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Proposing network analysis for early life adversity: An application on life event data

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ABSTRACT

Commonly used methods for modelling early life adversity (e.g., sum-scores, latent class or trajectory approaches, single-adversity approaches, and factor-analytical approaches) have not been able to capture the complex nature of early life adversity. We propose network analysis as an alternative way of modelling early life adversity (ELA). Our aim was to construct a network of fourteen adverse events (AEs) that occurred before the age of 16 in the TRacking Adolescents Individual Lives Survey (TRAILS, N = 1029). To show how network analysis can provide insight into why AEs are associated, we compared findings from the resulting network model to findings from tetrachoric correlation analyses. The resulting network of ELA comprised direct relationships between AEs and more complex, indirect relationships. A total of fifteen edges emerged in the network of AEs (out of 91 possible edges). The correlation coefficients suggested that many AEs were associated. The network model of ELA indicated, however, that several associations were attributable to interactions with other AEs. For example, the zero-order correlation between parental addiction and familial conflicts (0.24) could be explained by interactions with parental divorce. Our application of network analysis shows that using network analysis for modelling the ELA construct allows capturing the constructs' complex nature. Future studies should focus on gaining more insight into the most optimal model estimation and selection procedures, as well as sample size requirements. Network analysis provides researchers with a valuable tool that allows them as well as policy-makers and professionals to gain insight into potential mechanisms through which adversities are associated with each other, and conjunctively, with life course outcomes of interest.

1. Introduction

In recent years, a large number of studies have investigated associations between early life adversity (ELA) and relevant health, economic and social outcomes across the lifespan (Bunting et al., 2018; Hughes et al., 2017; Nelson et al., 2020; Rod et al., 2021). ELA can be thought of as an umbrella term that covers a variety of adverse experiences. Adverse experiences (AEs) can be defined as experiences that require significant adaptation by the developing child in terms of psychological, social, and neurodevelopmental systems, and are outside the normal expected environment (McLaughlin and Sheridan, 2016). A defining characteristic of ELA is its complex nature, as many of the individual AEs (e.g., parental mental health problems, financial difficulties, physical abuse) are assumed to co-occur. To date, commonly applied statistical approaches in the ELA literature (e.g., composite variable approaches, latent class or trajectory approaches, and factor-analytical approaches) have mostly been used to reflect the extent to which individuals have been exposed to ELA (Bussemakers et al., 2019; Grasso et al., 2016; Iob et al., 2020; Rod et al., 2020). However, these statistical approaches do not allow for identifying associations between specific AEs. As a result, there is little knowledge about underlying associations between the specific AEs that together make up ELA (Briggs et al., 2021; Lopez et al.,

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2021; Portwood and Lawler, 2021). Such insight is required to develop much-needed theoretical frameworks for ELA (Lacey and Minnis, 2019), which may subsequently guide the development of interventions for individuals at risk. In this study, we provide insight into how network analysis, a statistical approach that allows for estimating complex patterns of relationships between variables (Hevey, 2018), can be used as an alternative approach for modelling ELA. To that end, we first discuss the complex nature of ELA, and how this complexity has typically been modelled with a variety of statistical approaches. Thereafter, we apply network analysis to life event data from the TRacking Adolescents' Individual Lives Survey (TRAILS). In doing so, we illustrate how network analysis can explain how associations among a set of AEs arise. This information can provide researchers, policy-makers and professionals with insight into potential mechanisms through which specific adversities are associated with each other. Such insight is much needed for the development of efficient targeted interventions.

1.1. The complex nature of early life adversity

ELA is a complex construct that encompasses many individual AEs which are assumed to co-occur during childhood (Lacey and Minnis, 2019). One of the main reasons for the co-occurrence between AEs is that many AEs are likely direct consequences of other AEs. For example, conflicts in the family may lead to divorce and subsequent parental mental health problems; parental illness may lead to parental death and subsequent financial difficulties. Recently, several authors have attempted to formalize or examine such consequences (Briggs et al., 2021; Lopez et al., 2021). Drawing inspiration from Bronfenbrenner's ecological systems theory, Lopez et al. (2021) argued that AEs occur within different systems (micro-, meso-, exo-, and macro-systems), and that due to the strong interplay between these systems, AEs in one system may lead to cascades of AEs across the other systems. Briggs et al. (2021) examined synergies between 20 different AE pairings, and found that about 30–40% of variance in a range of outcomes can be accounted for by synergistic interactions between AEs. Most studies to date, however, have not been able to provide insight into direct effects, or interactions, between AEs or between AEs and outcomes of interest. The main reason for this is the inability of commonly applied statistical approaches to model such direct effects.

