−0·06, −0·02	−0·05***	−0·08, −0·03
BMI_{G3}->AA_{G4}	−0·01	−0·03, 0·01	−0·02	−0·04, 0·004	−0·05***	−0·07, −0·03
BMI_{G4}->AA_{G5}	−0·01	−0·03, 0·02	−0·01	−0·04, 0·005	−0·04**	−0·06, −0·02
Model fit indices	χ^2: 394·07 (33) RMSEA: 0·04; CFI: 0·99; TLI: 0·98		χ^2: 351·31 (33) RMSEA: 0·03; CFI: 0·99; TLI: 0·98		χ^2: 400·71 (33) RMSEA: 0·04; CFI: 0·99; TLI: 0·98	

n 8540. G represents grade.
* *P* < 0·05.
** *P* < 0·01.
*** *P* < 0·001.

Table 3. Results for boys: cross-lagged model with fixed effects without equality constraints

Models	Reading		Math		Science	
Paths	Standardised coefficients	Confidence interval	Standardised coefficients	Confidence interval	Standardised coefficients	Confidence interval
AA_K->AA_{G1}	0·33***	0·32, 0·35	0·38***	0·36, 0·39	0·30***	0·28, 0·32
AA_{G1}->AA_{G2}	0·32***	0·30, 0·34	0·36***	0·34, 0·37	0·29***	0·27, 0·31
AA_{G2}->AA_{G3}	0·28***	0·26, 0·30	0·36***	0·34, 0·38	0·29***	0·27, 0·30
AA_{G3}->AA_{G4}	0·29***	0·27, 0·31	0·36***	0·34, 0·38	0·28***	0·26, 0·30
AA_{G4}->AA_{G5}	0·29***	0·27, 0·31	0·37***	0·35, 0·39	0·28***	0·26, 0·30
BMI_K->BMI_{G1}	0·47***	0·43, 0·51	0·47***	0·43, 0·51	0·47***	0·43, 0·51
BMI_{G1}->BMI_{G2}	0·44***	0·40, 0·49	0·44***	0·40, 0·48	0·44***	0·40, 0·49
BMI_{G2}->BMI_{G3}	0·45***	0·40, 0·50	0·45***	0·40, 0·50	0·45***	0·40, 0·50
BMI_{G3}->BMI_{G4}	0·45***	0·40, 0·49	0·45***	0·40, 0·49	0·45***	0·40, 0·49
BMI_{G4}->BMI_{G5}	0·45***	0·40, 0·50	0·45***	0·40, 0·50	0·45***	0·40, 0·50
AA_K->BMI_{G1}	0·00	−0·01, 0·01	−0·00	−0·01, 0·01	0·00	−0·01, 0·02
AA_{G1}->BMI_{G2}	0·01	−0·01, 0·02	−0·00	−0·02, 0·01	0·01	−0·002, 0·03
AA_{G2}->BMI_{G3}	−0·01	−0·02, 0·01	−0·01	−0·03, 0·001	−0·00	−0·02, 0·01
AA_{G3}->BMI_{G4}	−0·01	−0·02, 0·01	−0·02	−0·03, 0·001	−0·00	−0·02, 0·01
AA_{G4}->BMI_{G5}	0·01	−0·01, 0·02	0·00	−0·02, 0·01	0·01	−0·003, 0·02
BMI_K->AA_{G1}	0·01	−0·01, 0·03	−0·01	−0·03, 0·004	0·00	−0·02, 0·02
BMI_{G1}->AA_{G2}	0·00	−0·02, 0·02	−0·03**	−0·05, −0·01	−0·01	−0·03, 0·01
BMI_{G2}->AA_{G3}	0·01	−0·01, 0·03	−0·00	−0·02, 0·02	−0·01	−0·03, 0·01
BMI_{G3}->AA_{G4}	−0·01	−0·03, 0·01	−0·00	−0·02, 0·02	−0·01	−0·03, 0·01
BMI_{G4}->AA_{G5}	0·03*	0·01, 0·05	−0·00	−0·02, 0·02	0·01	−0·01, 0·03
Model fit indices	χ^2: 443·81 (33) RMSEA: 0·04; CFI: 0·99; TLI: 0·98		χ^2: 470·49 (33) RMSEA: 0·04; CFI: 0·99; TLI: 0·98		χ^2: 479·83 (33) RMSEA: 0·04; CFI: 0·99; TLI: 0·97	

n 8940. G represents grade.
* *P* < 0·05.
** *P* < 0·01.
*** *P* < 0·001.

