Analysing Dynamic Change in Children's Socio-Emotional Development using the Strengths and Difficulties Questionnaire in a large UK Longitudinal Study

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Conflicts of interest/Competing interests: The authors have no conflicts of interest relevant to this article to disclose.

Acknowledgements We are very grateful to all the families who took part in the Millennium Cohort Study, and the whole MCS team, which includes interviewers, computer and laboratory technicians, clerical workers, research scientists, and volunteers. A preprint of this paper is available here: https://psyarxiv.com/wz9xc/

Ethics Approval: All sweeps of the Millennium Cohort Study were approved by the London Multicentre Research Ethics Committee. (Sweep-1: MREC/01/6/19; Sweep-2: MREC/03/2/022; Sweep-3: 05/MRE02/46; Sweep-4: 07/MRE03/32; Sweep-5: 11/YH/0203; Sweep-6: 13/LO/1786; Sweep-7: 17/NE/0341)

Funding: The Millennium Cohort Study is funded by the UK Economic and Social Research Council (ES/M001660/1). LGS was funded by the University of Edinburgh through a Principal's Careers Development Scholarship. HAH was funded by the UK Economic and Social Research Council (ESRC) (ES/R500938/1). BA was supported by the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No.813546, the Baily-Thomas Charitable Fund (TRUST/VC/AC/SG/469207686), the Data-Driven Innovation Initiative and the UK ESRC (ES/N018877/1). The study sponsors had no part in the design, data analysis and interpretation of this study, in the writing of the manuscript or in the decision to submit the paper for publication. The authors' work was independent of their funders.

Availability of data and material: The University of London Centre for Longitudinal Studies owns the copyright for the Millennium Cohort Study (MCS) data used in this study. The MCS data are held/curated by the UK Data Service. Anyone wishing to use the MCS data (found at: https://discover.ukdataservice.ac.uk/series/?sn=2000031) must register and submit a data request to the UK Data Service at http://ukdataservice.ac.uk/. Additional terms and conditions are outlined here: https://www.ukdataservice.ac.uk/get-data/how-to-access/conditions.

Code availability: The restructuring and merging script is provided here: https://github.com/Lydia-G-S/Millennium-Cohort-Study-Data-Restructuring-in-R

Authors' contributions: LGS conceptualized and designed the study, conducted analyses, drafted the initial manuscript, and reviewed and revised the manuscript. HAH contributed to data analysis and reviewed the manuscript for important intellectual content. AU provided critical feedback on data analysis and methodology, and reviewed the manuscript for important intellectual content. ML and BA made substantial contributions to the conception and design of the study and critically reviewed the manuscript for important intellectual content. ALM made substantial contributions to analysis and interpretation of data, the conception and design of the study and critically reviewed the manuscript for important intellectual content All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

Abstract

Background: Many children who suffer from one mental health issue also suffer from at least one co-occurring disorder and a range of developmental psychopathology theories, including developmental cascade and network models, have been proposed to explain this widespread comorbidity. Autoregressive latent trajectory models with structured residuals (ALT-SR) and multilevel graphical vector autoregression (GVAR) are recently proposed complementary approaches that can help operationalise and test these theories and provide new insights into the reciprocal relationships between multiple mental health domains to advance the understanding of comorbidity development.

Methods: This study uses ALT-SR and multilevel GVAR models to analyse the temporal, contemporaneous, and between-person relationships between key dimensions of child mental health: emotional problems, peer problems, conduct problems, hyperactivity/inattention and prosociality as measured by the parent-reported Strengths and Difficulties Questionnaire (SDQ) in 17,478 children from the UK Millennium Cohort Study at ages 3, 5, 7, 11, 14 and 17 years.

Results: Children's strengths and difficulties in different domains of psychosocial functioning were dynamically associated with each other over- and within-time. The ALT-SR highlighted that hyperactivity/inattention plays a central role in affecting other domains over developmental time, while the GVAR model highlighted comparably strong bidirectional relationships between conduct problems and prosociality as well as between emotional problems and peer problems.

Conclusion: This study confirms that mental health difficulties influence one another dynamically over time. The complementary techniques of ALT-SR and GVAR models offer different insights into comorbidity and hold promise for supporting the building of more comprehensive developmental psychopathological theories that acknowledge the inter-connectedness of different domains of mental health.

Keywords: developmental psychopathology; socio-emotional strengths and difficulties; ALT-SR; Graphical Vector Autoregression; Millennium Cohort Study

General Scientific Summary

Most mental health difficulties, such as emotional problems or hyperactivity, have their onset during childhood and adolescence with many children suffering from one mental health issue also suffering from at least one other. This study presents evidence for complex interactions between different mental health domains over children's development, highlighting the importance of studying mental health as a dynamic system.

Most mental health issues have their onset during childhood or adolescence with an estimated 10-20% of youths suffering from a mental health condition (WHO, 2018). The leading mental health concerns among children and adolescents are attention-deficit/hyperactivity disorder (ADHD), externalising problems such as conduct disorder and internalising problems such as anxiety and depression (Danielson et al., 2018; Ghandour et al., 2019). A much larger proportion of children is further affected by sub-clinical levels of difficulties; for instance, estimates for subthreshold ADHD symptoms are as high as 23% (Balázs & Keresztény, 2014). While ADHD symptoms usually first appear before age 6 but must have an age of onset before age 12 to warrant a diagnosis of ADHD (American Psychiatric Association, 2013), internalising problems and in particular anxiety disorders as well as externalising problems such as impulse control disorders have a median age of onset of 11 years (Kessler et al., 2005). Importantly, more than 40 percent of youths with a lifetime psychiatric disorder go on to develop at least one additional mental illness concurrently or later in life with most comorbidities having an onset before or during adolescence (Kessler et al., 2005; Reale et al., 2017).

Various theories have attempted to explain the high comorbidity rates of mental health problems. In particular, developmental cascade models such as the dual failure model (Capaldi, 1992) and the acting out model (Carlson & Cantwell, 1980) hypothesise that co-occurring mental health problems are the results of cascades from one mental health problem, for example conduct problems, to risk factors such as peer problems that then lead to problems in another domain, for example emotional problems (Masten & Cicchetti, 2010). Similarly, according to the ontogenic process model of externalizing psychopathology comorbidities are the result of complex longitudinal transactions between individual vulnerabilities (e.g., genetic factors) and contextual risk factors (e.g. hostile parenting) (Beauchaine & McNulty, 2013). To date, a substantial body of research has found support for these models (Han et al., 2020; Murray, Obsuth, Zirk-Sadowski, et al., 2020; van Lier & Koot, 2010; Yu et al., 2018), however, much of the existing evidence comes from studies that have used methods that did not adequately operationalise the processes implied by such cascade models. In particular, cross-lagged panel models (CLPMs) have often been the method of choice (e.g. Obsuth et al., 2020; van Lier et al., 2012). However, CLPMs suffer from a major limitation in that they conflate within- and between-person effects (Berry & Willoughby, 2017). Considering that the developmental relations of interest refer to within-person processes, it is vital to appropriately account for between-person differences. This is particularly important in the context of interventions which will have to be guided by within-person findings in order to be effective (Hamaker et al., 2015). Also, most studies to date investigating cascade models, including a limited number of studies that have used methods suitable for disaggregating within- from between-person effects, have only studied comorbidities between a small number of mental health issues (e.g., internalising and externalising problems) (e.g. Murray, Caye, McKenzie, et al., 2020; Murray, Eisner, & Ribeaud, 2020; Oh et al., 2020; van Lier & Koot, 2010). However, previous research suggests that almost all common socio-emotional issues, that is conduct problems, hyperactivity/inattention, emotional problems, peer problems and prosociality, are connected to all others (e.g. Andrade & Tannock, 2013; Murray, Eisner, & Ribeaud, 2020; Obsuth et al., 2015, 2020; Patalay et al., 2017). This implies that simultaneously examining all their relations and their development over time is critical to get a complete picture of mental health development