1.2. Capturing the complex nature of early life adversity

The field of ELA has witnessed the application of various statistical approaches for the modelling of ELA, which include composite variable approaches (i.e., sum scores of adversity) (Felliti et al., 1998), latent class or trajectory-based approaches (Bussemakers et al., 2019; Grasso et al., 2016; Rod et al., 2020), single adversity approaches (Alcalá et al., 2018; Bevilaqua et al., 2021; Merrick et al., 2017), and factor-analytical approaches (Afifi et al., 2020; Bethell et al., 2017; Brumley et al., 2019; Cohen-Cline et al., 2019; Lacey et al., 2020; Ospina et al., 2021). Several authors argue that the aforementioned statistical approaches cannot fully account for the complex nature of ELA (Briggs et al., 2021; Lacey and Minnis, 2019; Lopez et al., 2021). The aforementioned approaches allow to encapsulate the exposure to ELA (or singular AEs) in a relatively straightforward manner (i.e., most approaches result in summative measures that reflect the extent to which, or the type of AEs to which, an individual was exposed to adversity). However, neither of these methods allow for modelling direct effects between AEs which we, and others (Briggs et al., 2021; Lopez et al., 2021), argue are one of the main reasons why AEs co-occur. Latent variable approaches rest on the notion that correlations between AEs are solely due to unobserved latent variables, which refer to either continuous latent (in factor analysis) or discrete latent variables (in latent class- and trajectory analysis) (Bollen and Bauldry, 2011). After imposing a latent variable, no direct effects between AEs are assumed to remain (i.e., the conditional independence assumption). Single adversities approaches do allow to gain insight into direct effects between pairs of AEs, for example through investigating correlation coefficients between such pairs. However, single-adversity approaches suffer from the issue that correlations between pairs of AEs are not conditional on other AEs. Gaining insight into associations between AEs is a pre-requisite for the development of theoretical frameworks that can help explain the co-occurrence between AEs. Network analysis offers an alternative statistical approach for modelling ELA. Network analysis is a statistical approach that allows for estimating complex patterns of relationships between variables, that is, associations between variables conditional on all variables in the model (Hevey, 2018). Network analysis provides insight into the direct (and indirect) associations between AEs, because of its ability to model conditional associations between AEs, or between AEs and outcomes of interest, in a single model.

