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The relationship between cognitive ability and depression: a longitudinal data analysis

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Abstract
Purpose There is literature indicating cognitive ability and depression are related, but few studies have examined the direction of the relationship. This study examined the relationship between depression levels and cognitive abilities from adolescence to early adulthood.
Methods Using the National Longitudinal Study of Adolescent Health ($n = 14{,}322$), this study used path modeling to investigate the relationship between depression and cognitive ability at baseline and again 8 years later.
Results After controlling for initial levels of depression, cognitive ability, and other covariates, depressive symptoms in adolescence are related to cognitive ability in early adulthood, but adolescent cognitive ability is not related to adult depression levels. Moreover, after controlling for adolescent levels of depression and cognitive ability, the cognitive ability–depression relationship disappears in adulthood.
Conclusions The cognitive ability–depression relationship appears early in life, and it is likely that the presence of depressive symptoms leads to lower cognitive ability. Thus, intervening at early signs of depression not only can help alleviate depression, but will likely have an effect of cognitive ability as well.

Keywords Depression · Cognitive ability · Longitudinal study · National longitudinal study of adolescent health

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Introduction

Over the past two decades, many studies have been published examining the relationship between cognitive ability and a variety of health outcomes, including both physical and mental health [1–4]. Most of these types of studies have shown that having lower cognitive ability measured is a strong predictor of multiple psychiatric disorders, including depression [5–7], or one of its manifestations (e.g., suicide completion [8, 9], suicidal thoughts [10, 11]).

This relationship between cognitive ability and depression appears to manifest itself throughout the life cycle, including childhood [12], adulthood [13], or in the elderly [9, 14]. More than just a predictor, though, many studies have shown that cognitive ability measured at one time point is related to depression at a later time point [6, 15–17] indicating that cognitive ability might play a causative role in depression. As depression is problem that many individuals encounter in their life, including adults and children across the age spectrum [18, 19], and one with serious potential sequelae [20, 21], finding potential risk or causal factors, especially in children and adolescents, could be of much benefit in helping individuals obtain the treatment they need [22].

Problems with previous studies

There are two major problems with previous studies that have examined the depression–cognitive ability relationship. One problem is that many of the studies have used either a cross-sectional design, measuring both cognitive ability and depression concurrently, or a longitudinal design, measuring one variable at one time point and another variable at a later time point. As neither design controls for previous level cognitive ability nor depression, they are not able to examine if one variable has a causal connection to the other [23, 24].

The second problem with previous studies is that most of them focus on a clinical diagnosis of depression, often marked by severe change in life such as hospitalization or suicide attempt. This metric for depression is faulty for at least two reasons. First, it only captures those at the extreme end of the depressive spectrum and fails to take into account that depression falls onto a continuum [25]. Moreover, this metric only can capture those who are willing (or have friends/family who are willing) and have the means to obtain professional help.

Due in part to their design, most previous studies have not been able to determine if lower cognitive ability puts one at a higher risk for having depressive symptoms, if having depressive symptoms might put one at a higher risk for having lower cognitive ability, or if there might be a third variable that causing the relationship between the variables. Answering the "which comes first" question can be difficult, as it is impossible to assign people to depression/non-depression groups randomly, nor it is possible to assign people certain levels of cognitive ability. Consequently, the answer to the question of if cognitive ability is causatively related to depression (or visa versa) will have be gained through an observational study [26]. While there are a range of different observational methods, one specific type of study that can help answer the cognitive ability–depression question is a longitudinal design where cognitive ability and depression are measured at multiple time points and different potential causal pathways are statistically modeled [27]. The purpose of this current study is to examine the depression–cognitive ability relationship, specifically examining if there might be a causal relationship between the two variables.

