Wellbeing and cognition are coupled during development: A preregistered longitudinal study of 1136 children and adolescents

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Abstract

Wellbeing and cognition are linked in adulthood, but how the two domains interact during development is currently unclear. Using a complex systems approach, we preregistered and modelled the relationship between wellbeing and cognition in a prospective cohort of 1136 children, aged 6 - 7 up to 15 years. We found bidirectional interactions between wellbeing and cognition that unfold dynamically over time. Higher externalizing symptoms in childhood predicted fewer gains in planning over time (standardized estimate = - 0.14, p = .019), whereas higher childhood vocabulary predicted smaller increases in loneliness over time (standardized estimate = -0.34, p = < .001). These interactions were characterized by modifiable risk and resilience factors: Relationships to parents, friendship quality, socioeconomic status and puberty onset were all linked to both cognitive and wellbeing outcomes. As such, cognition and wellbeing are inextricably intertwined during development and may be malleable to social and biological factors.

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Wellbeing and cognitive ability are key to healthy development (Der et al., 2009; Feinstein & Bynner, 2004). Cognitive ability allows us to engage with the world around us; to reason, learn and remember (Flavell, 1999). Performance on standardized tests of cognitive ability increases steeply during childhood and adolescence (Chaku & Hoyt, 2019; Kail et al., 2015) and has predictive ability for a wide range of valued life outcomes, including education and job success, physical health and mortality (Batty et al., 2007; Murtza et al., 2020). Wellbeing reflects a global assessment of life satisfaction and feelings ranging from depression to happiness. Childhood and adolescence are a period of change in wellbeing. Individuals can experience high levels of loneliness during this time (Office for National Statistics, 2018) and mental health issues often first emerge between late childhood and adolescence (Jones, 2013). This has implications for lifespan health, as wellbeing is associated with outcomes like physical health and longevity (Steptoe et al., 2015; Trudel-Fitzgerald et al., 2019).

Wellbeing and cognitive ability traditionally occupy separate scientific and practical spheres. However, emerging evidence suggests that the two domains may be more closely linked than previously thought. Recent meta-analyses in adults have shown consistent links between cognition and wellbeing, with large to very large effect sizes (e.g. r = .32 - .46) (Irie et al., 2019; Rock et al., 2014). However, the directionality of this relationship is still unclear, with different theoretical frameworks making opposing predictions. The *interference hypothesis* (Stawski et al., 2006) suggests that psychological distress disrupts cognitive processes. Conversely, the *cognitive reserve hypothesis* (Barnett et al., 2006) suggests that good cognitive functioning (e.g. high intelligence) helps avoid or cope with stressful situations, protecting wellbeing. Some emerging empirical studies support the interference hypothesis (Llewellyn et al., 2008), while other studies support the cognitive reserve hypothesis (Askelund et al., 2019; Gooch et al., 2019). Others still, report bidirectional effects in the same sample (Masten et al., 2005).

Heterogeneity in populations further adds complexity to these relations. Clinical practice and emerging empirical research suggest children and adolescents differ in their developmental trajectories (Boogert et al., 2018). Risk and resilience factors are associated with differential cognitive and wellbeing trajectories. In particular, early puberty (Chaku & Hoyt, 2019), and social risk factors such as lower socioeconomic status and poorer relationships to parents and peers, are all linked to poorer cognitive and wellbeing outcomes (Hackman et al., 2015; Laursen & Collins, 2009; Ybarra et al., 2010).

These seemingly complex and contradictory empirical findings can be accommodated by modern *complex system approaches*. Rather than predicting linear effect of one domain on another, complex system approaches conceptualize development in terms of dynamic processes where different domains interact over time (Borsboom, 2017; Burger et al., 2020; Ioannidis et al., 2020; Kievit et al.; Lunansky et al., 2020; Van Der Maas et al., 2006). In the mental health domain, for instance, network models, as a complex systems approach, have been used to show that mental health disorders can arise from direct interactions between symptoms and the feedback generated by these interactions (Borsboom, 2017; Burger et al., 2020; Lunansky et al., 2020; McElroy et al., 2018). In the cognitive domain, the complex systems approach has been used to capture mutualistic relationships between different cognitive abilities strengthening one another over time (Kievit et al.; Van Der Maas et al., 2006).

Here, we leverage analytic frameworks used in complex systems science (Grimm et al., 2011; Ram & Grimm, 2009) to capture the coupling between wellbeing and cognition and to model heterogeneity in these relationships. Using latent growth models (LGMs) we provide rigorous, longitudinal tests of the relationship between wellbeing and cognition in a large, uniquely rich, longitudinal cohort: The Study of Early Childcare and Youth Development (SECCYD) (Eunice Kennedy Shriver National Institute of Child Health and Human Development, 2006). The Study followed 1136 children and adolescents between the ages of 6-7 and 15 years. Using growth mixture models (GMMs) we also studied heterogeneity in SECCYD and characterized risk and resilience profiles to guide applied and intervention research. We modelled three core cognitive domains (vocabulary, maths and planning) and three wellbeing domains (loneliness, internalizing and externalizing), as well as the influence of one biological (puberty) and three social risk and resilience factors (socioeconomic status, friendship quality and parental closeness). We also modelled gender differences, due to known gender differences in wellbeing (Kessler et al., 2005, 2007). We tested five hypotheses preregistered prior to data-access:

Hypothesis 1. Wellbeing remains stable or decreases over time, and wellbeing trajectories show individual differences.

Hypothesis 2. Cognitive abilities increase over time and trajectories show individual differences.

Hypothesis 3. Wellbeing and cognitive trajectories are linked cross-sectionally and longitudinally.

Hypothesis 4. Initial wellbeing predicts changes in cognitive trajectories, and vice versa.

Hypothesis 5. The coupling between wellbeing and cognition changes with puberty onset.

Methods

Cohort

We analysed data from the longitudinal SECCYD sample (Eunice Kennedy Shriver National Institute of Child Health and Human Development, 2006) as described in detail here: https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/00233. The aim of SECCYD was to provide information on early environments and long-term developmental outcomes. As such, a comprehensive developmental dataset was collected between 1991 and 2007 at ten locations across the United States following participants from birth (*N* = 1365, 51.7% male, 48.3% female) to 9th grade (aged 14-15). SECCYD was designed to be representative of families with children born in 1991 at one of the 24 hospitals across the US selected for the study. 18% of families were in receipt of public assistance. 76% of children were non-Hispanic white, 10% non-Hispanic black and 6% Hispanic (Eunice Kennedy Shriver National Institute of Child Health and Human Development, 2006). Attrition was generally low. The sample size for our data was N = 1078 (wave 1), N = 1064 (wave 2), N = 1054 (wave 3) and N = 1004 at wave 4. See Supplementary Figures 1 - 7 for a detailed breakdown of missingness in the sample used here. As per our preregistration (http://aspredicted.org/blind.php?x=i9fa7t) we analysed data from waves selected for including relevant cognitive and wellbeing data: grade one (henceforth *wave 1*, aged 6 – 7 years), grade three (henceforth *wave 2*, aged 8 – 9 years), grade five (henceforth *wave 3*, aged 10 -11 years) and age 15 (henceforth *wave 4*). The final sample analysed here included 1137 participants.

Measures

SECCYD contains gold-standard measures of core cognitive and wellbeing-techniques. As preregistered, we modelled cognitive development based on participants' scores in the Woodcock–Johnson Tests of Cognitive Abilities – Revised (Woodcock, 1997) and Towers of Hanoi task. For th, we modelled W-scores on the two subscales available for all waves: Applied Problems (covering maths problems, henceforth *maths*) and Picture Vocabulary (henceforth *vocabulary*). For the Towers of Hanoi, we modelled the total planning efficiency score (henceforth *planning*) for the first three waves. This measure was not available for the last wave. Maths, vocabulary and planning were chosen as cognitive domains to cover both crystallized (c.f., vocabulary) and fluid abilities (c.f., planning), and both applied (c.f., vocabulary and maths) and abstract cognitive measures (c.f., planning). The Woodcock-Johnsons Tests have been showing to have good test-retest reliabilities (test-retest correlations for speeded tests ranged mostly from 0.80 - 0.90). and to correlate highly with other measures of achievement (correlations between general intelligence scores were mostly in the 0.80s) (Madle, 2017). Prior to revisions in the 2000s, the Towers of Hanoi task showed only satisfactory levels of reliability (correlations between Towers of Hanoi and Towers of London ranged from 0.35 to 0.60). However, it was still considered and gold-standard measure of executive function and known to be sensitive to frontal lobe damage and clinical differences (Welsh & Huizinga, 2001)

For the wellbeing domain, we modelled, as preregistered, mother-rated sores on the Child Behaviour Checklist (Achenbach, 1991) and the child-rated scores on the Loneliness and Social Dissatisfaction Questionnaire (Asher et al., 1984). For the Child Behaviour Checklist, we analysed the internalizing and externalising *t*-scores (henceforth *internalising* and *externalizing*). For the Loneliness and Social Dissatisfaction Questionnaire, we analysed loneliness scores (henceforth *loneliness*). Internalizing, externalizing and loneliness were chosen as wellbeing domains to capture both traditional mental health indicators (c.f., internalizing and externalizing symptoms), as well as an indicator of psychosocial functioning (c.f., loneliness). The internalizing subscale shows a very high effect size (Hedges D = 1.55) for discrimination between youth with and without an anxiety disorder, for instance (Seligman et al., 2004). The Child Behaviour Checklist is a gold-standard measure of mental health in developmental populations and has been extensively validated, showing good discrimination between refereed and nonreferred children and associations with analogous scales and DSM criteria (Achenbach & Rescorla, 2001). The Loneliness and Social Dissatisfaction Questionnaire has been shown to have excellent internal reliability (Cronbach's alpha = 0.79 – 0.90) (Asher et al., 1984). We had also preregistered analysing the Child Depression Inventory (Kovacs & Beck, 1977) but found the data was unsuitable, because only available for the last two waves. Future studies of cohorts with data on depression at a minimum of three waves will be necessary to estimate depression trajectories using Latent Growth Models. We also did not analyse the Center for Epidemiologic Studies Depression Scale (Lewinsohn et al., 1997) or the Spielberger State – Trait Anger Expression Inventory (Spielberger & Sydeman, 1994), because the data pertained to parental wellbeing rather than the child's wellbeing.