Strengths and limitations

In this study, we use nationally representative data in the USA from a high quality federally sponsored data collection, reducing errors from measurement, coverage, sampling and non-response compared with prior studies[41]. We carefully examined reciprocal linkages for both girls and boys in multiple school subjects. Utilising reliable repeated measures, methodologically, the applied FE-CLPM is robust to unobserved time-varying and -invariant effects of stable confounders, providing a degree of confidence in our claims.

However, while we provided several theoretical explanations for the reciprocal link between BMI and academic performance, the underlying mechanisms were not directly tested in this study. It should also be noted that the observed relationship between BMI and academic performance may be different in other contexts. For instance, recent evidence from China suggests that there is a positive reciprocal relationship between BMI and subjective well-being, implying that excess weight has a very different psychosocial function in Chinese families, schools and society[42]. We acknowledge that our findings may be specific to the US contexts. Finally, this study only investigated the linear relationship between BMI and AA. Although the continuous form of BMI is widely used in previous CLPM studies[42–44], future studies will need to consider different thresholds for BMI as well as alternative body weight measures (e.g. waist circumference or waist hip ratio), which may better predict outcome variables[3]. For now, BMI is the best child weight indicator that we can obtain from the ECLS-K. Future studies may also need to consider alternative CLPM that can take into account a nested structure of data where individuals are cross-classified. Yet, to our knowledge the applied FE- and RI-CLPM are the preferred state-of-the-art models for examining within-person developmental processes.

Implications

We showed that there are significant reciprocal relationships between BMI and math/science achievement for girls, including a significant link between poor academic performance and increased BMI. What might explain the observed sex differences? It is well documented that girls are more vulnerable to obesity stigma[45]. Research also indicates that academic stress and psychosocial factors can contribute to weight gain in children[46]. Specifically, girls often exhibit higher academic anxiety than boys[18]. For example, Wiklund *et al.* found[47] that Swedish girls are more likely to feel pressure from school demands compared with boys. The student engagement literature has also documented that female students are more likely to face academic challenges in adjusting in particular to science, technology, engineering and mathematics fields, likely due to sex stereotyping or inadequate early experiences[19,20]. Thus, academic stress in math and science may lead to negative health behaviours affecting weight gain[12], establishing the reciprocal relationships between BMI and math/science achievement.

Our findings also highlight some methodological considerations in investigating the effects of BMI on academic performance, including ramifications for interpreting findings from traditional covariate-adjustment models. Evidence suggests that in studies of achievement growth, weight status is an endogenous variable confounded by numerous factors such as family socio-economic status, community/district contexts or genetic factors[1]. Yet limited attention has been paid to potential bias due to reverse causality from academic performance to BMI. In particular, when considering how these relationships unfold over multiple years, our findings show a particular pattern of relationships, with a negative path from prior-year academic performance to students' current BMI (–) and a positive path to current academic performance (+). Thus, in traditional models the effect of BMI will appear more strongly negative than it really is (for similar examples see Pearl[48]). Yet, the current results suggest that such bias would be relatively small in the early grades examined here. However, since we observed stronger associations between prior academic performance and BMI among girls in later grades, it may be important to utilise dynamic panel modelling and related approaches in understanding outcomes among adolescents and older youth[30]. Indeed evidence suggests that the obesity penalty for girls may be stronger in adolescence[49] and that academic stress increases over time[50]. Unfortunately, to date, secondary school data collected by the National Center for Education Statistics in the USA have had a simpler structure with fewer time points of data.

Conclusion

The ECLS-K data, when viewed through the lens of CLPM, provide the best evidence to date that weight status and AA are closely intertwined, especially for girls. These effects accumulate year after year, particularly in science and mathematics, the subjects where girls' engagement and motivation are most tenuous. Ecological Models of Childhood Obesity highlight the importance of a broad array of inter-connected child, family and societal characteristics that affect diet and exercise. Within this framework, our findings suggest specifically that difficulties in school contribute to obesity, and thus academic interventions may complement other obesity prevention strategies. Reducing academic anxiety and stress will lead to better academic performance[51], but it may also help to promote health behaviours and outcomes[52]. A recent study also emphasises that conventional physical education and other school-based physical activities alone are not sufficient to prevent the obesity epidemic[53]. Yet, further research is needed to expand this study to explore the achievement-obesity connection in secondary school settings and to reveal intervening social–psychological mechanisms.

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Supplementary material

For supplementary materials referred to in this article, please visit https://doi.org/10.1017/S0007114523001757

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