An alternative conceptualisation of comorbidities comes from the network approach to psychopathology (Borsboom, 2008). This approach views psychological disorders not as a collection of symptoms that can be explained by a unitary underlying abnormality (e.g., ineffective serotonin regulation) but as an interacting system of mutually reinforcing symptoms (e.g., insomnia leading to increased fatigue) (Jordan et al., 2020). This also means that difficulties thought to be characteristic of one disorder can drive the development of difficulties in another domain through so called ‘bridge symptoms’, activating another symptom network (Jordan et al., 2020). While a specific symptom network might be given a label such as depression, this conceptualisation of psychopathology highlights that all mental health domains are interconnected. Thus, the network approach to psychopathology further highlights that to better understand the pathogenesis of mental health problems and consequently improve mental health interventions, it is crucial to move beyond pairwise analyses of mental health problems and to comprehensively track the developmental interplay of commonly co-occurring mental health difficulties from early childhood into adulthood.

The current study applies two state-of-the-art methods to model dynamic relations of multiple mental health domains: autoregressive latent trajectory models with structured residuals (ALT-SR; Curran et al., 2014) and multilevel graphical vector autoregression (GVAR; Epskamp, 2020). As well as providing the means to model the concurrent and temporal inter-relations between multiple mental health issues predicted by various developmental cascade and network theories simultaneously, they have the advantage of allowing within- and between-person relations to be disentangled. This is an important advance over models such as cross-lagged panel models, which conflate between- and within-person effects and thus provide ambiguous results regarding the development of comorbidity (Berry & Willoughby, 2017). Beyond this, the ALT-SR and GVAR approaches offer complementary strengths. While GVAR models provide an intuitive visualisation of complex relations between multiple repeatedly measured variables making them particularly useful for the study of a large number of domains at once, they assume the same relation over the whole of development. This might be problematic when analysing mental health development as mental health risk factors, manifestations, and levels have been shown to change over development (Cherkasova et al., 2013; Meeus, 2016; Rapee et al., 2019). For instance, peer relationships have been found to become increasingly important during adolescence (Steinberg & Monahan, 2007) and given their hypothesised role in linking different mental health issues (Capaldi, 1992), this could engender fundamental shifts in the inter-relations between different domains of mental health. Some evidence for this has already been found in the empirical literature (e.g. Murray, Eisner, & Ribeaud, 2020). In contrast to GVAR models, ALT-SRs allow for the estimation of time-varying paths which allows the investigation of dynamics that might change over development. However, this means estimating a very large number of parameters, making interpretation difficult when moving beyond the analysis of pairwise relations.

ALT-SRs are already beginning to yield new insights into where existing developmental psychopathology theory holds and where it requires further development (e.g. Davis et al., 2018; Murray, Eisner, & Ribeaud, 2020; Murray, Obsuth, et al., 2021; Oh et al., 2020). For example, Murray et al. (2020) found that when using an ALT-SR, the direction of relations between externalising and internalising problems reversed between childhood and adolescence, suggesting that while the dual failure model captures the inter-relations between externalising and internalising problems in childhood, a different model might be required to explain their relations in adolescence. The use of ALT-SR was important for this insight. In it, the relevant negative effects emerged much more clearly than in a corresponding CLPM fit for comparison.

Multilevel GVAR models have their origin in the network approach to psychopathology and have not yet been applied to study how mental health relations unfold over childhood and adolescence. However, network models fit to cross-sectional data have provided important new insights that show the promise of this approach (e.g. Beard et al., 2016; Rouquette et al., 2018). For example, a symptom level analysis of emotional and behavioural problems found that these domains are highly interlinked during childhood with higher scores on bridge symptoms being predictive of later development of anxiety disorders (Rouquette et al., 2018). Thus, the recent development of multilevel longitudinal network models provides valuable opportunities for gaining a more comprehensive understanding of developmental psychopathology as these models allow for the inclusion of a much larger number of variables than models such as CLPMs or ALT-SRs.

In the present study, GVAR and ALT-SR models will be used to analyse socio-emotional development, as measured by the Strengths and Difficulties Questionnaire longitudinally at 3, 5, 7, 11, 14 and 17 years, in children participating in the Millennium Cohort Study, a British birth cohort study. This will contribute to a more complete picture of mental health development, giving insights into the dynamic relationships between different mental health domains over development.

Method

Participants

The Millennium Cohort Study (MCS) is a longitudinal birth cohort study of around 19,000 children born in the United Kingdom at the beginning of the 21st-century. To date, there have been seven sweeps of data collection at the children's following ages: 9 months, 3, 5, 7, 11, 14 and 17 years. For details, see MCS cohort profiles and documentation (Connelly & Platt, 2014; Joshi & Fitzsimons, 2016; Radu, 2019). The current study included all children who had complete SDQ data at least at one time-point between the ages of 3 and 17 (N = 17,478).

Ethical Considerations

The MCS is funded by the UK Economic and Social Research Council (ES/M001660/1; Shepherd & Gilbert, 2019) and was approved by the London Multicentre Research Ethics

Committee. Written consent was obtained from all participating parents at each sweep.

Measure

Children's socio-emotional strengths and difficulties were measured using the Strengths and Difficulties Questionnaire (SDQ), a behavioural screening tool that has been validated for use in 3 to 16-year olds (Goodman, 1997). The SDQ is widely used, not only for longitudinal analyses, but also in education and clinical settings where it contributes to clinical decision-making (Sosu & Schmidt, 2017). The questionnaire consists of 25 items divided equally between 5 subscales: emotional symptoms, conduct problems, hyperactivity/inattention, peer relationship problems and prosociality. Subscale scores are calculated by summation of the relevant item scores. Higher scores on any of the subscales indicate more behavioural problems, except for the prosociality subscale where higher scores indicate behavioural strengths. In the MCS, parents, predominantly mothers, completed the SDQ when the children were aged 3, 5, 7, 11, 14 and 17 years. At age 3, a modified version of the SDQ was administered, adapting two items in the conduct and one item in the hyperactivity subscale for age-appropriateness. The SDQ has good structural, discriminative and convergent validity (Kersten et al., 2016) and shows configural, metric and scalar gender and longitudinal invariance across all subscales for ages 5 to 14 in the MCS, supporting its use for comparing variances and covariances and to examine developmental trajectories (Murray, Speyer, et al., 2021). However, the same study suggested that invariance did not extend to ages 3 and 17, necessitating caution when interpreting possible age differences in symptom levels and relations at these ages compared with ages 5 to 14.

Statistical Analyses

Prior to analysis, using R (R Core Team, 2017), some of the datasets were restructured and merged to allow for longitudinal analysis (script: https://github.com/Lydia-G-S/Millennium-

Cohort-Study-Data-Restructuring-in-R). In the current study, sum-scores of the subscales of the SDQ were used for both the ALT-SR and the GVAR model since the high complexity of a latent variable measurement model would have likely led to estimation difficulties in both models. Additionally, previous research using the SDQ has shown that sum-score approaches yield similar results to latent modelling approaches (Vugteveen et al., 2020).