To assess potential risk and resilience factors, we included, as preregistered, socioeconomic status (total family income divided by the total household size at age 6 - 7) and friendship quality (child-rated friendship quality at age 8 – 9; SECCYD-provided score, based on SECCYD friendship interview) and parental engagement (in SECCYD structured interaction task with mother at age 6 – 7; SECCYD-provided score). See https://www.icpsr.umich.edu/web/ICPSR/series/00233/studies for details on all SECCYD measures. These risk- and resilience factors were chosen to capture a range of well-established societal (c.f. SES) familial (c.f. parental engagement) and peer-level (c.f. friendship quality) moderators.

Finally, and again in line with our preregistration, we investigated puberty as a potential moderator of the relationship between cognition and wellbeing by modelling nurse-rated Tanner stages at wave 3, age 10 -11 (supplemented by mother-rated Tanner stages where nurses' ratings were not available, correlation: r = 0.72, $t(705) = 27.31$, $p < .001$). Deviating from our preregistration, we did not assess age as a potential moderator because age did not vary sufficiently between participants at each wave.

Data Processing

As preregistered, we treated absolute univariate *z*-score greater than five as missing. This affected a maximum of four values for any given variable (see Supplementary Table 1 for a detailed breakdown). Other than that, we imposed no exclusion criteria.

We transformed data to the percentage of the maximum possible score on each measure at each wave (similar to Cohen et al., 1999). This resulted in easily interpretable scores ranging from 0 to 100 and amenable to longitudinal modelling. This step was not preregistered but was implemented to facilitate relating scores across domains and to support model convergence.

Latent Growth Models

Our analysis scripts can be obtained from: https://github.com/df1234/InteractionsWellbeingCognition. Access to the full dataset can be requested via https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/00233.

We modelled longitudinal changes in cognition and wellbeing using LGMs in R, utilizing the lavaan package (Rosseel, 2012) and Mplus for growth mixture models (Muthén & Muthén, 1998). All models were fit using maximum likelihood estimation with robust Huber-White standard errors and a scaled test statistic. Missing data was modelled using full information maximum likelihood estimation.

The model syntax for the bivariate LGMs was preregistered (see http://aspredicted.org/blind.php?x=i9fa7t), but we had to implement the following changes to achieve model convergence: First, we switched from linear growth factors (with fixed loadings of 0, 2, 4, 8) to an estimated basis function (fixing the first loading to 0 and the last to 1, while estimating the loadings for the intermittent waves, for all measures apart from internalizing, where a linear model provided better fit. Estimated basis functions facilitated convergence for most models by allowing for non-linear changes between waves (Grimm et al., 2011). To further facilitate convergence, we did not impose equality-constraints on the residual variances of the manifest variables over time, but instead estimated them freely for most models. Finally, for the model assessing couplings between planning and loneliness only, we also allowed for a residual covariance between manifest variables of loneliness at wave 2 and 3. This step was implemented to achieve acceptable model fit and was based on modification indices.

Growth Mixture Models

We fit GMMs to test for the presence of different cognitive and wellbeing trajectories in the cohort. These models were estimated using Mplus (Muthén & Muthén, 1998). GMMs are an exploratory tool that can be used to identify subpopulations in a cohort and to compare longitudinal trajectories between these subpopulations (Muthén & Muthén, 1998; Ram & Grimm, 2009). The number of subpopulations in a GMM is not predetermined. Instead, GMMs are fit iteratively with an increasing the number of possible subpopulations. GMMs are a powerful and flexible technique, but are also known to be vulnerable to overfitting and overinterpretation (Bauer, 2007). To ensure the robustness of our GMM findings, at each iteration, five criteria (Ram & Grimm, 2009) were evaluated to decide whether to test a GMM with more subpopulations:

1. Did the model converge and yield a proper solution?
2. Is the bootstrap-likelihood-ratio test comparing models with different classes significant?
3. Is the entropy high (e.g. greater than 0.8)?
4. Is there a reasonable proportion of the total population in each sub-population (i.e. > 1%)?
5. Are the resulting trajectories qualitatively different from one another?

We then regressed subpopulation membership on risk and resilience factors (e.g. socioeconomic status) using General Linear Models (for variables with two subpopulations) or Multinomial Logistic Regression (for variables with more than two subpopulations). Note that we had preregistered to investigate the effect of puberty using Structural Equation Modelling Trees. This novel tool yielded improper solutions, however, and was therefore not used at this time.

Results

To understand the interaction between wellbeing and cognition over developmental time, we employed LGMs in a preregistered, multi-step process. We started by building univariate LGMs, capturing changes in a single domain over time. We then used bivariate LGMs to capture interactions between the two domains over time. At each of these steps, we inspected the chi-square test, Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI) and the Standardized Root Mean Square Residual (SRMR) to evaluate model fit. Good fit was defined as CFI > 0.97 and SRMR < 0.05; acceptable fit as CFI = 0.95 - 0.97, SRMR = 0.05 - 0.10 (Schermelleh-Engel et al., 2003). We note that LGMs are generally prone to showing relatively poor absolute model fit, even when the true model is estimated (DeRoche, 2009). We also inspected parameter estimates of each model to understand the directionality, statistical significance and strength of relationships between wellbeing and cognition. Following recommendations by Gignac & Szodorai (2016), we consider standardized path estimates of 0.10, 0.20, and 0.30 as relatively small, typical, and relatively large.

Trajectories of wellbeing and cognition

<u>Wellbeing.</u> To understand changes in wellbeing over time, we first modelled the wellbeing variables (externalizing, internalizing and loneliness) as separate univariate

LGMs. We examined individual differences in slopes to understand children's wellbeing trajectories over time. To understand what drives this heterogeneity, we tested for the presence of subpopulations showing different wellbeing trajectories using GMMs. Using regression models, we then tested whether subpopulations differed in terms of social risk and resilience factors (parental closeness, friendship quality, socioeconomic status), as well as a biological predictor (puberty).

Univariate LGMs of wellbeing showed acceptable model fit for externalizing and internalizing (Supplementary Table 2). Scores in both decreased slightly over time as indicated by significant, negative, slope intercepts (Figure 1, Supplementary Table 2). Because these scores were based on normed *t*-scores, all changes were relative to the general population. The directionality observed was in line with our preregistered Hypothesis 1. Loneliness showed poor model fit, likely due to the existence of subpopulations showing diverging loneliness trajectories (see Figure 2).

All wellbeing domains showed individual differences in trajectories, as indicated by significant slope variances (Supplementary Table 2), and in line with Hypothesis 1. GMMs further extended this finding by providing evidence for the existence of subpopulations in the cohort: two for externalizing (Figure 2; entropy = 0.59; BLR(3) = 55.09, $p < .001$) and internalizing (Figure 2; entropy = 0.55; BLR(3) = 33.55, $p < .001$) and five for loneliness (Figure 2; entropy = 0.70; BLR(3) = 17.91, $p < .001$). See Supplementary Table 3 for a detailed break-down of model fit.

The two subpopulations for externalizing showed different levels of symptoms at age 6 - 7 (higher vs. lower externalizing) and slightly *diverging* trajectories over time (Figure 2, top panel). The subpopulation with low externalizing symptoms at age 6 - 7 showed a slight decrease in symptoms over time, while symptoms in the subpopulation with high externalizing symptoms at age 6 – 7 remained stable until age 15. Regressing externalizing subpopulation membership on risk and resilience factors showed that the subpopulation with high and stable externalizing scores (see Figure 2), was characterized by lower socioeconomic status ($\chi^2(1) = 11.41$, $p < .001$) and lower parental closeness ($\chi^2(1) = 9.26$, $p = .002$), while friendship quality did not differ significantly between subpopulations ($\chi^2(1) = 1.94$, $p = .163$). In an exploratory analysis suggested by a reviewer, we tested whether externalizing trajectories were related to diagnoses of neurodevelopmental conditions. We found that Attention Deficit Hyperactivity Disorder (ADHD) diagnosis predicted subpopulation membership ($\chi^2(1) = 47.60$, $p < .001$), such that teenagers with an ADHD diagnosis were more likely to be in the group showing higher externalizing symptoms. An Autism Spectrum Disorder diagnosis did not predict subpopulation membership ($\chi^2(1) = 0.36$, $p = .548$).

The two subpopulations for internalizing showed different levels at age 6 - 7 (higher vs. lower internalizing) and slightly *converging* trajectories over time (Figure 2, middle panel). The subpopulation with low internalizing symptoms at age 6 - 7 remained stable over time while the subpopulation with higher internalizing symptoms at age 6 - 7 showed a reduction in symptoms over time. These subpopulations did not differ significantly in socioeconomic status ($\chi^2(1) = 1.72$, p = .189), parental closeness ($\chi^2(1) = 0.55$, p = .545), or friendship quality ($\chi^2(1) = 2.76$, p = .096).