Method

Sample

The sample for this study came from the National Longitudinal Study of Adolescent Health (Add Health [13]). Add Health was initiated in 1994, as has been collected in multiple waves, largely through the use of in-home questionnaires. It was designed to be the largest, most comprehensive survey of adolescents ever undertaken to study the health-related behaviors of adolescents and their outcomes in young adulthood. This study used Add Health participants who completed the in-home surveys during Wave I (1994–1995) and Wave III (2001–2002), for a total of 14,322 participants. While there was some attrition between the data collection waves, using the appropriate Add Health sampling weights, which accounts for the attrition, produces unbiased parameter estimates [28]. Demographic information about the sample is given in Table 1.

Variables

Cognitive ability

The measure of cognitive ability used in this study is the Add Health Picture Vocabulary Test (AHPVT), an abridged version of the revised Peabody Picture Vocabulary Test (PPVT-R; [29]). The AHPVT contains half the items from the original PPVT-R and uses the same illustrations; thus there is a strong correlation (0.96) between scores on the two instruments. Vocabulary tests are often used as a measure of cognitive ability in health research [30], as vocabulary is consistently found to be one of the strongest measures of overall cognitive ability [31–33]. Moreover, some even advocate its usage over other measures when using a sample of highly diverse individuals [34], and, because measures like the AHPVT require no comprehensive reading skills, it is particularly appropriate for measuring cognitive abilities of people at the lower end of the ability spectrum.

Depression

Wave I and III of the Add Health study does not measure depression directly, but many of the items in the In-Home surveys ask about symptoms commensurate with a clinical diagnosis of depression [35] and other instruments designed to measure depressive symptoms [36]. Consequently, this study formed depression questionnaires for Wave I and Wave III by taking all the items related to depression within each wave and factor analyzing them to develop a single-construct measure of depression [37]. Because the items the In-Home surveys asked in Waves I and III were not exactly the same, the questionnaires for the two waves are not identical; however, there was considerable overlap between the instruments (six items), which allowed the scores from both instruments to be equated [38]. The item stems, factor pattern coefficients, and reliability coefficients for the depression instruments' scores are given in Table 2.

To make sure the instruments were measuring the same construct over time, we tested for measurement invariance of the six items that overlapped both waves' data [39, 40]. Assessing for invariance is a multi-step procedure that examines if items are working the same across different groups [41]. While the groups are often defined by demographic variables, they can also be defined by time (e.g., comparing item performance at Wave I versus Wave III

Table 1 Descriptive statistics

Variable	Mean	Standard deviation	Range
Age Wave I (years)	15.98	1.42	11.42–21.38
Age Wave III (years)	22.35	1.42	17.86–28.05
AHPVT Wave I	100.61	14.61	10–141
AHPVT Wave III	102.22	13.20	11–123
Male (%)	50.22		
Race			
Caucasian (%)	76.31		
African American (%)	16.74		
American Indian (%)	2.57		
Asian/Pacific Islander (%)	4.22		
Biracial (%)	0.05		
Hispanic origin (%)	11.83		

All statistics are weighted. The AHPVT was scaled to have a mean of 100 and standard deviation of 15