Autoregressive Latent Trajectory Model with Structured Residuals (ALT-SR)

Autoregressive latent trajectory models with structured residuals (ALT-SR) combine the key feature of Latent Trajectory Models (LTM) and cross-lagged panel models (CLPM). In LTM, variables are modelled longitudinally by estimating latent growth curve factors that capture how one variable changes over time (Curran et al., 2014). CLPMs describe repeatedly measured variables as a function of its own and other variables' past values. Hence, the predictors of the variable are the time delayed values, also called lags, of this series of measures. Most commonly, a lag of 1 is chosen which assumes that the current value of a variable depends on its own first lag, i.e., its value at the preceding time point (Epskamp et al., 2018).

ALT-SRs allow for the estimation of latent growth curves and autoregressive and cross-lagged effects within one model (Curran et al., 2014). The growth curve part of the ALT-SR includes an intercept and linear slope factor (additional slope factors can be included to capture higher-order growth). The intercept and slope factor means capture the initial levels and change in symptoms, while their variances capture individual differences in initial levels and change (Mund & Nestler, 2019). The autoregressive and cross lagged effects are defined between the variables' residuals after estimating the growth curve and reflect deviations from the person-specific growth curves at a certain time points. For a schematic illustration of a two-outcome ALT-SR, see Figure S1 in the online supplementary materials. This specification thus allows within-person relations to be separated from between-person variation. Autoregressive and cross-lagged parameters capture the relationships between these within-person residuals and the same or a different variable's within-person residuals at a consecutive time point, respectively. Covariances at each time estimate within-time associations between constructs (e.g., associations between conduct and peer problems at age 3) (Mund & Nestler, 2019). In order to facilitate model identification, it is necessary to place constraints on some part of the model structure, especially when investigating the interrelations of multiple constructs over time. One option is to constrain autoregressive, cross-lagged and covariances to take the same value across time (e.g. Mund & Nestler, 2019), thus assuming that the developmental relations of interest are stable across development as is also assumed in the GVAR model. Alternatively, if the interest lies in how developmental relations might change over time, these paths can be allowed to vary and constraints can be placed on the slope variance and covariance structures (e.g. Berry & Willoughby, 2017). Constraining slope variances and covariances to zero implies that there are no systematic between-person relations among the latent curve components. Thus, if this assumption is violated, the residuals might still, to a limited extent, be confounded by between-person differences.

Since relations in children's socio-emotional development may vary over the developmental period (Meeus, 2016; Murray, Eisner, & Ribeaud, 2020), we fit two ALT-SRs, one model including time-varying paths and another model including constrained paths to fully account for between-person effects. Both ALT-SRs were fit using the R package *lavaan* (Rosseel, 2012). First a model with constraints placed on the residual structure was fitted. For the latent growth curve part of the model, intercepts and linear as well as quadratic slopes were fitted for all SDQ domains since previous research has found that children's and adolescents' mental health trajectories follow a curvilinear trend (Murray, Eisner, Nagin, et al., 2020). Intercept factor loadings were fixed to 1, and time intervals for slope factor loadings were fixed proportional to the spacing between measurement occasions. Intercept and slope factor means, as well as intercept, slope factor and residual factor variances were freely estimated. In order to obtain an admissible model solution, quadratic slope factor variances were constrained to zero. Autoregressive and cross-lagged effects as well as residual factor covariances between all domains at each time point were estimated and constrained to be equal across all lags. In addition, residual covariances for the first time point were freely estimated while covariances between residuals for the first time point and intercepts and slopes were constrained to zero as the first measurement wave has to be treated as predetermined (there are no past variables that can predict these values) (Mund & Nestler, 2019). The model including time-varying paths was estimated following the same structure, except that autoregressive and cross-lagged effects as well as residual factor covariances were allowed to vary over time, while all slope variances and covariances were fixed to zero. Both ALT-SRs were estimated using Full Information Maximum Likelihood (FIML) to account for missing data. Model fit was judged to be acceptable if Comparative Fit Index (CFI) was >.90, Tucker Lewis Index (TLI) >0.90 and Root Mean Square Error of Approximation (RMSEA) <.05 (Kline, 2005) .

Multilevel Graphical Vector Autoregression Model

In a vector autoregression (VAR), each variable is modelled as a combined function of its past values as well as the past values of other variables included in the model. VAR models are mostly used to understand temporal relationships between different variables, but they can also be used to understand contemporaneous relationships, that is, how variables are associated with each other at one specific time point (Wild et al., 2010). To guard against overfitting, regularisation or pruning can be incorporated into the estimation procedure. The resulting sparse, structural relationships can then be modelled and represented as a Gaussian Graphical Model (GGM) which offers advantages in interpretation as it intuitively visualises the complex dependency structure in a system of variables in the form of a partial correlation network. This type of constrained VAR is commonly called graphical vector autoregression (GVAR, Epskamp et al., 2018).

In a graphical model, measured variables are represented by nodes that are connected by edges to indicate relations between variables. In the temporal network, these edges are directed and therefore include arrows to indicate the direction of effect, that is, whether one variable predicts another at the next measurement occasion. In the contemporaneous network which is based on the residualised covariance structure after accounting for the effects of past measurements, edges are undirected and only indicate conditional dependencies between these variables. Finally, in the between-person network, undirected edges are used to describe the relationships between the stationary means of all subjects, again indicating conditional dependencies between variables (Epskamp et al., 2018).

Structurally, the GVAR model is closely related to the ALT-SR as it is based on the random-intercept cross-lagged panel model (RI-CLPM) (Epskamp, 2020). RI-CLPMs only include random-intercepts to account for between-person processes (Hamaker et al., 2015) while ALT-SRs additionally fit a latent curve model before estimating autoregressive and cross-lagged effects. GVAR models further adapt the RI-CLPM to model the within-person and between-person covariance structures in the form of GGMs rather than as marginal variance-covariance matrices. In addition, GVAR models assume stationary relations in order to avoid the estimation of a variance–covariance structure for the first measurement wave, hence, in contrast to ALT-SRs, they do not treat the first measurement wave as exogenous (Epskamp, 2020). Overall, the between-person network in the GVAR model is similar to the intercept factor covariance structure of the ALT-SR, while the contemporaneous and the temporal GVAR networks can be thought of as analogous to the residual factor within-time covariances and the autoregressive and cross-lagged relations from the ALT-SR respectively.

To analyse the temporal, contemporaneous and between-person relations between the different subscales of the SDQ, a multilevel GVAR was conducted. The GVAR model was fit using the *psychonetrics* package version 0.8 (Epskamp, 2020). To meet the stationarity assumption of the GVAR model, the data was detrended for linear, quadratic and cubic age-related effects and standardised across time points prior to fitting a saturated model. Further, unequal measurement occasions were accounted for by specifying non-measured time points as missing (e.g., missing for measurement at age 9 to account for different measurement intervals between ages 5 and 7 compared to 7 and 11). The model was estimated using FIML to account for missing data. The resulting model was pruned to reduce complexity and decrease the chance of finding false positives. After this, the following model fit statistics were computed: CFI, TLI and RMSEA. The estimated networks were visualised using the R package *qgraph* (Epskamp et al., 2012). Finally, 25% case-drop bootstrapping routines (N = 1000) were employed to gain information on stability of parameter estimates (Epskamp, 2020).