Loneliness was characterized by five subpopulations with strikingly dissimilar trajectories. The largest subpopulation (51% of the sample) reported low and stable loneliness (yellow coloured in the bottom panel of Figure 2). This subpopulation served as the reference group, to which all other subpopulations were compared. Three of the other subpopulations showed increases in loneliness over time, while one subpopulation showed decreases in loneliness - see Figure 2, bottom panel). Subpopulations differed in socioeconomic status overall ($\chi^2(4) = 9.69$, p =.046), although none of the specific comparisons between subpopulations were significant (Supplementary Table 4). Parental closeness showed no effect overall ($\chi^2(4) = 3.55$, p = .470), while friendship quality differed significantly between subpopulations ($\chi^2(4) = 19.76$, $p < .001$). Comparisons between the subpopulations showed that the three subpopulations showing increasing loneliness over time also reported lower friendship quality than the reference group (yellow coloured in the bottom panel of Figure 2, see also Supplementary Table 4).

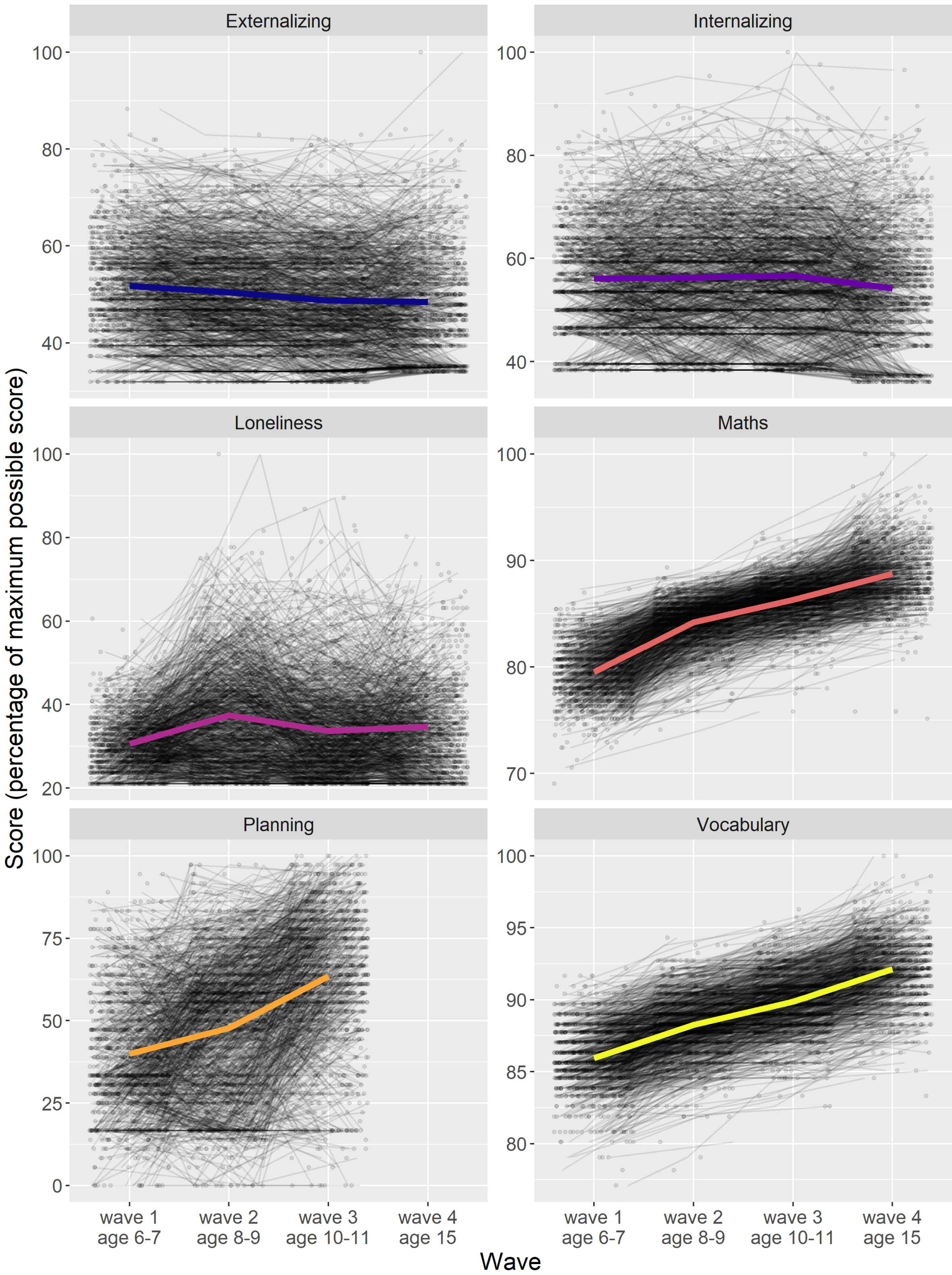
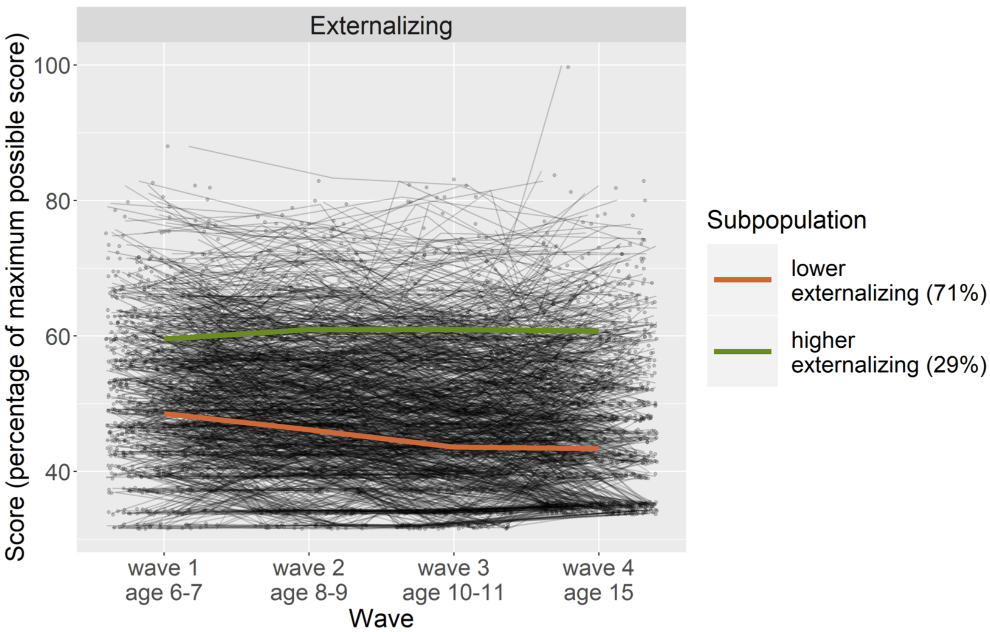
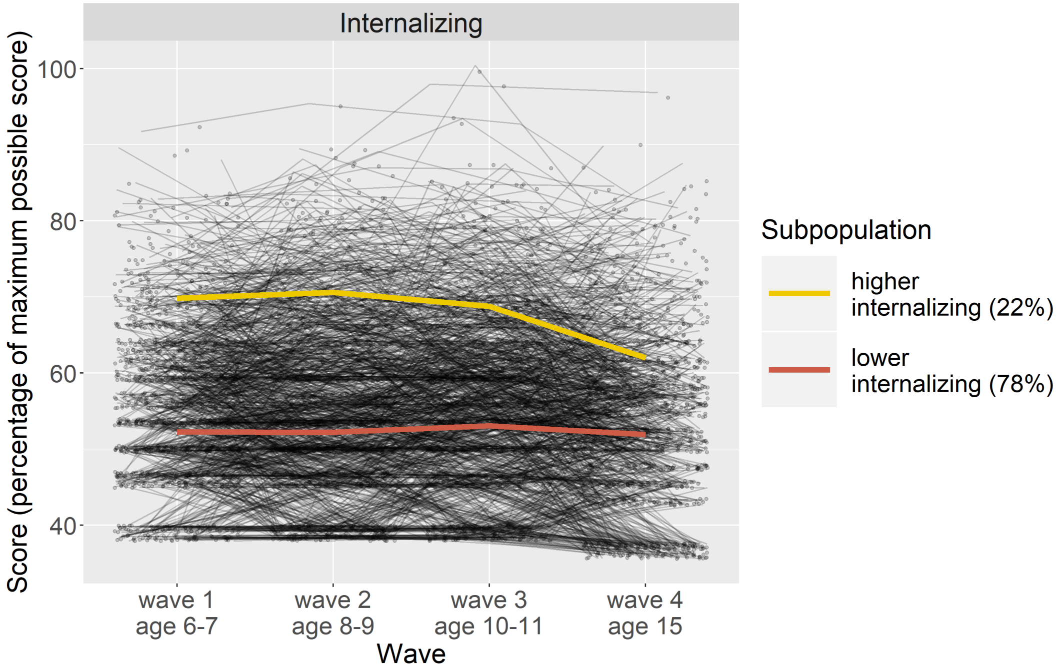


Figure 1. Changes in Wellbeing and Cognition over Time. Spaghetti plots of participants' scores (shown as percentage of maximum possible scores) over time as well as mean trajectories. There was no suitable data for planning at G9.

Overall, we found good evidence for Hypothesis 1. Internalizing and externalizing decreased over time. As predicted, trajectories of wellbeing showed individual differences and were related to social risk and resilience factors: Lower socioeconomic status and parental closeness were related to less favourable trajectories of externalizing. Lower friendship quality was associated with increases in loneliness over time.