AHPVT Add Health Picture Vocabulary test

Table 2 Psychometric analyses for depression instruments

Variable name	Wave	Item stem	Pattern coefficient	Standard error
H1FS1	1	In the past 7 days, how often were you bothered by things that usually don't bother you?	0.65	0.02
H1FS2	1	In the past 7 days, how often did you not feel like eating/poor appetite?	0.50	0.02
H1FS3	1	In the past 7 days, how often could you not shake off the blues, even with help from your family and your friends?	0.80	0.01
H1FS5	1	In the past 7 days, how often did you have trouble keeping your mind on what you were doing?	0.58	0.02
H1FS6	1	In the past 7 days, how often were you depressed?	0.86	0.01
H1FS9	1	In the past 7 days, how often did you feel your life had been a failure?	0.76	0.02
H1FS10	1	In the past 7 days, how often did you feel fearful?	0.60	0.02
H1FS13	1	In the past 7 days, how often were you lonely?	0.75	0.01
H1FS16	1	In the past 7 days, how often were you sad?	0.81	0.01
H1FS17	1	In the past 7 days, how often did you feel people disliked you?	0.60	0.02
H1FS19	1	In the past 7 days, how often did you feel your life was not worth living?	0.76	0.02
H3SP2	3	In the past 12 months, how often have you cried a lot?	0.47	0.02
H3SP5	3	In the past 7 days, how often were you bothered by things that usually don't bother you?	0.68	0.02
H3SP6	3	In the past 7 days, how often could you not shake off the blues, even with help from your family and your friends?	0.83	0.01
H3SP8	3	In the past 7 days, how often did you have trouble keeping your mind on what you were doing?	0.60	0.02
H3SP9	3	In the past 7 days, how often were you depressed?	0.93	0.01
H3SP10	3	In the past 7 days, how often were you too tired to do things?	0.48	0.02
H3SP11	3	In the past 7 days, how often did you enjoy life?	0.63	0.02
H3SP12	3	In the past 7 days, how often were you sad?	0.84	0.01
H3SP13	3	In the past 7 days, how often did you feel people disliked you?	0.56	0.02

The correlation between the latent depression scores from Waves I and III was 0.41. The model fit statistics were $\chi^2_{(df = 169)}$: 1,309.74, comparative fit index: 0.98, Tucker Lewis index: 0.98, root mean square error of approximation: 0.02. Reliability estimates were 0.92 (omega) and 0.91 (alpha) for Wave I and 0.89 (omega) and 0.87 (alpha) for Wave III. Reliability estimates were obtained using non-weighted polychoric correlations [72]

[42]) although when the groups are defined by time the residual variances of the same variables are often modeled to covary [43].

Traditionally, tests of invariance used the change in χ^2 values ($\Delta\chi^2$). If the $\Delta\chi^2$ values does not "significantly" change as the models grow more restrictive (i.e., more invariance constraints are added), this is taken to indicate that the more restrictive model fits the data as well as the less restrictive model. Thus, the more restrictive (i.e., more parsimonious) model is favored over the less restrictive one. The use of $\Delta\chi^2$ values has been criticized because of its sensitivity to sample size [44]. Thus, many researchers [45, 46] currently suggest using a more practical perspective when examine invariance. Specifically, that the multigroup factor model exhibits an adequate fit to the data and the change in alternative fit indices values from the less restrictive to the more restrictive model is negligible. Cheung and Rensvold [44] and Meade et al. [47] have argued that the Comparative Fit Index (CFI) and McDonald's [48] Noncentrality Index (Mc) are more robust indices to use than the χ^2 when examining invariance.

To test invariance, we used three models. First, we fit a baseline model allowing the latent variables and residuals across the six identical items to covary across time, but imposing no parameter constraints. Second, we constrained the six overlapping items to have the same pattern coefficient across time, but allowed the variance of the depression factor at Wave III to be free. Third, we constrained the six identical items' thresholds to be the same across time, but allowed the mean of the depression factor at Wave III to be free. If the third model fits the data as well as models one and two, this would indicate that that the latent variables are comparable [41]. In all three models, we allowed the residual variances of the same variables across time points to covary.

Covariates

The respondents' sex and self-reported race and ethnicity were used as covariates. Because the AHPVT used English vocabulary words, we used English language fluency (i.e., if English was the primary language to speak with his/her family or friends) as a covariate. In addition, we used the highest education obtained by the residential parent(s) as a proxy for SES and used it as a predictor of depression and cognitive ability at both data collection waves.

Data inspection

There were missing data on all variables except for the participant's sex. As there were no distinguishable patterns in the missing data, and each variable had responses from at least 99 % of sample, it is likely that the data are missing at random or completely at random [49].