1.3. A network for early life adversity

A network refers to any structure of variables, which are typically referred to as nodes, and relationships between those nodes, referred to as edges (Hevey, 2018). As outlined above, ELA is a result of complex interactions between AEs, which could be captured by constructing a network of ELA. In a network of ELA, the nodes represent the AEs that make up the network, whilst the edges represent the associations between the AEs. Edges between nodes generally take two forms: undirected and directed edges. Undirected edges signify that a mutual relationship between nodes is present, whereas directed edges include arrowheads which represent one-way effects (Epskamp et al., 2017). Networks with undirected edges are referred to as 'undirected networks', whilst networks with directed edges are referred to as 'directed networks' (Newman, 2010). Edges may be positive or negative, representing either positive or negative relationships between the nodes. In addition, edges may be weighted or unweighted. Unweighted edges merely represent that a relationship between nodes is present; weighted edges reflect the strength of the relationship between nodes (Hevey, 2018). Although both undirected and directed networks can be valuable for the field of ELA, in this study we focus on undirected networks. The main reason for that is that there is a lack of theoretical insight into associations between AEs, a situation which lends itself better for undirected networks. Undirected networks can be used to generate hypotheses about the causal nature of associations between AEs through the conditional independencies between AEs (Pearl, 2009). Such insight can serve as input for theoretical developments, which may subsequently be tested using directed networks (i.e., by feeding information from undirected networks into algorithms that can be used to estimate direct acyclic graphs from data). Undirected weighted networks can be modelled using Pairwise Markov random fields (PMRF), otherwise known as undirected graphical models (Kindermann and Snell, 1980). In a PMRF, edges represent conditional dependence relationships between the nodes that are included in the network. The presence of an edge between nodes implies an association between those nodes that cannot be explained by any other node included in the model. When an edge between nodes is not present, those nodes are said to be conditionally independent given all other nodes included in the network. (Hevey, 2018). Depending on the data at hand, PMRF models can be estimated on the basis of various statistical parameters (e.g. logistic regression coefficients for binary data such as AEs) (Borsboom et al., 2021; Hevey, 2018). For ELA data, the Ising model and Mixed Graphical Model are particularly suitable. The Ising model (van Borkulo et al., 2014) can be applied when the variables of interest are binary in nature, where edges are parametrized as log-linear relationships (Borsboom et al., 2021). The Mixed Graphical Model (MGM) can be used when the data contains a mix of categorical, count and continuous variables (Haslbeck and Waldorp, 2020), where edges are parametrized as regression coefficients as in generalized linear regression models (Borsboom et al., 2021). Although AEs are often binary, MGMs would be suitable if for example data on the frequency of AEs is available. Another commonly applied model is the Gaussian Graphical Model (GGM), which is applicable when data are continuous or ordinal (Lauritzen, 1996). The GGM is arguably less applicable for ELA, as GGMs can only be estimated on ordinal and continuous data, which is less common the field of ELA. After estimating a network structure, the network can be further inspected in various ways. Most notably, investigating the network structure can help to elucidate the conditional independencies among a set of nodes (e.g., are two AEs conditionally independent given a third AE) (Borsboom et al., 2021). Besides, there are several measures available that provide insight into either the overall network, or the individual nodes in the network. For example, several centrality measures provide insight into properties of a node relative to all other nodes included in the network (Newman, 2010). Commonly used centrality indices that are of relevance for ELA-related studies include 'degree' (the number of connections a node of interest has with other nodes) and 'clustering' (the proportion of edges that exist between the neighbors of a node of interest relative to the total number of possible edges between neighbors) (Newman, 2010; Saramäki et al., 2007). For a detailed overview of available indices, see the article by Lü et al. (2016).

1.4. A real-life application of network analysis for early life adversity

As an example of a real-life application, we aim to model ELA using data from the TRacking Adolescents' Individual Lives Survey (TRAILS) (Huisman et al., 2008; Oldehinkel et al., 2015) by means of network analysis. To illustrate the added value of network analysis, we first estimate zero-order correlations between AEs. We opted for a correlation analytical approach because it follows most closely the notion that associations between AEs arise due to direct effects between them (Briggs et al., 2021; Lopez et al., 2021). We then contrast the findings from the correlational analyses to the resulting network model. In doing so, we illustrate how we can use the conditional dependence relations that arise from the network of ELA to provide insight into how and why specific AEs are associated. By modelling ELA using network analysis, we intend to show how network analysis helps to inform new research that aims to further elucidate the complex associations between AEs and outcomes of interest.

2. Methods

2.1. TRacking Adolescents' Individual Lives Survey (TRAILS)

The real-life application included participants from the TRacking Adolescents' Individual Lives Survey (TRAILS) study with information on the occurrence of AEs between the ages 0 and 16 (N = 1339, 60.1% of the original baseline sample). TRAILS is a prospective cohort of Dutch adolescents (Huisman et al., 2008; Oldehinkel et al., 2015). Due to missing data on any of the AEs included in this study, 310 participants were excluded. The final sample thus consisted of 1029 individuals with complete data (46.2% of the baseline sample). No data was imputed because the statistical model applied in this study does not allow for pooling of results. Individuals with incomplete data were significantly more likely to be male and to have parents with a lower educational background. A recent meta-analysis has shown that individuals from a lower socio-economic background are more likely to experience more adversity (Walsh, McCartney, Smith et al., 2019). As such, it is likely that the results presented in this study underestimate the associations between AEs. More in-depth information about the design, sample, procedures and non-response has been presented elsewhere (De Winter et al., 2005; Huisman et al., 2008; Oldehinkel et al., 2015). TRAILS was approved by the Dutch Central Committee Involving Human Subjects (CCMO; www.ccmo.nl).