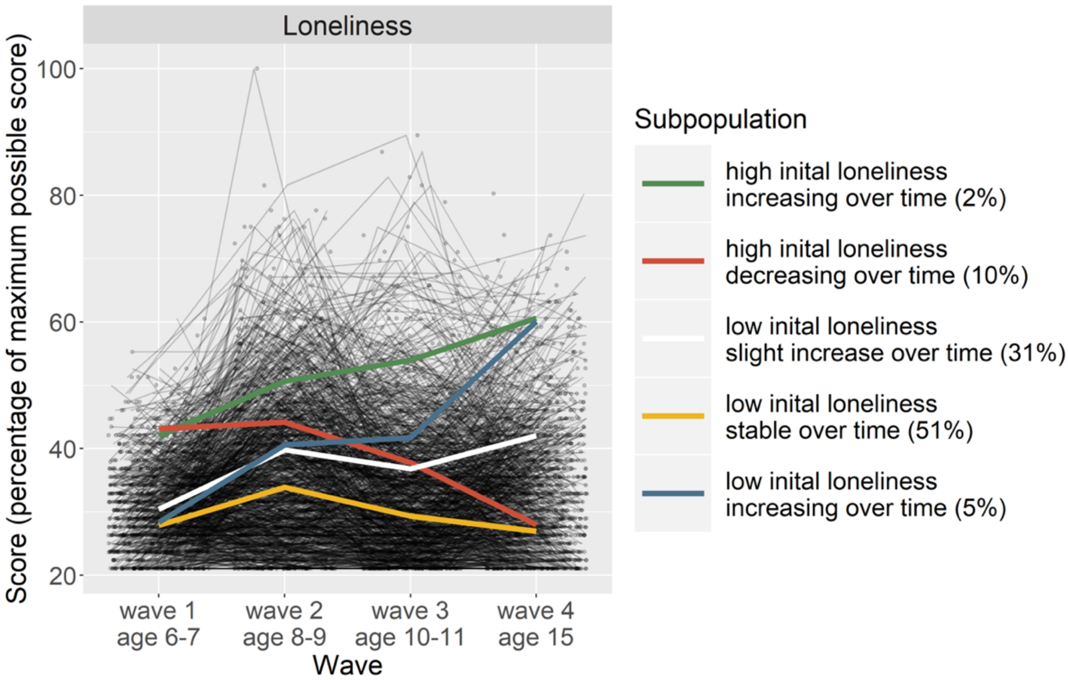


Figure 2. Trajectories of Wellbeing in Subpopulations. Spaghetti plots of participants' scores (shown as percentage of maximum possible scores) over time as well as mean trajectories in different subpopulations as identified by GMMs. Proportions of the subpopulations are shown in brackets.

Cognition. Univariate LGMs of cognition showed acceptable fit overall (Supplementary Table 2). Scores of maths, vocabulary and planning showed a clear increase over time as indicated by their significant, positive, slope intercepts (Figure 1, Supplementary Table 2). This finding was in line with the previous literature (Kail et al., 2015) and our preregistered Hypothesis 2. Only vocabulary showed a significant slope variance, indicating that there were individual differences for this measure only (Supplementary Table 2), and thus providing only partial support for Hypothesis 2. None of the trajectories showed evidence for the existence of subpopulations (Supplementary Table 3).

Overall, these results provide partial support for our preregistered Hypothesis 2. We found strong evidence that cognitive performance increased over time. Contrary to our hypothesis, however, individual differences in development were only evident for vocabulary.

Couplings between wellbeing and cognition

We used bivariate LGMs to examine the relationships between the intercepts and slopes of wellbeing and cognition (Figure 3). This allowed us to assess Hypothesis 3 and 4, namely that wellbeing and cognition are linked cross-sectionally and longitudinally and show bidirectional coupling over time.

All bivariate LGMs showed good or acceptable fit, apart from the bivariate LGMs modelling the relationships between maths and the three wellbeing domains (Supplementary Table 5). The latter models should be interpreted with caution, therefore.

Intercepts showed significant small to large negative correlations for most domains, indicating that wellbeing and cognition were associated at baseline (6 - 7 years of age; Supplementary Table 5). This finding is consistent with the notion that lower wellbeing was cross-sectionally associated with lower cognitive ability (Hypothesis 3).

For vocabulary and loneliness, slopes were also significantly correlated indicating that changes in loneliness were related to changes in vocabulary over time. This correlation was positive, however, and not in line with the direction of the other paths in the model. None of the other models showed correlated slopes. Overall, we found little evidence for longitudinal correlations between wellbeing and cognition (Hypothesis 3).

Next, we investigated our main hypothesis (Hypothesis 4): Is there bidirectional longitudinal coupling between wellbeing and cognition? To answer this question, we inspected regression path estimates to understand the relationship between intercepts in one domain and slopes in the other domain. We found that higher levels of externalizing at age 6 - 7 predicted fewer improvements in planning, with a small to medium effect size (standardized estimate = -0.14, p = .019; Supplementary Table

5). Conversely, higher levels of vocabulary at age 6 - 7 longitudinally predicted fewer increases in loneliness with a large effect size (standardized estimate = -0.34, $p < .001$; Supplementary Table 5). Loneliness and maths showed an unexpected, positive longitudinal coupling (Supplementary Table 5) between baseline levels of loneliness and changes in maths. This unexpected directionality may be explained by poor model fit. Overall, these findings highlighted the existence of complex, bidirectional and domain-specific longitudinal relationships between cognition and wellbeing. This provides partial support for Hypothesis 4.