Determining model fit

When comparing statistical models, one needs to have criteria upon which to evaluate them [50]. For overall model fit, we used (a) the root mean square error of approximation (RMSEA), (b) the comparative fit index (CFI), (c) Akaike's information criterion (AIC), and (d) McDonald's [51] noncentrality index (Mc). These indices were chosen as they represent a variety of fit criteria and they tend to perform well in evaluating different models [52]. To test the change-in-fit between nested models for invariance, we used the change in CFI and Mc values (ΔCFI and ΔMc, respectively).

For this study's criteria of overall model-data fit, we used the following: (a) RMSEA ≤ 0.08 [53, 54]; (b) CFI ≥ 0.96 [55]; and (c) Mc ≥ 0.90 [56, 57]. AIC values do not indicate how well a model (absolutely) fits the data; rather, they are used in a relative fashion. Models with lower AIC values indicate a better fit than models with higher values, after penalizing each model for its complexity (i.e., number of parameter estimates). While information-based fit measures are typically used with maximum likelihood estimation, the AIC can be estimated using least squares via AIC $= \chi^2 + 2K$, where K is the total number of estimated parameters [58].

Cheung and Rensvold [44] and Meade et al. [47] differ on the amount of change needed in the CFI and Mc fit indices to reject invariance, but both would agree than a ΔCFI > 0.01 and a Δ Mc difference >0.02 in the NCI would indicate a rejection of invariance.

Parameter estimation

All data analysis was done using Mplus [59], using its robust weighted least squares estimator, which works well with large sample sizes and non-normal data [60].

Consequently, the missing data were handled using Mplus' four-step estimation, which is similar to full information maximum likelihood estimation, in that it uses all the information from the respondents instead of removing those with missing data [61]. The exception is for those individuals missing data on one of the covariates ($n = 999$), which Mplus excluded listwise when using the robust weighted least squares estimator.

Results

Invariance in the depression measure

The results from the invariance analysis are given in Table 3. Using the ΔCFI and ΔMc criteria, it appears as if the overlapping items are essentially acting identically at both waves of data collection. That is, the models that impose constraints on the loadings (I2) and thresholds (I3) do not fit the data any worse than the baseline model that allows the parameters to be freely estimated. Thus, the two depression measures can be considered to be measuring the same construct. Consequently, this analysis used the latent variable formed from the items at each wave as the measure of depression. The odds of having a clinical diagnosis of depression at one standard deviation above the mean on this depression scale versus having a score one standard deviation below the mean is 2.88 for the Wave I measure and 5.38 for the Wave III measure, indicating that the items forming this scale are measuring depression.

Depression and cognitive ability relationship

First, we obtained the correlations between the cognitive ability and depression variables at both waves (results are given in Table 4). As expected, there is a negative relationship between cognitive ability and depression in both data waves. Moreover, there were strong, positive relationships between cognitive ability scores (0.69) at Wave I and Wave III and depression scores (0.41) across these two waves, this showing the stability of the constructs.

To test the structural pathways, we initially posited a cross-lagged model where cognitive ability and depression at Wave I predicted cognitive ability and depression at Wave III (Model 1a in Table 5). We subsequently fit two alternative models. First, we constrained the cross-lagged paths in Model 1a to be equal to each other (Model 1b). Second, we removed the paths from Model 1a with weak relationships (i.e., estimate-to-standard error ratios <3), which resulted in removing the direct path from IQ at Wave I to Depression at Wave III (Model 1c). The most parsimonious model (1c) appeared to fit the data no worse than the more complex models (with the AIC indicating it better than the more complex models). The path model (with coefficient values) is shown in Fig. 1. The results indicate that after controlling for Wave I scores, cognitive ability at Wave I does not directly relate to depression at Wave III, but depression at Wave I does directly relate to cognitive ability at Wave III although the relationship is relatively small.