Results

Descriptive Statistics for all SDQ subscales at each measurement occasion are presented in Table S1 in the online supplementary materials. The ALT-SR with cross-lagged, autoregressive and residual covariances constrained to be equal across time had a good fit (*CFI* = .946, *TLI* = 0.935 and *RMSEA* = .038 with 90% *CI:* .037 to .039, *BIC* = 1394847.303). Autoregressive and cross-lagged effects are presented in Table S2, available online, and visualised in the form of a network of significant regression coefficients (Figure 1(a)). Results showed that the different SDQ domains were dynamically associated with each other, and that all domains were autocorrelated. In particular, the hyperactivity/inattention domain appeared to play a central role as it shared directed links with all other domains of socio-emotional development.

[Figure 1 about here]

Results for within-time relationships (residual covariances) are visualised as a covariance network in Figure 1(b). These networks indicate that increases in any of the SDQ domains were significantly associated with higher scores on any of the other domains, except for prosociality which was associated with lower scores. This reflects the fact that the prosociality domain indicates strengths while the other domains indicate difficulties. For parameter estimates of within- and between-person associations see Table S2, available online.

The ALT-SR with time-varying residual covariances, cross-lagged and autoregressive paths had a marginally better fit than the constrained model according to *BIC* (ΔBIC = 418.615) and *CFI* but a slightly worse fit according to *TLI* and *RMSEA* (*CFI* = .954, *TLI* = 0.921 and *RMSEA* = .042 with 90% *CI:* .041 to .043, *BIC* = 1394428.688). Results mostly confirmed findings from the constrained ALT-SR with all autoregressive and within-person relations being stable across all lags. Most cross-lagged relations were also stable across all lags, however, a few differences must be noted. In contrast to the constrained ALT-SR, conduct problems were also found to be associated with increases in hyperactivity/inattention, peer problems and prosociality across all ages, while peer problems were further also predictive of increases in conduct problems but only in middle childhood and early adolescence. Additional paths were also identified for prosociality to conduct problems in early childhood and emotional problems to hyperactivity/inattention in adolescence. Thus, the time-varying ALT-SR shows some evidence that not all developmental relations between mental health domains have the same effects over the whole developmental period. For parameter estimates of cross-lagged, autoregressive and within-time effects, see Table S3, available online.

The saturated GVAR model, estimating edges between all variables, had reasonable fit (*CFI* = .890, *TLI* = 0.890 and *RMSEA* = .049 with 90% *CI:* .049 to .050, *BIC* = 932661.180). The pruned model also showed reasonable fit (*CFI* = .892, *TLI* = 0.893 and *RMSEA* = .049 with 90% *CI*: .048 to .049, *BIC* = 932595.850) and performed slightly better than the saturated model (Δ*BIC* = 65.32). The fact that the GVAR model fit reasonably well indicates that imposing the assumption of equal relations across time is not a serious misspecification. Figure 2 provides information on the structures of the temporal (a), contemporaneous (b) and between-person (c) networks. For parameter estimates of the standardized networks, see Table S4 in the online supplementary materials.

[Figure 2 about here]

Consistent with the ALT-SR, the temporal GVAR network highlights that most SDQ domains were autocorrelated and that they were dynamically associated with each other (see Figure 2(a)). While most domains were connected to each other, the temporal network further suggested that there are comparably strong bidirectional negative relationships between conduct problems and prosociality, with higher scores on conduct problems leading to less prosocial behaviour and vice versa. Similar results were found for emotional problems and peer problems, with higher scores in one domain resulting in more problems in the other domain. For the contemporaneous network, Figure 2(b) shows the relationships of all domains after accounting for between-person differences and within-person temporal relationships, highlighting that the SDQ domains also affected each other at shorter timescales than the overall development. The between-person network in Figure 2(c) shows the average associations between the different SDQ domains at the between-person level. In terms of the relative magnitude of associations, results indicated that between-person relations were stronger than within-person relations, however, comparisons of effect sizes of between- and within-person effects are not particularly meaningful in the context of understanding the development of comorbidities which refer to within-person processes (Berry & Willoughby, 2017). Results of the 25% case-drop bootstraps are summarised in Table S5 in the online supplementary materials, showing the number of times each parameter was included out of 1000 bootstrap samples. The bootstrap results indicated a high level of stability in the contemporaneous and between-person network with most parameters included in the original model also included in the majority of the 1000 bootstrap samples. The temporal network seemed to be slightly less stable, indicating that it is potentially less sparse than what was estimated in the original analysis.

Discussion

The aim of the current study was to apply two state-of-the-art methods that are currently available to model dynamic relationships of multiple mental health domains and thereby gain new insights into the dynamic relationships of children's socio-emotional strengths and difficulties. Such methods are needed to operationalise developmental psychopathology theories that address the wide-ranging inter-connections between different domains of mental health. In particular, these models can be helpful for bridging developmental psychopathology approaches that provide in-depth treatment of the connections between a small number of core domains and network theories that provide bigger picture views of how issues across a wide landscape of mental health issues are linked together. Results of the cross-temporally constrained ALT-SR and the multilevel GVAR model both suggested that the different domains measured by SDQ were dynamically associated with each other over the developmental period as well as within shorter timescales. Since the GVAR model assumes equal effects over development, we additionally estimated an ALT-SR with time-varying paths to investigate whether the observed associations were indeed stable across development. This analysis confirmed that most of the observed relations were stable over the whole developmental period.

Results suggest that ADHD symptoms in particular play a central role in the development of socio-emotional difficulties as symptoms in this domain were found to precede difficulties in all other domains. This is consistent with the existing literature on comorbidities in ADHD and models such as the ontogenic process model of externalizing psychopathology (Beauchaine & McNulty, 2013; Murray, Caye, McKenzie, et al., 2020). It is noted, for example, that children who show symptoms of hyperactivity and inattention often struggle in their peer interactions as they, for example, miss social cues or struggle with waiting for their turn. As a result, they may be excluded by normative peers and are thus more likely to affiliate with antisocial peers, escalating their antisocial behaviour through a process of 'peer deviancy training' (Bennett et al., 2004). They also receive more negative attention from adults and often struggle academically, damaging their self-esteem and potentially leading to depression or anxiety (Roy et al., 2015). At the contemporaneous level, hyperactivity/inattention was found to be strongly associated with conduct problems, indicating that these two domains are related to each other over shorter timescales as well as in the long term. Hyperactivity/inattention and conduct problems were also most strongly related in the between-person network, which, overall, showed stronger associations than the contemporaneous network and suggested that children who has higher overall hyperactivity levels also tended to have higher overall conduct problems.

The results further indicate that prosocial behaviour and conduct problems share a bidirectional relationship across development. Links between lower levels of prosociality and aggressive behaviour at different developmental stages have already been established (e.g. Nantel-Vivier et al., 2014); however, evidence for directional relations has so far been limited to conduct problems being shown to predict lower prosociality at later time points (Chen et al., 2010; Obsuth et al., 2015). Findings from the current study suggest that this relationship is, in fact, bi-directional. This may be because children who engage in aggressive behaviour tend to elicit negative reactions from their social contacts which might lead them to have fewer opportunities to develop their prosocial skills (e.g. Obsuth et al., 2015). Conversely, prosocial behaviour facilitates better social relationships which might protect against engaging in conduct problem behaviour to the extent that children are motivated to avoid jeopardising these relationships. Interestingly, *high* prosociality has previously also been found to be predictive of emotional problems in kindergarten-aged children (Perren et al., 2007). Results from the current study suggest that this generalises across childhood and most of adolescence. In the context of interventions seeking to increase empathy skills, this highlights the need to take a careful approach: promoting sensitivity to the needs of others without equipping children with a broader range of socio-emotional skills to help them cope effectively with this could have the unintended effect of increasing children's risk of developing emotional problems.