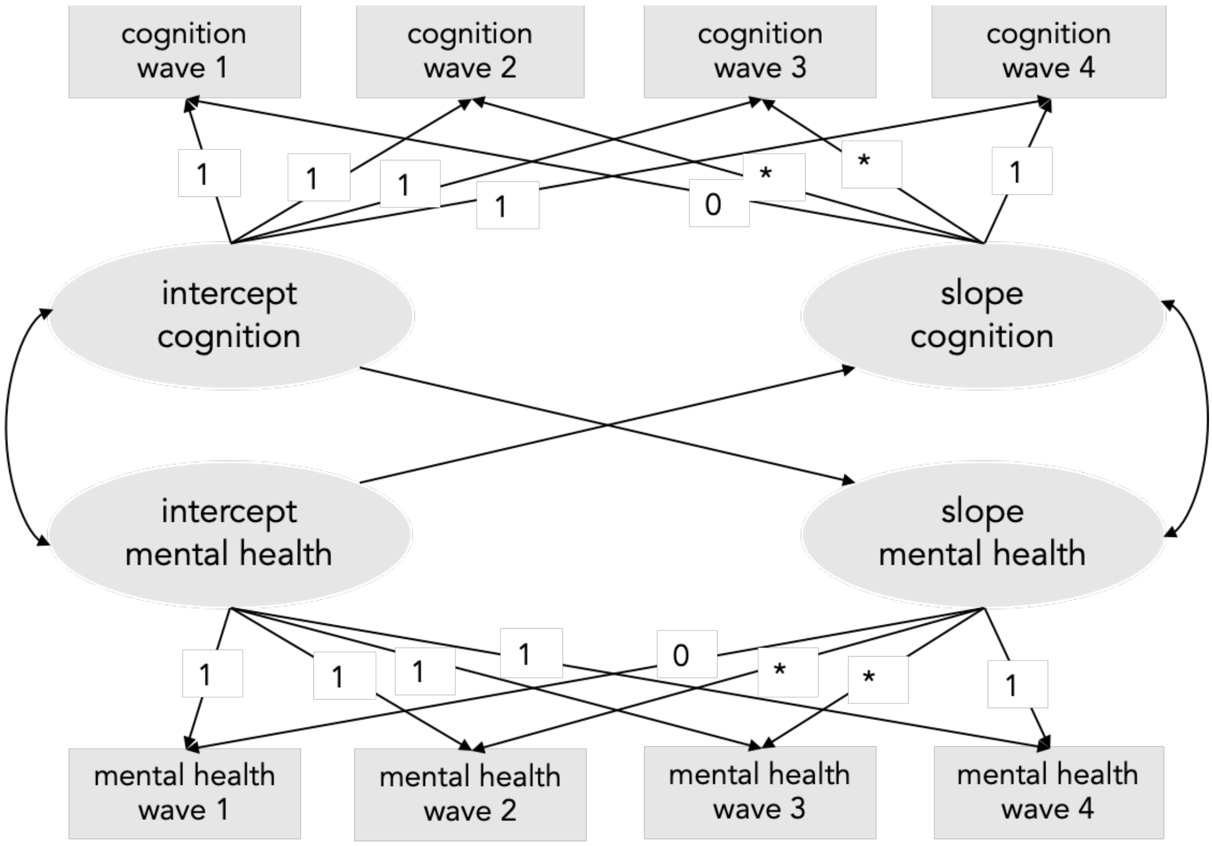


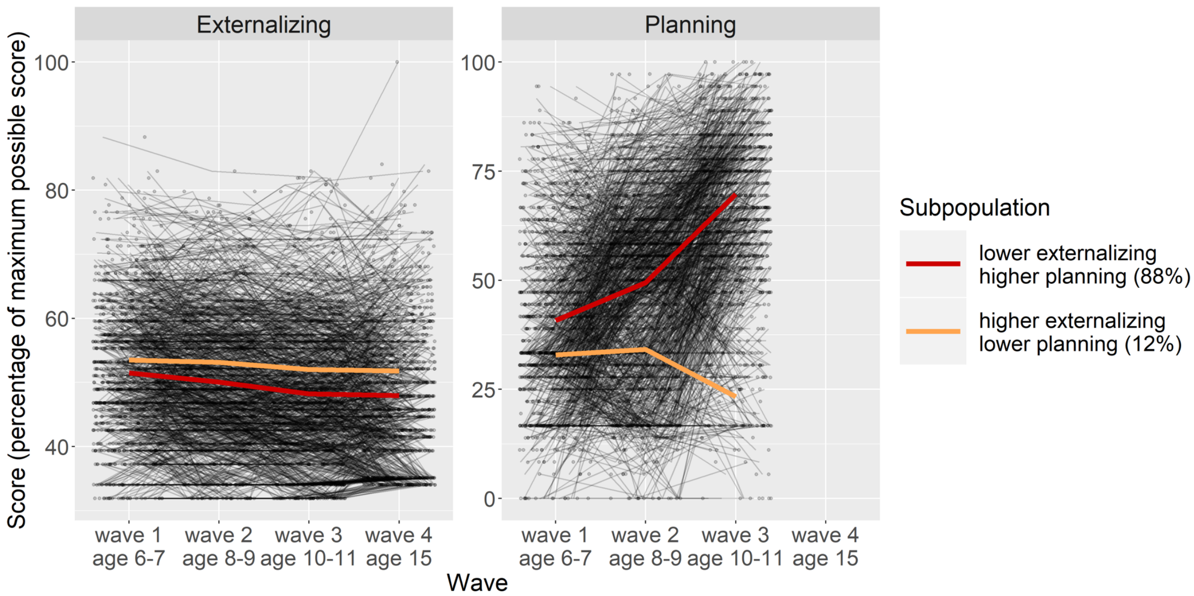
Figure 3. Schematic Path Diagram of the Bivariate LGMs. Numbers indicate factor loadings; stars indicate that factor loadings were freely estimated.

Risk and resilience factors

We characterized heterogeneity in the coupling between cognition and wellbeing. Specifically, we used GMMs to identify subpopulations with distinct trajectories over time for bivariate LGMs with significant regressions paths. We then investigated whether subpopulation membership was predicted by pubertal maturation (Hypothesis 5). We also carried out exploratory, non-preregistered, analyses investigating whether social risk and resilience factors (socioeconomic status, parental closeness and/or friendship quality) predicted subpopulation membership.

GMMs showed that the longitudinal coupling between externalizing and planning was characterized by heterogeneity: Two distinct subpopulations were identified (Figure 4; entropy = 0.81; BLR(5) = 147.45, $p < .001$). See Supplementary Table 6 for a detailed break-down of model fit. One subpopulation showed higher externalizing and lower planning, the other showed lower externalizing and higher planning (Figure 4). Trajectories for planning diverged visibly after ages 8 – 9. Contrary to our hypothesis, subpopulations did not differ in pubertal maturation ($\chi^2(1) = 0.64$, $p = .423$). Subpopulations did, however, differ in parental closeness: The subpopulation with higher externalizing and shallower improvements in planning was more distant from their parents ($\chi^2(1) = 5.23$, $p = .022$). There was no difference between subpopulations in socioeconomic status ($\chi^2(1) = 2.21$, $p = .137$), or friendship quality ($\chi^2(1) = 1.25$, $p = .264$).

We identified two subpopulations for the coupling between loneliness and maths (Figure 4; entropy = 0.78; BLR(5) = 108.27, p < .001; Supplementary Table 6). One showed higher maths skills combined with consistently low loneliness, while the other showed lower maths skills together with a pronounced spike in loneliness around wave 2 (ages 8 – 9, Figure 4). This subpopulation showed higher pubertal status ($\chi^2(1) = 5.54$, $p = .019$), less parental closeness ($\chi^2(1) = 7.85$, $p = .005$), lower socioeconomic status ($\chi^2(1) = 57.39$, $p < .001$), and lower friendship quality ($\chi^2(1) = 12.94$, $p < .001$).



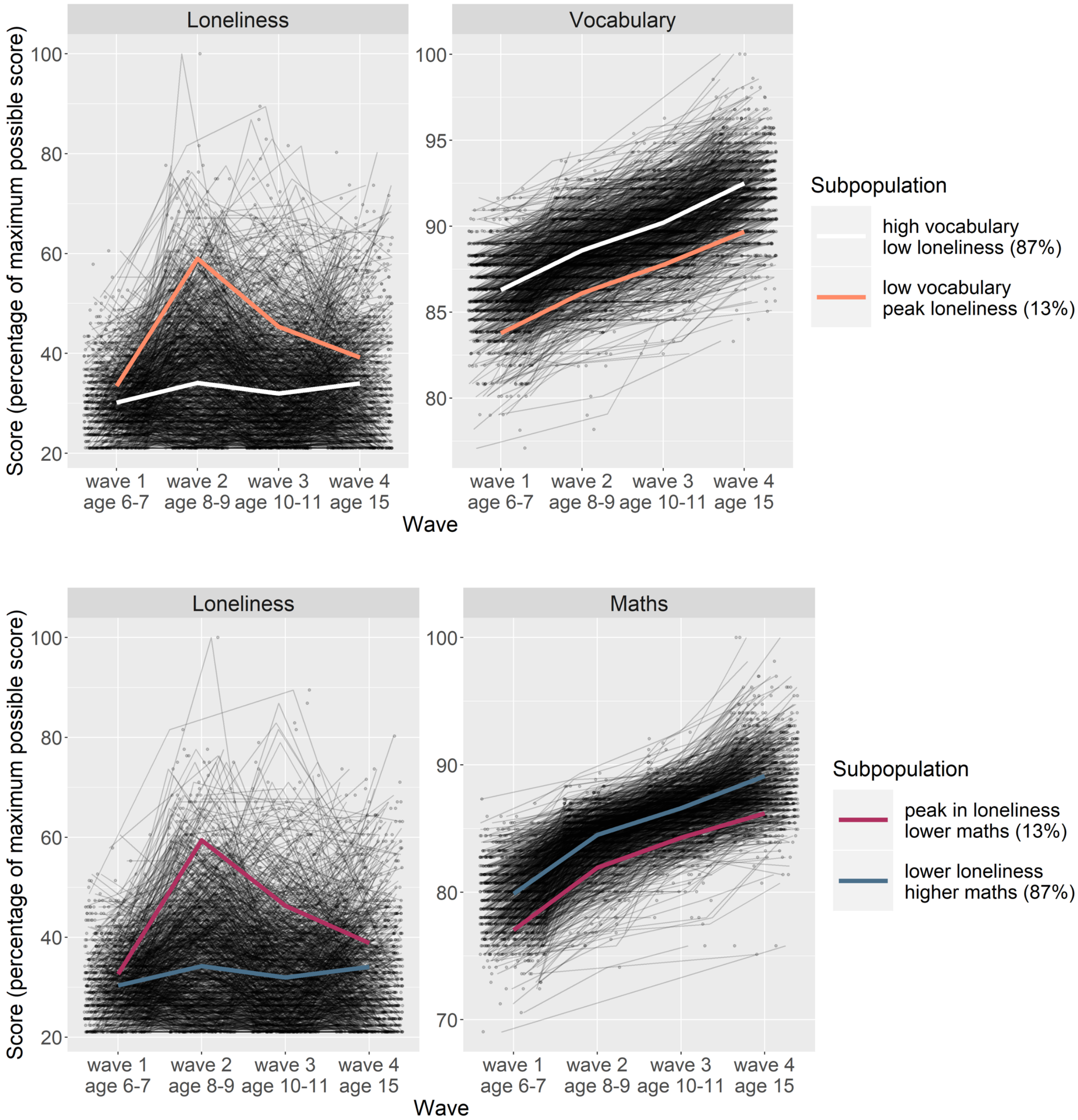


Figure 4. Bivariate Coupling of Trajectories in Subpopulations. Spaghetti plots of participants' scores (shown as percentage of maximum possible scores) over time as well as mean trajectories in different subpopulations as identified by GMMs. Proportions of the subpopulations are shown in brackets.

We identified two subpopulations for the coupling between loneliness and vocabulary (Figure 4; entropy = 0.79, BLR(5) = 131.15, $p < .001$; Supplementary Table 6), which were visually similar to the subpopulations for loneliness and maths: One showed a peak in loneliness at age 8-9 and low vocabulary scores, while the other has lower and stable loneliness levels and higher vocabulary scores (Figure 4). Subpopulations were characterized by differences in pubertal status ($\chi^2(1) = 8.53$, $p = .003$), such that the subpopulation with low vocabulary and a peak in loneliness showed higher puberty status. Subpopulations also differed in parental closeness ($\chi^2(1) = 16.88$, $p = .001$), socioeconomic status ($\chi^2(1) = 69.55$, $p < .001$) and friendship quality ($\chi^2(1) = 15.38$, $p < .001$). The subpopulations with a peak in loneliness showed lower socioeconomic status, friendship quality and parental closeness. The subpopulation with intermediate vocabulary and a peak in loneliness also showed lower parental closeness.

Overall, these findings provide partial support for Hypothesis 5: The coupling between wellbeing and cognition changes with puberty, such that earlier maturation is related to poorer outcomes. Higher socioeconomic status, a closer relationship to parents and better friendship quality were each linked to more favourable trajectories of wellbeing and cognitive development.