Next, we added the covariates to Models 1a and 1c (Models 2a and 2b, respectively, in Table 5). As with Model 1, after controlling for Wave I scores, cognitive ability at Wave I does not directly relate to depression at Wave III, but depression at Wave I does directly relate to cognitive ability at Wave III, although the relationship is still relatively small. There appeared to be a weak relationship between parent education level and the depression score at Wave III, so we removed it and refit the model (Model 2c). This final model appeared to fit the data as well or better than model 2a or 2b. The full model with covariates is shown in Fig. 2, with the weak relationships shown using a dashed line. The coefficients associated with model 2c are given in Table 6. Even after controlling for the covariates, depression at Wave I directly relates to cognitive ability at Wave III, albeit with a relatively weak magnitude. Moreover, while parental education does directly relate to cognitive ability at Wave I and III and depression at Wave I, it is not directly related to depression at Wave III.

Discussion

This study investigated the relationship between depression and cognitive ability. While many previous studies have been able to show that the two constructs are related to each other, there has been no answer to the question of if there is a causal relationship. To help answer that question, this study used data from the National Longitudinal Study of Adolescent Health (Add Health; [62]), examining cognitive ability and depression at Wave I and Wave III (approximately 8 years apart).

As with most other studies examining cognitive ability and depression, this study found that cognitive ability and depression were negatively related to each other at both Wave I and Wave III. Moreover, depression at Wave I was related to depression at Wave III, and likewise for cognitive ability, which shows the stability of both constructs through a very tumultuous time in development [63]. When

Table 3 Invariance assessment of depression instrument for overlapping items

Model	Model description	χ^2	*df*	$\Delta\chi^2$	*P*	CFI	ΔCFI	RMSEA	Mc	ΔMc
I1	Baseline	1,202.98	163	–		0.985		0.02	0.964	–
I2	Constrained factor structure coefficients (but free factor variance at Wave III)	1,210.08	169	27.77	<0.00	0.985	0.000	0.02	0.966	−0.001
I3	Constrain thresholds (but free factor mean at Wave III)	1,710.64	187	530.69	<0.00	0.981	0.004	0.02	0.957	0.009

$\Delta\chi^2$ represents the robust χ^2 difference test (i.e., DIFFTEST) [73]

CFI comparative fit index, *RMSEA*, root mean square error of approximation, *Mc* McDonald's [48] noncentrality index

Table 4 Zero-order correlations among depression and cognitive ability variables

	Cognitive ability Wave I	Cognitive ability Wave III	Depression Wave I
Cognitive ability Wave III	0.69		
Depression Wave I	−0.20	−0.17	
Depression Wave III	−0.11	−0.12	0.40

Correlations are model-based estimates

Table 5 Fit of different models testing the cognitive ability and depression relationship

Model	Description	χ^2	*df*	RMSEA	CFI	Mc	AIC	$R^2_{\text{WIII-ADPVT}}$	$R^2_{\text{WIII-Dep}}$
1a	Full cross-lagged model without covariates	1,486.30	199	0.02	0.98	0.96	1,680	0.48	0.16
1b	Model 1a, but cross-lagged paths are constrained to be equal	1,491.04	200	0.02	0.98	0.96	1,683	0.49	0.16
1c	Model 1a, constraining the coefficients for weak relationships to zero	1,465.38	200	0.02	0.98	0.96	1,653	0.48	0.17
2a	Model 1a with all covariates	1,444.03	343	0.02	0.98	0.96	1,658	0.46	0.15
2b	Model 1c with all covariates	1,436.81	344	0.02	0.98	0.96	1,649	0.46	0.15
2c	Model 2b constraining the coefficients for weak relationships to zero	1,430.82	345	0.02	0.98	0.96	1,641	0.46	0.15

CFI comparative fit index, *TLI* Tucker Lewis index, *RMSEA* root mean square error of approximation, *Mc* McDonald's [48] noncentrality index, *AIC* Akaike information criterion