A particular advantage of the GVAR model is that it allows for the identification of nodes that might be particularly relevant in the spread of mental health issues across domains by acting as 'bridge symptoms'. Results from the GVAR model suggested that the co-occurrence between externalising (hyperactivity/inattention, conduct problems) and internalising difficulties (emotional problems, peer problems) could be related to prosocial behaviour as this domain was connected to both. However, prosocial behaviour does not currently feature prominently in the dominant frameworks that seek to explain externalising-internalising comorbidity, for example, in developmental cascade models such the dual failure model (Capaldi, 1992) or the acting out model (Carlson & Cantwell, 1980). Our results suggest that future investigations would benefit from considering prosociality as providing a potential route by which externalising and internalising symptoms may become linked.

Our results also suggest that emotional problems have a comparably strong reciprocal relationship with peer problems. This is consistent with the existing literature on emotional difficulties and peer relationships which has already found evidence for a bi-directional relationship between these domains (Forbes et al., 2019). Children with symptoms of anxiety or depression have been found to struggle with establishing high quality peer relationships (e.g. La Greca & Lopez, 1998; Rubin et al., 1989), while peer problems have been found to lead to an increase in self-reported anxiety (e.g. Vernberg et al., 1992). In the GVAR model, peer problems were further associated with conduct problems, thus our findings also support two prominent developmental cascade models; the dual failure and the acting out model (Capaldi, 1992; Carlson & Cantwell, 1980). The dual failure model hypothesises that internalising difficulties are the result of an unidirectional cascade from externalising difficulties to peer problems (social failure) and academic underachievement (academic failure) which lead to increased internalising difficulties (Capaldi, 1992). The acting out model proposes that children suffering from internalising difficulties may “act out” to express their distress which may lead to conflict with family and friends which in turn may lead to increased externalising problems (Carlson & Cantwell, 1980).

The majority of the above-mentioned theories and models primarily focus on explaining pairs of comorbidities. There is, for example, in addition to the externalising and internalising models discussed above, a vast body of theories on the effects of ADHD symptoms on conduct problems (e.g. Beauchaine et al., 2010; Harvey et al., 2016), and on the effects of ADHD symptoms on emotional problems (e.g. Murray, Caye, McKenzie, et al., 2020), but comparatively little research that has attempted to connect these disparate bodies of work to illuminate how ADHD symptoms, emotional symptoms, and conduct problems may connect together. The results of this study, however, emphasise the need for more encompassing theories of developmental psychopathology.

The current study illustrates how two complementary methods: GVAR and ALT-SR may be helpful for supporting the development and testing of these theories. The main advantage of the GVAR model is that it provides an easy to interpret visualisation and can be easily extended to model large numbers of repeatedly measured variables, facilitating, for example, modelling temporal relations at the symptom level rather than at the domain level. This may prove particularly useful in the study of mental health symptom networks and how specific symptoms may act as bridges between several mental health disorders. Analyses of this type can provide new and unique insights into how co-occurring disorders develop. However, the GVAR model assumes equal relations over time, an assumption that does not necessarily hold when investigating the development of psychopathology over longer timescales. ALT-SRs, on the other hand, do allow for the investigation of time-varying effects but are not well suited to model more than a handful of constructs simultaneously since the addition of any additional construct leads to a sharp increase in number of parameters that need to be estimated, often leading to estimation difficulties and making interpretations of results challenging. ALT-SRs can, however, be particularly useful when applied to only few domains that are expected to share different relations over time. They offer additional flexibility in estimating cross-lagged effects and are further well suited to investigate potential mediators of those developmental relations. Thus, ALT-SRs can be invaluable tools in advancing developmental cascade theories such as the dual failure or the acting out model, by facilitating the investigation of mediating factors such as peer problems and academic underachievement in the development of co-occurring mental health problems.

There are a number of limitations that need to be considered when interpreting the results of this study. The data used relies exclusively on parent-reports of children and adolescents' socio-emotional strengths and difficulties. This is a particular limitation for the later time points as the validity of parent-reports likely declines in adolescence as parental monitoring decreases (Masche, 2010). Ideally, this study should be replicated using teacher- and self-reports in addition to parent-reports. In addition, invariance analyses of the SDQ in the current sample have shown that for age 3 and age 17, the hypothesised five dimensional structure of the SDQ is not a good fit for the data, thus suggesting that there might be differences in the manifestation or reporting of symptoms in these age groups (Murray, Speyer, et al., 2021). Further, the analyses presented here assumed a simple random sampling design as GVAR models are not yet able to accommodate complex sampling designs. For the ALT-SR, sensitivity analyses accounting for the complex sampling design of the MCS, however, showed essentially the same results. Finally, it is important to note that even though we used statistical tools which appropriately operationalise the developmental processes of interest, these models still only provide insights into associations based on temporal ordering over time which do not necessarily correspond with any causal effects. Hence, further research is needed to evaluate whether the observed associations indeed reflect causal relationships. Approaches such as the analysis of the effects of interventions in the context of comorbidity, counterfactual approaches (e.g., matching-based techniques), instrumental variable analysis (e.g., Mendelian randomisation), and discordant monozygotic twin (MZ) designs to account for familial confounding can help determine which of the paths indicated as potentially reflecting directional effects are also suggested as potentially causal based on these complementary approaches.

Conclusion

This study suggests that conduct problems, emotional problems, hyperactivity/inattention, peer problems and prosociality, as measured by the SDQ, are dynamically associated with one another over time and concurrently, highlighting the value of investigating mental health issues as networks using longitudinal data. The ALT-SR and the GVAR model are two complementary approaches that are well suited to study such dynamics. Overall, the findings of this study highlight that there is a clear need for more integrative theories of comorbidities. Advancing theories such as the developmental cascade model to consider more than two domains at once would facilitate more encompassing theories of developmental psychopathology and help inform interventions that can target the symptoms that are most important for leading to the development of others.

References

American Psychiatric Association. (2013). *Diagnostic and Statistical Manual of Mental Disorders*. American Psychiatric Association. https://doi.org/10.1176/appi.books.9780890425596

Andrade, B. F., & Tannock, R. (2013). The Direct Effects of Inattention and Hyperactivity/Impulsivity on Peer Problems and Mediating Roles of Prosocial and Conduct Problem Behaviors in a Community Sample of Children. *Journal of Attention Disorders*, *17*(8), 670–680. https://doi.org/10.1177/1087054712437580

Balázs, J., & Keresztény, Á. (2014). Subthreshold attention deficit hyperactivity in children and adolescents: A systematic review. In *European Child and Adolescent Psychiatry* (Vol. 23, Issue 6, pp. 393–408). Dr. Dietrich Steinkopff Verlag GmbH and Co. KG. https://doi.org/10.1007/s00787-013-0514-7

Beard, C., Millner, A. J., Forgeard, M. J. C., Fried, E. I., Hsu, K. J., Treadway, M. T., Leonard, C. V., Kertz, S. J., & Björgvinsson, T. (2016). Network analysis of depression and anxiety symptom relationships in a psychiatric sample. *Psychological Medicine*, *46*(16), 3359–3369. https://doi.org/10.1017/S0033291716002300