Discussion

We investigated the interactions between cognition and wellbeing in a large longitudinal cohort of 1137 children and adolescents. Replicating previous, and largely cross-sectional, work (Irie et al., 2019; Rock et al., 2014) we showed pervasive cross-sectional links between cognition and wellbeing, indicating that cognition and wellbeing were already linked at 6 - 7 years of age. Once we modelled longitudinal changes over time, however, a more subtle pattern emerged. Longitudinal links existed only for very specific domains and showed evidence of dynamic coupling.

Lower externalizing symptomology in childhood predicted more favourable planning trajectories. Externalizing symptoms include overactivity, poor impulse control, noncompliance, and aggression. Externalizing symptoms are linked to deficits in planning and similar executive function tasks in children with ADHD (Kuja-Halkola et al., 2015). We here show that ADHD in our study, too, predicts externalizing trajectories. Our findings extend this literature by showing similar associations in the general population. Our findings further indicate that behavioural symptoms may precede cognitive problems. Speculatively, behavioural problems may lead to social issues in school (Timmons & Margolin, 2015), which, in turn, may hamper academic attainment and cognitive development (Okano et al., 2020).

The opposite directionality emerged for the link between vocabulary and loneliness: Higher vocabulary in childhood predicted less loneliness in adolescence. The link is intuitive: Better verbal skills may allow children to relate better to others and protect against loneliness (Fritz et al., 2018). However, there is currently surprisingly little research investigating longitudinal links between vocabulary and loneliness, let alone longitudinal links in the general population (but see Forrest et al., 2018). We know that loneliness is linked to physical and mental health (Eccles et al., 2020; Matthews et al., 2016). Self-reported loneliness has been shown to be predictive of sleep (Eccles et al., 2020) and depression (Matthews et al., 2016) - and more so than more objective measures of social isolation (Matthews et al., 2016).

The complexity of our models required several statistical decisions that were not anticipated at the time of preregistration. For instance, we preregistered using linear latent growth curve models but found universally poor fit for these models. We therefore used a latent basis function approach which allowed us to freely estimate growth shapes, and significantly improved model fit. Some statistical issues persisted even after attempts to improve model fit. The models assessing interactions between maths and wellbeing showed poor model fit, for instance. These models, therefore, need to be interpreted with caution. For transparency, we clearly highlight deviations from our preregistration throughout the paper.

Our findings suggest that interventions aimed at addressing behavioural problems and fostering verbal skills could be promising for improving cognition and wellbeing outcomes. Past research has shown that behavioural problems can be targeted by interventions, including measures such as parent training, family support, and school-based programs. However, long-term effectiveness has been studied little so far (Smedler et al., 2015) and we know little about possible effects on cognitive development. There is comparatively good evidence that loneliness is malleable to interventions. Most loneliness interventions have targeted older adults (Cattan et al., 2005) and used strategies such as improving social skills, enhancing social support, increasing opportunities for social contact, and addressing maladaptive social cognition (Masi et al., 2011). A meta-analysis showed that these are generally effective at reducing loneliness, particularly when targeting social cognition (Masi et al., 2011). Fewer interventions exist for young people and of those available, most target loneliness as a side effect of physical health conditions. Because of the potential ramifications of loneliness for physical and mental health, we recommend replicating and extending our findings in future research to better understand how vocabulary relates to loneliness and test whether interventions improving vocabulary have positive effects on loneliness.

On a theoretical level, our findings of bidirectional relations between specific domains of cognition and wellbeing in childhood and adolescence provide evidence for mutualistic relationships between cognition and wellbeing that unfold dynamically over development. Small individual differences in externalizing in childhood may set children on different planning trajectories. Small differences in vocabulary may predict different trajectories of loneliness. This supports the complex systems account of mental health problems and cognitive development (Borsboom, 2017; Burger et al., 2020; Fritz et al., 2018; Kievit et al.; Lunansky et al., 2020; McElroy et al., 2018;

Van Der Maas et al., 2006). Our study shows that, not only are cognition and wellbeing complex systems in and of themselves, but they also interact with one another during development, generating yet further dynamic processes.

Risk and resilience factors explain heterogeneity in trajectories

Relationships between wellbeing and cognition were highly heterogeneous, particularly for loneliness and its relationship with cognition. Lower vocabulary was associated with a spike in loneliness around 8 - 9 years, for 12% of the sample. Around ages 10 - 11 adolescents in the US transition from elementary to middle school. However, there are no obvious school transitions around ages 8 – 9 in the US, making it more likely that spikes in loneliness around this age reflect a more intrinsic developmental pattern. Previous work suggests that the period between late childhood and early adolescence represents a time of biological and social change (Andersen & Teicher, 2008; Blakemore & Mills, 2014; Fuhrmann et al., 2019). This may lead to increases in loneliness and reduced wellbeing for a subset of young people.

In our sample, this subset of young people was characterized by risk factors, including earlier puberty, lower socioeconomic status, lower friendship quality and poorer relationships with parents. This is in line with previous work highlighting the links between early physical maturation and mental health (Lewis et al., 2018; Sequeira et al., 2017). Early puberty onset has also been associated with worse performance, particularly on self-control and risk-taking tasks (Laube et al., 2020), as well as lower academic attainment (Cavanagh et al., 2007). Developmental theories suggest that early puberty may accentuate pre-existing differences in childhood (Caspi & Moffitt, 1991), or impair plasticity and learning (Schulz et al., 2009). It is worth noting, however, that several empirical (Chaku & Hoyt, 2019; Koerselman & Pekkarinen, 2017) and theoretical studies (Belsky et al., 2007; Laube & Fuhrmann, 2020) now suggest, that, in supportive environments, early puberty can be linked to more positive cognitive outcomes, too. The effects appear to be domain-specific: Haku and Hoyt (2019) showed that early maturation may be associated with lower self-control but also better attention. The social context also shapes outcomes after early puberty (Belsky et al., 2007). Preliminary evidence suggests that supportive contexts may allow early maturers to benefit from new learning opportunities in adolescence (Klopack et al., 2020).

Overall, these findings underline that biological factors intersect with social risk and resilience factors, such as socioeconomic status, parental closeness and friendship quality. All three were here found to be independently linked to poorer cognitive and wellbeing outcomes (after controlling for the other two social risk factors). This finding is in line with an emerging body of literature highlighting that socioeconomic status (Hackman et al., 2015), friendship quality (van Harmelen et al., 2016, 2017; Ybarra et al., 2010) and relationships to parents (Laursen & Collins, 2009) are linked to cognitive, wellbeing and mental health outcomes. This underscores the importance of social interventions in schools to improve wellbeing.

These findings highlight several promising avenues for future research. We used a rich longitudinal dataset for this study, with high-quality measures of cognition and well-being, covering major aspects of each domain. Future studies could explore other interesting aspects of cognition (e.g., working memory) and wellbeing (e.g., life satisfaction and depression). While SECCYD allowed us to assess developmental sequences and identify potential risk and resilience factors in a large and diverse cohort, the observational nature of the sample precludes any assessments of causality. Future experimental and intervention research will therefore need to establish cause and effect in the development of cognition and wellbeing. The heterogeneity in loneliness trajectories observed here using exploratory methods, also invites further study. Future studies of heterogeneity are needed to confirm which young people are most at risk of loneliness, at what point in their life and to test candidate mechanisms (e.g., pubertal changes) and later life outcomes (e.g., mental health). Loneliness itself is a heterogenous experience: It may be experienced as neutral or even positive depending on the individual and circumstances. Better understanding and more specific measurement of negative and positive experiences of loneliness in adolescence, as well as the relationship between loneliness, social dissatisfaction and social isolation will allow us to better tease apart the underlying mechanisms. Finally, alternative analytic approaches may yield complementary insights into developmental processes. Cross-lagged panel models, for instance, could isolate cross-lagged effects from one wave to the next, which could be particularly interesting for developmental transitions.

Conclusion

We characterized the relationship between cognition and wellbeing trajectories across developmentally sensitive periods between childhood and adolescence. We found pervasive cross-sectional links and two robust longitudinal effects: Externalizing symptoms predicted changes in planning; and vocabulary predicted changes in loneliness. Less favourable trajectories in both domains were related to earlier puberty, lower socioeconomic status, a more distant relationship to parents and lower friendship. This work highlights the complex longitudinal dynamics of cognition and wellbeing in childhood and underlines the need to support both peer and parent relationships to foster cognitive health and wellbeing across the lifespan.

Acknowledgments

The authors would like to thank the volunteers and researchers involved in the NICHD Study of Early Child Care and Youth Development. The authors are also grateful to Louise Arseneault for helpful comments on the findings.

Author Contributions

DF conceived the study. DF and RAK designed the study and analysed the data. All authors contributed to the writing of the manuscript.

References

Achenbach, T. M. (1991). *Manual for the Child Behaviour Checklist/ 4-18.* University of Vermont, Department of Psychiatry.

Achenbach, Thomas M, & Rescorla, L. (2001). *Manual for the ASEBA school-age forms & profiles: An integrated system of multi-informant assessment*. Burlington, VT : ASEBA.