2.2. Adverse experiences

Fourteen AEs were included for the purpose of this study: bullying, peer rejection, familial death, parental illness, sibling illness, parental mental health, parental addiction, family conflicts, parental divorce, financial difficulties, parental unemployment, sexual abuse, emotional abuse, and physical abuse. All included AEs have been previously included in other studies on AEs (e.g., Bellis et al., 2019, 2015; Felliti and Anda, 1999; Karatekin and Hill, 2019; Laditka and Laditka, 2019). The AEs were reported by either the participant or by (one of) the parents of the participant. Information on the occurrence of any of the AEs was obtained from the reporter who was most directly involved in its occurrence (e.g., information on parental addiction was obtained from parents, information on peer rejection was obtained from children/adolescents). Information on the occurrence of AEs before the age of 16 was acquired during the first, second, third, and fourth measurement waves of TRAILS. For the purpose of our illustration, we combined the information from these four measurement waves. The mean ages of the participants across measurement waves were 11.08 (SD = 0.54), 13.51 (SD = 0.52), 16.17 (SD = 0.62), and 18.71 (SD = 0.45), respectively. Supplementary tables S1 and S2 contain a description of the fourteen adversities and how these were assessed.

2.3. Demographic characteristics

Information on the participants' age and sex, parental educational level (low, medium, high) and the number of parents in the household during the first measurement wave of TRAILS were obtained to describe the study sample.

2.4. Statistical analysis

2.4.1. Correlation analysis

We estimated tetrachoric correlation coefficients between all AEs to gain insight into zero-order correlations (unconditional on other AEs) between these variables. The analysis was conducted using the R-package psych (version 2.1.6).

2.4.2. Network estimation

We used the Ising model to estimate a weighted, undirected network model with the IsingFit R-package (version 0.3.1). The Ising model is suitable for dichotomized data, as is the case for the AEs in the current study. The IsingFit package (van Borkulo et al., 2014) estimates the model parameters using nodewise logistic regressions, and uses a least absolute shrinkage and selection operator (LASSO) to obtain a sparse network model in combination with the Extended Bayesian Information Criterion (EBIC) for model selection (i.e., regularization). LASSO shrinks edge weights towards zero and reduces small weights to zero (i.e., the parameters are estimated within a bounded parameter space). LASSO uses a tuning parameter to regulate the degree of regularization. The tuning parameter for the LASSO regularization can be selected by minimizing the EBIC (Epskamp et al., 2017). The EBIC itself uses a hyperparameter indicating the extent to which the EBIC prefers sparser models. We used the default hyperparameter of 0.25. The 0, 1 (as opposed to the −1, 1) parametrization was used for the variables that were included in the model, which is preferred when dealing with occurrence versus non-occurrence type variables (Haslbeck et al., 2020). We used the "AND" rule for obtaining the edge weights in the network, which indicates that an edge weight is included when both nodes involved in that edge (e.g., A and B) predict the other.

2.4.3. Network visualization

The network was visualized with the qgraph package (version 1.6.9). We used the Fruchterman-Reingold algorithm to determine the layout of the network (Fruchterman and Reingold, 1991). The algorithm ensures that nodes with less strength and fewer connections are placed further apart, while nodes with higher strength and more connections are placed closer to each other.

2.4.4. Sensitivity analyses

We estimated three additional network models with different hyperparameters (i.e., hyperparameter of 0.0 instead of 0.25) and a different rule for the inclusion of edges in the model (i.e., the OR-rule instead of the AND-rule) to assess and illustrate the impact of our modelling choices on the resulting network model. The OR-rule indicates that only one node involved in a pair of nodes is required to predict the other in order to be included in the model. The three additional models will lead to less conservative network models.

2.4.5. Network stability and accuracy

Non-parametric bootstrapping was used to gain insight into the stability of the edge weights, which is useful in determining the uncertainty surrounding the estimated edge weights as well as whether edge weights can be compared (Epskamp et al., 2017). One thousand bootstraps were performed for each of the estimated models (the main model as well as the models within the context of the sensitivity analyses). All bootstrapping procedures were performed in the Bootnet R-package (version 1.4.3).