Beauchaine, T. P., Hinshaw, S. P., & Pang, K. L. (2010). Comorbidity of Attention-Deficit/Hyperactivity Disorder and Early-Onset Conduct Disorder: Biological, Environmental, and Developmental Mechanisms. *Clinical Psychology: Science and Practice*, *17*(4), 327–336. https://doi.org/10.1111/j.1468-2850.2010.01224.x

Beauchaine, T. P., & McNulty, T. (2013). Comorbidities and continuities as ontogenic processes: Toward a developmental spectrum model of externalizing psychopathology. *Development and Psychopathology*, *25*(4 PART 2), 1505–1528. https://doi.org/10.1017/S0954579413000746

Bennett, D. S., Pitale, M., Vora, V., & Rheingold, A. A. (2004). Reactive vs. proactive antisocial behavior: Differential correlates of child ADHD symptoms? *Journal of Attention Disorders*, *7*(4), 197–204. https://doi.org/10.1177/108705470400700402

Berry, D., & Willoughby, M. T. (2017). On the Practical Interpretability of Cross-Lagged Panel Models: Rethinking a Developmental Workhorse. In *Child Development* (Vol. 88, Issue 4, pp. 1186–1206). Blackwell Publishing Inc. https://doi.org/10.1111/cdev.12660

Borsboom, D. (2008). Psychometric perspectives on diagnostic systems. *Journal of Clinical Psychology*, *64*(9), 1089–1108. https://doi.org/10.1002/jclp.20503

Capaldi, D. M. (1992). Co-occurrence of conduct problems and depressive symptoms in early adolescent boys: II. A 2-year follow-up at Grade 8. *Development and Psychopathology*, *4*(1), 125–144. https://doi.org/10.1017/S0954579400005605

Carlson, G. A., & Cantwell, D. P. (1980). Unmasking masked depression in children and adolescents. *American Journal of Psychiatry*, *137*(4), 445–449. https://doi.org/10.1176/ajp.137.4.445

Chen, X., Huang, X., Chang, L., Wang, L., & Li, D. (2010). Aggression, social competence, and academic achievement in Chinese children: A 5-year longitudinal study. *Development and Psychopathology*, *22*(3), 583–592. https://doi.org/10.1017/S0954579410000295

Cherkasova, M., Sulla, E. M., Dalena, K. L., Pondé, M. P., & Hechtman, L. (2013). Developmental course of attention deficit hyperactivity disorder and its predictors. *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, *22*(1), 47–54. https://doi.org/10.1007/s00787-012-0322-5

Connelly, R., & Platt, L. (2014). Cohort Profile: UK Millennium Cohort Study (MCS). *International Journal of Epidemiology*, *43*(6), 1719-1725. https://academic.oup.com/ije/article/43/6/1719/703283

Curran, P. J., Howard, A. L., Bainter, S. A., Lane, S. T., & McGinley, J. S. (2014). The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals. *Journal of Consulting and Clinical Psychology*, *82*(5), 879–894. https://doi.org/10.1037/a0035297

Danielson, M. L., Bitsko, R. H., Ghandour, R. M., Holbrook, J. R., Kogan, M. D., & Blumberg, S. J. (2018). Prevalence of Parent-Reported ADHD Diagnosis and Associated Treatment Among U.S. Children and Adolescents, 2016. *Journal of Clinical Child & Adolescent Psychology*, *47*(2), 199–212. https://doi.org/10.1080/15374416.2017.1417860

Davis, J. P., Dumas, T. M., Dumas, T. M., Espelage, D. L., Tan, K., Madden, D., & Hong, J. S. (2018). Examining the pathways between bully victimization, depression, academic achievement, and problematic drinking in adolescence. *Psychology of Addictive Behaviors*, *32*(6), 605–616. https://doi.org/10.1037/adb0000394

Epskamp, S. (2020). Psychometric network models from time-series and panel data. *Psychometrika*, *85*(1), 206–231. https://doi.org/10.1007/s11336-020-09697-3

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). Qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software*, *48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018). The Gaussian Graphical Model in Cross-Sectional and Time-Series Data. *Multivariate Behavioral Research*, *53*(4), 453–480. https://doi.org/10.1080/00273171.2018.1454823

Forbes, M. K., Fitzpatrick, S., Magson, N. R., & Rapee, R. M. (2019). Depression, Anxiety, and Peer Victimization: Bidirectional Relationships and Associated Outcomes Transitioning from Childhood to Adolescence. *Journal of Youth and Adolescence*, *48*(4), 692–702. https://doi.org/10.1007/s10964-018-0922-6

Ghandour, R. M., Sherman, L. J., Vladutiu, C. J., Ali, M. M., Lynch, S. E., Bitsko, R. H., & Blumberg, S. J. (2019). Prevalence and Treatment of Depression, Anxiety, and Conduct Problems in US Children. *Journal of Pediatrics*, *206*, 256-267.e3. https://doi.org/10.1016/j.jpeds.2018.09.021

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A Research Note. *Journal* *of Child Psychology and Psychiatry*, *38*(5), 581–586. https://doi.org/10.1111/j.1469-7610.1997.tb01545.x

Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. P. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*(1), 102–116. https://doi.org/10.1037/a0038889

Han, G. T., Chen, Y. L., Tsai, F. J., & Gau, S. S. F. (2020). Temporal and Reciprocal Relations Between ADHD symptoms and Emotional Problems in School-Age Children. *Journal of Attention Disorders*, *24*(7), 1032–1044. https://doi.org/10.1177/1087054718787891

Harvey, E. A., Breaux, R. P., & Lugo-Candelas, C. I. (2016). Early development of comorbidity between symptoms of attention-deficit/hyperactivity disorder (ADHD) and oppositional defiant disorder (ODD). *Journal of Abnormal Psychology*, *125*(2), 154–167. https://doi.org/10.1037/abn0000090

Jordan, D. G., Winer, E. S., & Salem, T. (2020). The current status of temporal network analysis for clinical science: Considerations as the paradigm shifts? *Journal of Clinical Psychology*, *76*(9), 1591–1612. https://doi.org/10.1002/jclp.22957

Joshi, H., & Fitzsimons, E. (2016). The UK millennium cohort study: The making of a multipurpose resource for social science and policy. *Longitudinal and Life Course Studies*, *7*(4), 409–430. https://doi.org/10.14301/llcs.v7i4.410

Kersten, P., Czuba, K., McPherson, K., Dudley, M., Elder, H., Tauroa, R., & Vandal, A. (2016). A systematic review of evidence for the psychometric properties of the Strengths and Difficulties Questionnaire. *International Journal of Behavioral Development*, *40*(1), 64–75. https://doi.org/10.1177/0165025415570647

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. In *Archives of General Psychiatry* (Vol. 62, Issue 6, pp. 593–602). American Medical Association. https://doi.org/10.1001/archpsyc.62.6.593

Kline, R. B. (2005). *Principles and Practice of Structural Equation Modeling, Second Edition*. Guilford Publications. https://books.google.at/books?id=EkMVZUxZrgIC

La Greca, A. M., & Lopez, N. (1998). Social Anxiety among Adolescents: Linkages with peer relations and friendships. *Journal of Abnormal Child Psychology*, *26*(2), 83–94. https://doi.org/10.1023/A:1022684520514

Masche, J. G. (2010). Explanation of normative declines in parents' knowledge about their adolescent children. *Journal of Adolescence*, *33*(2), 271–284. https://doi.org/10.1016/j.adolescence.2009.08.002