Andersen, S. L., & Teicher, M. H. (2008). Stress, sensitive periods and maturational events in adolescent depression. *Trends in Neurosciences*, *31*(4), 183–191. https://doi.org/10.1016/j.tins.2008.01.004

Asher, S. R., Hymel, S., & Renshaw, P. D. (1984). Loneliness in Children. *Child Development*, *55*(4), 1456–1464. JSTOR. https://doi.org/10.2307/1130015

Askelund, A. D., Schweizer, S., Goodyer, I. M., & van Harmelen, A.-L. (2019). Positive memory specificity is associated with reduced vulnerability to depression. *Nature Human Behaviour*, *3*(3), 265–273. https://doi.org/10.1038/s41562-018-0504-3

Barnett, J. H., Salmond, C. H., Jones, P. B., & Sahakian, B. J. (2006). Cognitive reserve in neuropsychiatry. *Psychological Medicine*, *36*(8), 1053–1064. Cambridge Core. https://doi.org/10.1017/S0033291706007501

Batty, G. D., Deary, I. J., & Gottfredson, L. S. (2007). Premorbid (early life) IQ and later mortality risk: Systematic review. *Annals of Epidemiology*, *17*(4), 278–288. https://doi.org/10.1016/j.annepidem.2006.07.010

Bauer, D. J. (2007). Observations on the Use of Growth Mixture Models in Psychological Research. *Multivariate Behavioral Research*, *42*(4), 757–786. https://doi.org/10.1080/00273170701710338

Belsky, J., Bakermans-Kranenburg, M. J., & van IJzendoorn, M. H. (2007). For Better and For Worse: Differential Susceptibility to Environmental Influences. *Current Directions in Psychological Science*, *16*(6), 300–304. https://doi.org/10.1111/j.1467-8721.2007.00525.x

Blakemore, S. J., & Mills, K. L. (2014). Is adolescence a sensitive period for sociocultural processing? *Annual Review of Psychology*, *65*, 187–207. https://doi.org/10.1146/annurev-psych-010213-115202

Boogert, N. J., Madden, J. R., Morand-Ferron, J., & Thornton, A. (2018). Measuring and understanding individual differences in cognition. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *373*(1756), 20170280. https://doi.org/10.1098/rstb.2017.0280

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, *16*(1), 5–13. https://doi.org/10.1002/wps.20375

Burger, J., van der Veen, D. C., Robinaugh, D. J., Quax, R., Riese, H., Schoevers, R. A., & Epskamp, S. (2020). Bridging the gap between complexity science and clinical practice by formalizing idiographic theories: A computational model of functional analysis. *BMC Medicine*, *18*(1), 99. https://doi.org/10.1186/s12916-020-01558-1

Caspi, A., & Moffitt, T. E. (1991). Individual differences are accentuated during periods of social change: The sample case of girls at puberty. *Journal of Personality and Social Psychology*, *61*(1), 157–168. https://doi.org/10.1037/0022-3514.61.1.157

Cattan, M., White, M., Bond, J., & Learmouth, A. (2005). Preventing social isolation and loneliness among older people: A systematic review of health promotion interventions. *Ageing and Society*, *25*(1), 41–67. Cambridge Core. https://doi.org/10.1017/S0144686X04002594

Cavanagh, S. E., Riegle-Crumb, C., & Crosnoe, R. (2007). Puberty and the Education of Girls. *Social Psychology Quarterly*, *70*(2), 186–198. https://doi.org/10.1177/019027250707000207

Chaku, N., & Hoyt, L. T. (2019). Developmental Trajectories of Executive Functioning and Puberty in Boys and Girls. *Journal of Youth and*

Adolescence, *48*(7), 1365–1378. https://doi.org/10.1007/s10964-019-01021-2

Cohen, P., Cohen, J., Aiken, L. S., & West, S. G. (1999). The Problem of Units and the Circumstance for POMP. *Multivariate Behavioral Research*, *34*(3), 315–346. https://doi.org/10.1207/S15327906MBR3403_2

Der, G., Batty, G. D., & Deary, I. J. (2009). The association between IQ in adolescence and a range of health outcomes at 40 in the 1979 US National Longitudinal Study of Youth. *Intelligence, Health and Death: The Emerging Field of Cognitive Epidemiology*, *37*(6), 573–580. https://doi.org/10.1016/j.intell.2008.12.002

DeRoche, K. K. (2009). *Functioning of global fit statistics in latent growth curve modeling*.

Eccles, A. M., Qualter, P., Madsen, K. R., & Holstein, B. E. (2020). Loneliness in the lives of Danish adolescents: Associations with health and sleep. *Scandinavian Journal of Public Health*, *48*(8), 877–887. https://doi.org/10.1177/1403494819865429

Eunice Kennedy Shriver National Institute of Child Health and Human Development, NIH, DHHS. (2006). *The NICHD Study of Early Child Care and Youth Development (SECCYD): Findings for Children up to Age 4 1/2 Years*. U.S. Government Printing Office. https://www.nichd.nih.gov/publications/product/20

Feinstein, L., & Bynner, J. (2004). The Importance of Cognitive Development in Middle Childhood for Adulthood Socioeconomic Status, Mental Health, and Problem Behavior. *Child Development*, *75*(5), 1329–1339. https://doi.org/10.1111/j.1467-8624.2004.00743.x

Flavell, J. H. (1999). Cognitive Development: Children's Knowledge About the Mind. *Annual Review of Psychology*, *50*(1), 21–45. https://doi.org/10.1146/annurev.psych.50.1.21

Forrest, C. L., Gibson, J. L., Halligan, S. L., & St Clair, M. C. (2018). A longitudinal analysis of early language difficulty and peer problems on later emotional difficulties in adolescence: Evidence from the Millennium Cohort Study. *Autism & Developmental Language Impairments*, *3*, 2396941518795392. https://doi.org/10.1177/2396941518795392

Fritz, J., Fried, E. I., Goodyer, I. M., Wilkinson, P. O., & van Harmelen, A.-L. (2018). A Network Model of Resilience Factors for Adolescents with and without Exposure to Childhood Adversity. *Scientific Reports*, *8*(1), 15774. https://doi.org/10.1038/s41598-018-34130-2

Fuhrmann, D., Casey, C. S., Speekenbrink, M., & Blakemore, S.-J. (2019). Social exclusion affects working memory performance in young adolescent girls. *Developmental Cognitive Neuroscience*, *40*, 100718. https://doi.org/10.1016/j.dcn.2019.100718

Gooch, D., Sears, C., Maydew, H., Vamvakas, G., & Norbury, C. F. (2019). Does Inattention and Hyperactivity Moderate the Relation Between Speed of Processing and Language Skills? *Child Development*, *90*(5), e565–e583. PubMed. https://doi.org/10.1111/cdev.13220

Grimm, K. J., Ram, N., & Hamagami, F. (2011). Nonlinear growth curves in developmental research. *Child Development*, *82*(5), 1357–1371. PubMed. https://doi.org/10.1111/j.1467-8624.2011.01630.x

Hackman, D. A., Gallop, R., Evans, G. W., & Farah, M. J. (2015). Socioeconomic status and executive function: Developmental trajectories and mediation. *Developmental Science*, *18*(5), 686–702. https://doi.org/10.1111/desc.12246

Ioannidis, K., Askelund, A. D., Kievit, R. A., & van Harmelen, A.-L. (2020). The complex neurobiology of resilient functioning after childhood maltreatment. *BMC Medicine*, *18*(1), 32. https://doi.org/10.1186/s12916-020-1490-7

Irie, T., Yokomitsu, K., & Sakano, Y. (2019). Relationship between cognitive behavioral variables and mental health status among university students: A meta-analysis. *PLOS ONE*, *14*(9), e0223310. https://doi.org/10.1371/journal.pone.0223310

Jones, P. B. (2013). Adult mental health disorders and their age at onset. *British Journal of Psychiatry*, *202*(s54), s5–s10. Cambridge Core. https://doi.org/10.1192/bjp.bp.112.119164

Kail, R. V., Lervåg, A., & Hulme, C. (2015). Longitudinal evidence linking processing speed to the development of reasoning. *Developmental Science*, *19*(6), 1067–1074. https://doi.org/10.1111/desc.12352

Kessler, R. C., Amminger, G. P., Aguilar-Gaxiola, S., Alonso, J., Lee, S., & Ustun, T. B. (2007). Age of onset of mental disorders: A review of recent literature. *Current Opinion in Psychiatry*, *20*(4), 359–364. https://doi.org/10.1097/YCO.0b013e32816ebc8c

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Merikangas, K. R., & Walters, E. E. (2005). Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry*, *62*(6), 593–602. https://doi.org/10.1001/archpsyc.62.6.593

Kievit, R. A., Lindenberge, U., Goodyer, I., Jones, P. B., Fonagy, P., Bullmore, E. T., NSPN Consortium, the, & Dolan, R. J. Mutualistic coupling between vocabulary and reasoning supports cognitive development during late adolescence and early adulthood. *Psychological Science*.

Klopack, E. T., Sutton, T. E., Simons, R. L., & Simons, L. G. (2020). Disentangling the Effects of Boys' Pubertal Timing: The Importance of Social Context. *Journal of Youth and Adolescence*, *49*(7), 1393–1405. https://doi.org/10.1007/s10964-019-01141-9

Koerselman, K., & Pekkarinen, T. (2017). *The Timing of Puberty and Gender Differences in Educational Achievement* (IZA Discussion Papers No. 10889). Institute of Labor Economics (IZA). http://hdl.handle.net/10419/170873

Kovacs, M., & Beck, A. T. (1977). An empirical-clinical approach toward a definition of childhood depression. In *In: Schulterbrandt J. G., Raskin A., editors. Depression in childhood: Diagnosis, treatment and conceptual models* (pp. 1–25). Raven Press.

Kuja-Halkola, R., Lichtenstein, P., D’Onofrio, B. M., & Larsson, H. (2015). Codevelopment of ADHD and externalizing behavior from childhood to adulthood. *Journal of Child Psychology and Psychiatry*, *56*(6), 640–647.