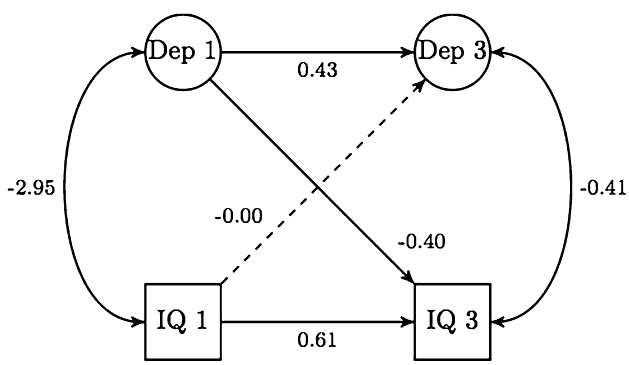

Fig. 1 Path model without covariates with unstandardized coefficients

looking specifically at the cognitive ability–depression relationships, we found that depression and cognitive ability at Wave I were related to cognitive ability and depression, respectively, at Wave III. When modeling a relationship between the Wave I and Wave III variables, we found that depression at Wave I had a small, negative relationship with cognitive ability at Wave III, but cognitive ability at Wave I did not have a relationship with depression at Wave III that was statistically different than zero. Moreover, after controlling for depression and cognitive ability at Wave I, the relationship between depression and cognitive ability at Wave III was not statistically different than zero. This relationship pattern held even after controlling for parental education and the respondents' sex, race, and English language proficiency.

The results from this study are important for multiple reasons. First, it confirmed the stability of depression and cognitive ability during adolescence and young adulthood, a very tumultuous time of development. Second, it went beyond showing that cognitive ability and depression were related to each other to showing that depression levels in adolescence possibly have a causal relationship to cognitive ability levels in early adulthood. The direction of the effects align themselves with other studies that have shown depression to have an effect on various aspects of cognitive ability [16, 64, 65] and some going so far as to state that the effect of depression of cognition is similar to having moderately severe traumatic brain injury [66].

Third, and perhaps the most interesting finding, this study showed that after controlling for early measures of cognitive ability and depression in adolescence, the depression–cognitive ability relationship in early adulthood disappeared. Likely, this indicates that the relationship that depression and cognitive ability have on each other develops in childhood/adolescence, but does not necessarily grow as adolescents move into adulthood. There are likely multiple reasons for this effect, but one probable agent is parental influence. As parental education was related to both depressive symptoms and cognitive ability at Wave I, but only slightly related to cognitive ability at Wave III, this could be an indication that parental influence, at least for these constructs, is most potent when the children are at the age where they are living with them. As the respondents move into adulthood, genetic [67] and other influences [68] become more important, while the effects of parents' ability begins to wane [69].