Masten, A. S., & Cicchetti, D. (2010). Developmental cascades. In *Development and Psychopathology* (Vol. 22, Issue 3, pp. 491–495). Dev Psychopathol. https://doi.org/10.1017/S0954579410000222

Meeus, W. (2016). Adolescent psychosocial development: A review of longitudinal models and research. *Developmental Psychology*, *52*(12), 1969–1993. https://doi.org/10.1037/dev0000243

Mund, M., & Nestler, S. (2019). Beyond the Cross-Lagged Panel Model: Next-generation statistical tools for analyzing interdependencies across the life course. *Advances in Life Course Research*, *41*, 100249. https://doi.org/10.1016/j.alcr.2018.10.002

Murray, A. L., Caye, A., McKenzie, K., Auyeung, B., Murray, G., Ribeaud, D., Freeston, M., & Eisner, M. (2020). Reciprocal Developmental Relations Between ADHD and Anxiety in Adolescence: A Within-Person Longitudinal Analysis of Commonly Co-Occurring Symptoms. *Journal of Attention Disorders*, 108705472090833. https://doi.org/10.1177/1087054720908333

Murray, A. L., Eisner, M., Nagin, D., & Ribeaud, D. (2020). A multi-trajectory analysis of commonly co-occurring mental health issues across childhood and adolescence. *European Child and Adolescent Psychiatry*, *1*, 3. https://doi.org/10.1007/s00787-020-01679-1

Murray, A. L., Eisner, M., & Ribeaud, D. (2020). Within-person analysis of developmental cascades between externalising and internalising problems. *Journal of Child Psychology and Psychiatry*, *61*(6), 681–688. https://doi.org/10.1111/jcpp.13150

Murray, A. L., Obsuth, I., Speyer, L., Murray, G., McKenzie, K., Eisner, M., & Ribeaud, D. (2021). Developmental Cascades from Aggression to Internalizing Problems via Peer and Teacher Relationships from Early to Middle Adolescence. *Journal of Youth and Adolescence*. https://doi.org/10.1007/s10964-021-01396-1

Murray, A. L., Obsuth, I., Zirk-Sadowski, J., Ribeaud, D., & Eisner, M. (2020). Developmental Relations Between ADHD Symptoms and Reactive Versus Proactive Aggression Across Childhood and Adolescence. *Journal of Attention Disorders*, *24*(12), 1701–1710. https://doi.org/10.1177/1087054716666323

Murray, A. L., Speyer, L. G., Hall, H. A., Valdebenito, S., & Hughes, C. (2021). A Longitudinal and Gender Invariance Analysis of the Strengths and Difficulties Questionnaire Across Ages 3, 5, 7, 11, 14, and 17 in a Large U.K.-Representative Sample. *Assessment*, 107319112110093. https://doi.org/10.1177/10731911211009312

Nantel-Vivier, A., Pihl, R. O., Côté, S., & Tremblay, R. E. (2014). Developmental association of prosocial behaviour with aggression, anxiety and depression from infancy to preadolescence. *Journal of Child Psychology and Psychiatry*, *55*(10), 1135–1144. https://doi.org/10.1111/jcpp.12235

Obsuth, I., Eisner, M. P., Malti, T., & Ribeaud, D. (2015). The developmental relation between aggressive behaviour and prosocial behaviour: A 5-year longitudinal study. *BMC Psychology*, *3*(1), 1–15. https://doi.org/10.1186/S40359-015-0073-4

Obsuth, I., Murray, A. L., Di Folco, S., Ribeaud, D., & Eisner, M. (2020). Patterns of Homotypic and Heterotypic Continuity Between ADHD Symptoms, Externalising and Internalising Problems from Age 7 to 15. *Journal of Abnormal Child Psychology*, *48*(2), 223–236. https://doi.org/10.1007/s10802-019-00592-9

Oh, Y., Greenberg, M. T., Willoughby, M. T., Vernon-Feagans, L., Blair, C. B., Burchinal, M. R., Cox, M., Garrett-Peters, P. T., Frank, J. L., & Mills-Koonce, W. R. (2020). Examining Longitudinal Associations between Externalizing and Internalizing Behavior

Problems at Within- and Between-Child Levels. *Journal of Abnormal Child Psychology*, *48*(4), 467–480. https://doi.org/10.1007/s10802-019-00614-6

Patalay, P., Moulton, V., Goodman, A., & Ploubidis, G. B. (2017). Cross-Domain Symptom Development Typologies and Their Antecedents: Results From the UK Millennium Cohort Study. *Journal of the American Academy of Child and Adolescent Psychiatry*, *56*(9), 765-776.e2. https://doi.org/10.1016/j.jaac.2017.06.009

Perren, S., Stadelmann, S., Von Wyl, A., & Von Klitzing, K. (2007). Pathways of behavioural and emotional symptoms in kindergarten children: What is the role of pro-social behaviour? *European Child and Adolescent Psychiatry*, *16*(4), 209–214. https://doi.org/10.1007/s00787-006-0588-6

R Core Team. (2017). *R: A Language and Environment for Statistical Computing*. https://www.rproject.org/

Radu, M. (2019). *Millennium Cohort Study Seventh-Sweep Technical Report*.

Rapee, R. M., Oar, E. L., Johnco, C. J., Forbes, M. K., Fardouly, J., Magson, N. R., & Richardson, C. E. (2019). Adolescent development and risk for the onset of social-emotional disorders: A review and conceptual model. In *Behaviour Research and Therapy* (Vol. 123). Elsevier Ltd. https://doi.org/10.1016/j.brat.2019.103501

Reale, L., Bartoli, B., Cartabia, M., Zanetti, M., Costantino, M. A., Canevini, M. P., Termine, C., Bonati, M., Conte, S., Renzetti, V., Salvoni, L., Molteni, M., Salandi, A., Trabattoni, S., Effedri, P., Filippini, E., Pedercini, E., Zanetti, E., Fteita, N., … Rossi, G. (2017). Comorbidity prevalence and treatment outcome in children and adolescents with ADHD. *European Child and Adolescent Psychiatry*, *26*(12), 1443–1457. https://doi.org/10.1007/s00787-017-1005-z

Rhee, S. H., Lahey, B. B., & Waldman, I. D. (2015). Comorbidity Among Dimensions of Childhood Psychopathology: Converging Evidence From Behavior Genetics. *Child Development Perspectives*, *9*(1), 26–31. https://doi.org/10.1111/cdep.12102

Rosseel, Y. (2012). {lavaan}: An {R} Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2), 1–36. http://www.jstatsoft.org/v48/i02/

Rouquette, A., Pingault, J. B., Fried, E. I., Orri, M., Falissard, B., Kossakowski, J. J., Vitaro, F., Tremblay, R., Cote, S. M., & Borsboom, D. (2018). Emotional and Behavioral Symptom Network Structure in Elementary School Girls and Association with Anxiety Disorders and Depression in Adolescence and Early Adulthood: A Network Analysis. *JAMA Psychiatry*, *75*(11), 1173–1181. https://doi.org/10.1001/jamapsychiatry.2018.2119

Roy, A., Hartman, C. A., Veenstra, R., & Oldehinkel, A. J. (2015). Peer dislike and victimisation in pathways from ADHD symptoms to depression. *European Child and Adolescent Psychiatry*, *24*(8), 887–895. https://doi.org/10.1007/s00787-014-0633-9