Laube, C., & Fuhrmann, D. (2020). Is early good or bad? Early puberty onset and its consequences for learning. *Evolution, Development and Genetics *Sensitive and Critical Periods**, *36*, 150–156. https://doi.org/10.1016/j.cobeha.2020.10.005

Laube, C., Lorenz, R., & van den Bos, W. (2020). Pubertal testosterone correlates with adolescent impatience and dorsal striatal activity. *Developmental Cognitive Neuroscience*, *42*, 100749. https://doi.org/10.1016/j.dcn.2019.100749

Laursen, B., & Collins, W. A. (2009). Parent—Child Relationships During Adolescence. In *Handbook of Adolescent Psychology*. American Cancer Society. https://doi.org/10.1002/9780470479193.adlpsy002002

Lewinsohn, P. M., Seeley, J. R., Roberts, R. E., & Allen, N. B. (1997). Center for Epidemiologic Studies Depression Scale (CES-D) as a screening instrument for depression among community-residing older adults. *Psychology and Aging*, *12*(2), 277–287. https://doi.org/10.1037/0882-7974.12.2.277

Lewis, G., Ioannidis, K., van Harmelen, A.-L., Neufeld, S., Stochl, J., Lewis, G., Jones, P. B., & Goodyer, I. (2018). The association between pubertal status and depressive symptoms and diagnoses in adolescent females: A population-based cohort study. *PloS One*, *13*(6), e0198804–e0198804. PubMed. https://doi.org/10.1371/journal.pone.0198804

Llewellyn, D. J., Lang, I. A., Langa, K. M., & Huppert, F. A. (2008). Cognitive function and psychological well-being: Findings from a population-based cohort. *Age and Ageing*, *37*(6), 685–689. PubMed. https://doi.org/10.1093/ageing/afn194

Lunansky, G., van Borkulo, C., & Borsboom, D. (2020). Personality, Resilience, and Psychopathology: A Model for the Interaction between Slow and Fast Network Processes in the Context of Mental Health. *European Journal of Personality*, *n/a*(n/a). https://doi.org/10.1002/per.2263

Madle, R. A. (2017). *Test review of Woodcock-Johnson® IV*. http://marketplace.unl.edu/buros/

Masi, C. M., Chen, H.-Y., Hawkley, L. C., & Cacioppo, J. T. (2011). A meta-analysis of interventions to reduce loneliness. *Personality and Social Psychology*

Review : An Official Journal of the Society for Personality and Social Psychology, Inc, *15*(3), 219–266. PubMed. https://doi.org/10.1177/1088868310377394

Masten, A. S., Roisman, G. I., Long, J. D., Burt, K. B., Obradović, J., Riley, J. R., Boelcke-Stennes, K., & Tellegen, A. (2005). Developmental Cascades: Linking Academic Achievement and Externalizing and Internalizing Symptoms Over 20 Years. *Developmental Psychology*, *41*(5), 733–746. https://doi.org/10.1037/0012-1649.41.5.733

Matthews, T., Danese, A., Wertz, J., Odgers, C. L., Ambler, A., Moffitt, T. E., & Arseneault, L. (2016). Social isolation, loneliness and depression in young adulthood: A behavioural genetic analysis. *Social Psychiatry and Psychiatric Epidemiology: The International Journal for Research in Social and Genetic Epidemiology and Mental Health Services*, *51*(3), 339–348. https://doi.org/10.1007/s00127-016-1178-7

McElroy, E., Belsky, J., Carragher, N., Fearon, P., & Patalay, P. (2018). Developmental stability of general and specific factors of psychopathology from early childhood to adolescence: Dynamic mutualism or p-differentiation? *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *59*(6), 667–675. PubMed. https://doi.org/10.1111/jcpp.12849

Murtza, M. H., Gill, S. A., Aslam, H. D., & Noor, A. (2020). Intelligence quotient, job satisfaction, and job performance: The moderating role of personality type. *Journal of Public Affairs*, *n/a*(n/a), e2318. https://doi.org/10.1002/pa.2318

Muthén, L. K., & Muthén, B. O. (1998). *Mplus User's Guide* (Eighth Edition) [Computer software]. Muthén & Muthén.

Office for National Statistics. (2018). *Children's and young people's experiences of loneliness.* https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/articles/childrensandyoungpeoplesexperiencesofloneliness/2018

Okano, L., Jeon, L., Crandall, A., Powell, T., & Riley, A. (2020). The Cascading Effects of Externalizing Behaviors and Academic Achievement Across Developmental Transitions: Implications for Prevention and Intervention. *Prevention Science*, *21*(2), 211–221. https://doi.org/10.1007/s11121-019-01055-9

Ram, N., & Grimm, K. J. (2009). Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *International Journal of Behavioral Development*, *33*(6), 565–576. PubMed. https://doi.org/10.1177/0165025409343765

Rock, P. L., Roiser, J. P., Riedel, W. J., & Blackwell, A. D. (2014). Cognitive impairment in depression: A systematic review and meta-analysis.

Psychological Medicine, *44*(10), 2029–2040. Cambridge Core. https://doi.org/10.1017/S0033291713002535

Rosseel, Y. (2012). Lavaan: An R package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of Structural Equation Models: Tests of significance and descriptive goodness-of-fit measures. *Methods of Psychological Research*, *8*(2), 23–74.

Schulz, K. M., Molenda-Figueira, H. A., & Sisk, C. L. (2009). Back to the future: The organizational-activational hypothesis adapted to puberty and adolescence. *Hormones and Behavior*, *55*(5), 597–604. PubMed. https://doi.org/10.1016/j.yhbeh.2009.03.010

Seligman, L. D., Ollendick, T. H., Langley, A. K., & Baldacci, H. B. (2004). The Utility of Measures of Child and Adolescent Anxiety: A Meta-Analytic Review of the Revised Children's Manifest Anxiety Scale, the State–Trait Anxiety Inventory for Children, and the Child Behavior Checklist. *Journal of Clinical Child & Adolescent Psychology*, *33*(3), 557–565. https://doi.org/10.1207/s15374424jccp3303_13

Sequeira, M.-E., Lewis, S. J., Bonilla, C., Smith, G. D., & Joinson, C. (2017). Association of timing of menarche with depressive symptoms and depression in adolescence: Mendelian randomisation study. *British Journal of Psychiatry*, *210*(1), 39–46. Cambridge Core. https://doi.org/10.1192/bjp.bp.115.168617

Smedler, A.-C., Hjern, A., Wiklund, S., Anttila, S., & Pettersson, A. (2015). Programs for Prevention of Externalizing Problems in Children: Limited Evidence for Effect Beyond 6 Months Post Intervention. *Child & Youth Care Forum*, *44*, 251–276. PubMed. https://doi.org/10.1007/s10566-014-9281-y

Spielberger, C. D., & Sydeman, S. J. (1994). State-Trait Anxiety Inventory and State-Trait Anger Expression Inventory. In *The use of psychological testing for treatment planning and outcome assessment.* (pp. 292–321). Lawrence Erlbaum Associates, Inc.

Stawski, R. S., Sliwinski, M. J., & Smyth, J. M. (2006). Stress-related cognitive interference predicts cognitive function in old age. *Psychology and Aging*, *21*(3), 535–544. https://doi.org/10.1037/0882-7974.21.3.535

Steptoe, A., Deaton, A., & Stone, A. A. (2015). Subjective wellbeing, health, and ageing. *Lancet (London, England)*, *385*(9968), 640–648. PubMed. https://doi.org/10.1016/S0140-6736(13)61489-0

Timmons, A. C., & Margolin, G. (2015). Family Conflict, Mood, and Adolescents' Daily School Problems: Moderating Roles of Internalizing and Externalizing Symptoms. *Child Development*, *86*(1), 241–258. https://doi.org/10.1111/cdev.12300

Trudel-Fitzgerald, C., Millstein, R. A., von Hippel, C., Howe, C. J., Tomasso, L. P., Wagner, G. R., & VanderWeele, T. J. (2019). Psychological well-being as part of the public health debate? Insight into dimensions, interventions, and policy. *BMC Public Health*, *19*(1), 1712. https://doi.org/10.1186/s12889-019-8029-x

Van Der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842–861. https://doi.org/10.1037/0033-295X.113.4.842

van Harmelen, A.-L., Gibson, J. L., St Clair, M. C., Owens, M., Brodbeck, J., Dunn, V., Lewis, G., Croudace, T., Jones, P. B., Kievit, R. A., & Goodyer, I. M. (2016). Friendships and Family Support Reduce Subsequent Depressive Symptoms in At-Risk Adolescents. *PLOS ONE*, *11*(5), e0153715. https://doi.org/10.1371/journal.pone.0153715

van Harmelen, A.-L., Kievit, R. A., Ioannidis, K., Neufeld, S., Jones, P. B., Bullmore, E., Dolan, R., Fonagy, P., & Goodyer, I. (2017). Adolescent friendships predict later resilient functioning across psychosocial domains in a healthy community cohort. *Psychological Medicine*, *47*(13), 2312–2322. Cambridge Core. https://doi.org/10.1017/S0033291717000836

Welsh, M. C., & Huizinga, M. (2001). The Development and Preliminary Validation of the Tower of Hanoi-Revised. *Assessment*, *8*(2), 167–176. https://doi.org/10.1177/107319110100800205

Woodcock, R. W. (1997). The Woodcock-Johnson Tests of Cognitive Ability—Revised. *Contemporary Intellectual Assessment: Theories, Tests, and Issues.*, 230–246.

Ybarra, O., Winkielman, P., Yeh, I., Burnstein, E., & Kavanagh, L. (2010). Friends (and Sometimes Enemies) With Cognitive Benefits: What Types of Social Interactions Boost Executive Functioning? *Social Psychological and Personality Science*, *2*(3), 253–261. https://doi.org/10.1177/1948550610386808