Fig. 2 Final path model with covariates with unstandardized coefficients

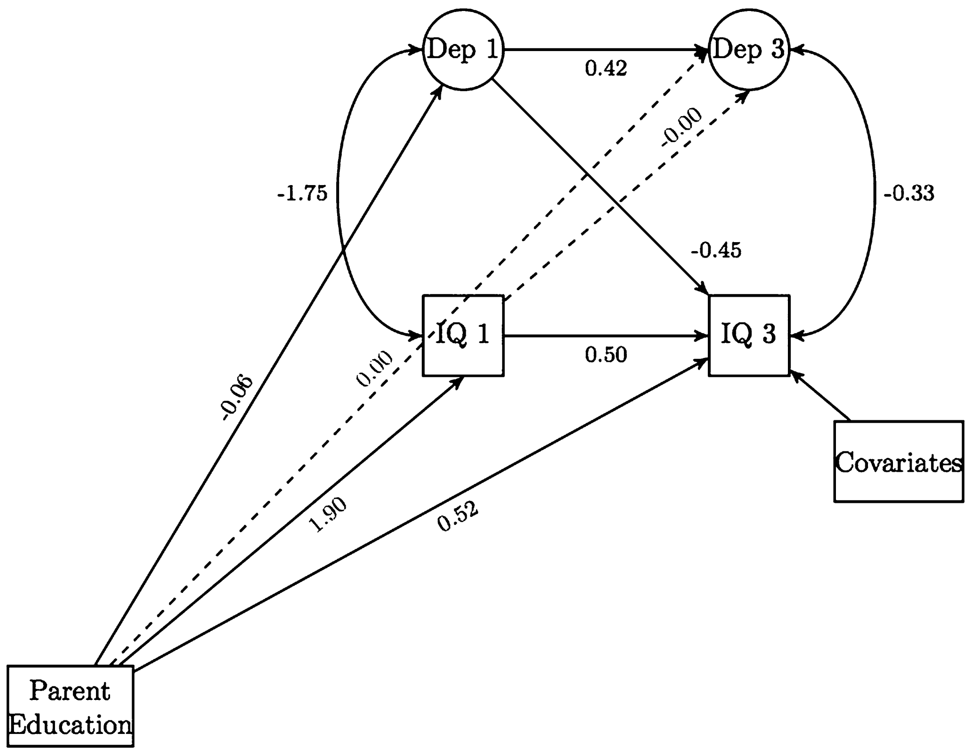

Table 6 Unstandardized coefficients for Model 2c

From	To	B	SE	B*
Depression (Wave I)	Depression (Wave III)	0.42	0.02	0.39
Highest parent education	Depression (Wave I)	−0.06	0.01	−0.14
Depression (Wave I)	Cognitive ability (Wave III)	−0.43	0.12	−0.03
Cognitive ability (Wave I)	Cognitive ability (Wave III)	0.50	0.01	0.53
Highest parent education	Cognitive ability (Wave III)	0.52	0.07	0.10
English fluency	Cognitive ability (Wave III)	7.87	0.63	0.09
Hispanic[a]	Cognitive ability (Wave III)	−2.00	0.52	−0.05
African American[b]	Cognitive ability (Wave III)	−7.35	0.46	−0.28
American Indian[b]	Cognitive ability (Wave III)	−3.18	0.99	−0.04
Asian[b]	Cognitive ability (Wave III)	−1.10	0.79	−0.02
Other[b]	Cognitive ability (Wave III)	4.14	3.91	0.01
Highest parent education	Cognitive ability (Wave I)	1.90	0.12	0.33
Depression (Wave I)[c]	Cognitive ability (Wave I)	−1.79	0.16	−0.14
Depression (Wave III)[c]	Cognitive ability (Wave III)	−0.42	0.16	−0.04

B unstandardized path coefficient, *SE* standard error, *B** standardized path coefficient

[a] Hispanic origin was coded as a separate variable than race

[b] The race variable was coded using weighted effects with white being the reference group

[c] No causal directionality was specified, so this is a covariance estimate

Limitations

There were a few limitations with the study. First, the time between Wave I and Wave III measures was approximately 8 years. While these 8 years span one of the most tumultuous time periods in development, perhaps a longer time span would show a relationships of different magnitudes. Second, while measure of depression used in this study had sound psychometric properties, it was developed from items in the Add Health In-Home questionnaire and not a standardized measure of depressive symptoms. While the items used were typical of depression questionnaires, more valid evidence should be gathered on it. Third, this study did not examine possible moderating events (e.g., social support, school or family problems) that may affect the risk of depression. Future studies should examine if the depression–cognitive ability relationship is moderated by such environmental factors.

Clinical implications

The results from this study show the importance of addressing depressive symptoms during childhood/adolescence. Depressive symptoms are occurring in childhood and adolescence more frequently now than before [70], and the results from this study indicate that this time in development is likely when depressive symptoms become associated with cognitive ability. Thus, while early intervention is important to treating depression [71], such intervention could likely have a positive influence on later cognitive ability, as well.

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Conflict of interest The authors declare they have no conflict of interest.

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