Rubin, K. H., Hymel, S., & Mills, R. S. L. (1989). Sociability and Social Withdrawal in Childhood: Stability and Outcomes. *Journal of Personality*, *57*(2), 237–255. https://doi.org/10.1111/j.1467-6494.1989.tb00482.x

Shepherd, P., & Gilbert, E. (2019). *Millennium Cohort Study Ethical Review and Consent*. www.cls.ucl.ac.ukwww.cls.ucl.ac.uk

Sosu, E. M., & Schmidt, P. (2017). Tracking Emotional and Behavioral Changes in Childhood: Does the Strength and Difficulties Questionnaire Measure the Same Constructs Across Time? *Journal of Psychoeducational Assessment*, *35*(7), 643–656. https://doi.org/10.1177/0734282916655503

Steinberg, L., & Monahan, K. C. (2007). Age Differences in Resistance to Peer Influence. *Developmental Psychology*, *43*(6), 1531–1543. https://doi.org/10.1037/0012-1649.43.6.1531

van Lier, P. A. C., & Koot, H. M. (2010). Developmental cascades of peer relations and symptoms of externalizing and internalizing problems from kindergarten to fourth-grade elementary school. *Development and Psychopathology*, *22*(3), 569–582. https://doi.org/10.1017/S0954579410000283

van Lier, P. A. C., Vitaro, F., Barker, E. D., Brendgen, M., Tremblay, R. E., & Boivin, M. (2012). Peer victimization, poor academic achievement, and the link between childhood externalizing and internalizing problems. *Child Development*, *83*(5), 1775–1788. https://doi.org/10.1111/j.1467-8624.2012.01802.x

Vernberg, E. M., Abwender, D. A., Ewell, K. K., & Beery, S. H. (1992). Social Anxiety and Peer Relationships in Early Adolescence: A Prospective Analysis. *Journal of Clinical Child Psychology*, *21*(2), 189–196. https://doi.org/10.1207/s15374424jccp2102_11

Vugteveen, J., de Bildt, A., Serra, M., de Wolff, M. S., & Timmerman, M. E. (2020). Psychometric Properties of the Dutch Strengths and Difficulties Questionnaire (SDQ) in Adolescent Community and Clinical Populations. *Assessment*, *27*(7), 1476–1489. https://doi.org/10.1177/1073191118804082

WHO. (2018). WHO | Child and adolescent mental health. *WHO*. http://www.who.int/mental_health/maternal-child/child_adolescent/en/

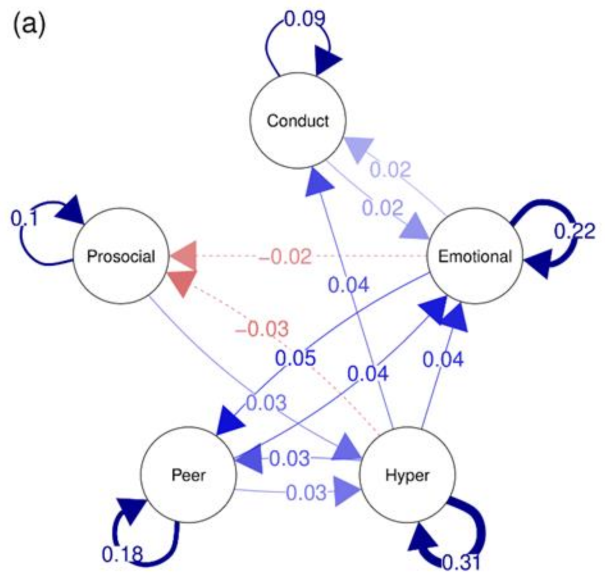
Wild, B., Eichler, M., Friederich, H. C., Hartmann, M., Zipfel, S., & Herzog, W. (2010). A graphical vector autoregressive modelling approach to the analysis of electronic diary data. *BMC Medical Research Methodology*, *10*(1), 28. https://doi.org/10.1186/1471-2288-10-28

Yu, R., Branje, S., Meeus, W., Koot, H. M., van Lier, P., & Fazel, S. (2018). Victimization Mediates the Longitudinal Association Between Depressive Symptoms and Violent Behaviors in Adolescence. *Journal of Abnormal Child Psychology*, *46*(4), 839–848. https://doi.org/10.1007/s10802-017-0325-2

Figure Captions

Figure 1

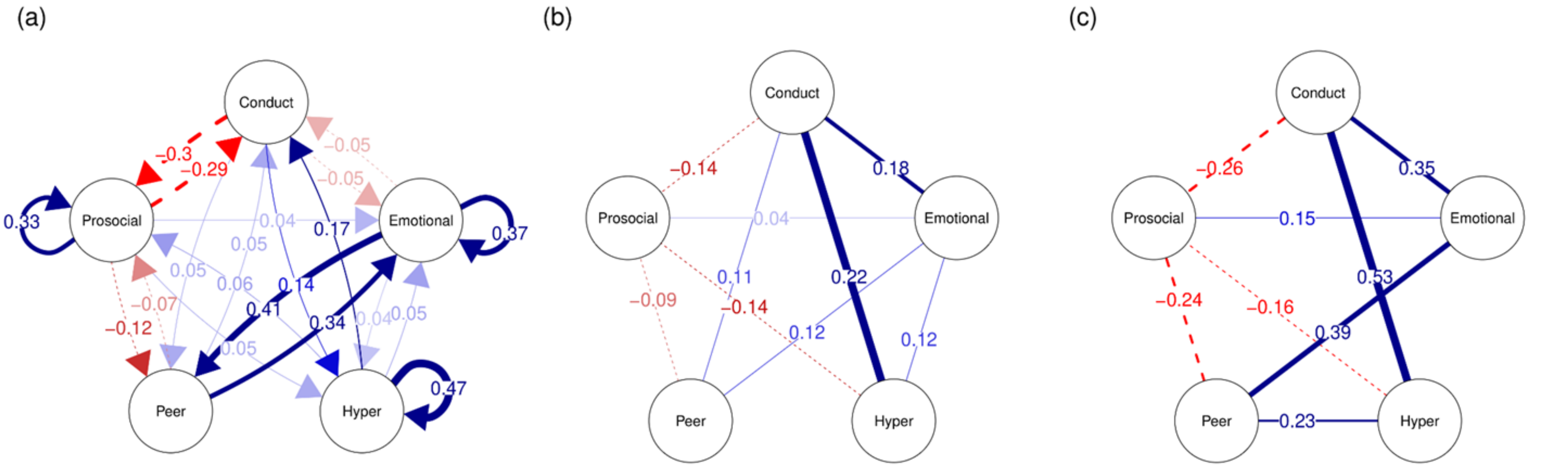
ALT-SR: Constrained Autoregressive/Cross-lagged Effects and Residual Covariances Networks



Note. (a) represents the estimated within-person autoregressive and cross-lagged effects of the ALT-SR in the form of significant regression coefficients; (b) represents the estimated within-person within-time associations of the ALT-SR as a covariance network; solid edges (blue) indicate positive effects, dashed edges (red) negative effects; edge widths are proportional to the strength of association of all included edges.

Figure 2

GVAR Model: Temporal, Contemporaneous and Between Person Networks



Note. (a) represents the estimated fixed-effect within-person temporal GVAR network standardised to directed partial correlations, (b) represent the estimated fixed-effect within-person contemporaneous partial correlation network; (c) represents the estimated random-effects between-person partial correlation network; solid edges (blue) indicate positive effects, dashed edges (red) negative effects; edge widths are proportional to the strength of association of all included edges.