3. Results

The majority of the respondents were female (56.9%). Fifteen-and-a-half percent of the sample had parents with a low educational level, 63.1% with a medium educational level and 21.4% with a high educational level. Ninety percent of respondents lived in a two-parent household at baseline. Table 1 contains an overview of the prevalence of AEs in the included sample.

3.1. Zero-order correlations between adverse experiences

Table 1 contains the zero-order tetrachoric correlation coefficients between the fourteen AEs included in this study (N = 1029). We observed marked heterogeneity in the strength of the associations across all pairs of AEs. Only two pairs of AEs were strongly correlated: bullying and peer rejection, and physical abuse and emotional abuse. Eight pairs of AEs had correlation coefficients ranging between 0.30 and 0.50. These pairs included, for example, emotional abuse and financial difficulties (0.30), parental unemployment and financial difficulties (0.46), parental illness and familial death (0.36) and parental divorce and parental addiction (0.40). Fourteen pairs of AEs had correlation coefficients ranging between 0.20 and 0.30. These pairs included, for example, familial conflicts and parental addiction (0.24), parental addiction and peer rejection (0.25), parental divorce and peer rejection (0.23) and physical abuse and peer rejection (0.28). The remainder of the pairs of AEs had negligible correlation coefficients ranging between −0.16 and 0.20. These included, for example, parental illness and sibling illness (0.15), parental divorce and parental unemployment (0.14) and parental illness and financial difficulties (0.12). The correlation coefficients indicate that many AEs co-occurred. In the following, we show how network analysis can be used to provide insight as to how these correlations between AEs arose.

3.2. Network structure of ELA

Fig. 1 shows the network of AEs. A total of 15 edges were included in the model. The network in Fig. 1 can be read as follows: an edge between any pair of AEs suggests that those AEs are conditionally dependent, given all other AEs included in the model. When no edge exists between any pair of AEs, those AEs are suggested to be conditionally independent, given all other AEs included in the model. The resulting network is largely in line with the tetrachoric correlation analyses showed previously. AEs with a relatively high correlation coefficient (i.e., above 0.30) all have edges between them. The associations between these AEs cannot be explained by any other AE included in the model.

We observed a similar pattern for many of the AE pairs with correlation coefficients ranging between 0.20 and 0.30. A notable exception is that the network model shows that parental addiction and familial conflicts, which had a correlation coefficient of 0.24, are conditionally independent given parental divorce. This suggest that the association between parental addiction and familial conflicts, as shown in the correlational analysis, is due to the fact that both parental addiction and familial conflicts are associated with parental divorce. In addition, the correlation between parental addiction and familial conflicts might be partially explained by parental mental health, as this AE is also associated with both parental divorce and parental addiction. The AEs pairs with correlation coefficients ranging between −0.16 and 0.20 had no edge connecting them in the network model. It is possible that some of these relatively weak correlations are indicative of indirect pathways between AEs. Parental illness and financial difficulties for example (r = 0.12), are both directly associated with parental unemployment. It is possible that parental illness may lead to parental unemployment, which could subsequently lead to financial difficulties. However, it is also likely that the weak correlations, and a lack of any edge, are simply due to an absence of an association between a pair of AEs. Due to the undirected nature of the network model presented here, it is not possible to draw firm conclusions about potential causal pathways through which variables are associated. From a statistical point of view, all potential pathways are equivalent (e.g., familial conflicts could lead to parental divorce and parental addiction could lead to parental divorce, but parental divorce could also lead to parental addiction on the one hand, and familial conflicts on the other). Nevertheless, the model does

Table 1
Prevalence (rates) and tetrachoric correlation coefficients between adverse experiences before the age of 16.

	N (%)	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	63 (6.1)	–													
2	45 (4.4)	0.78	–												
3	168 (18.1)	0.08	0.23	–											
4	153 (14.9)	−0.09	−0.14	0.31	–										
5	170 (16.5)	0.08	0.14	0.14	−0.02	–									
6	69 (6.7)	0.15	0.14	0.39	0.19	0.46	–								
7	93 (9.04)	−0.09	0.00	0.05	0.05	0.08	−0.06	–							
8	315 (30.6)	0.04	0.06	0.01	0.08	0.30	0.12	0.15	–						
9	390 (37.9)	0.00	0.05	0.22	0.12	0.27	0.28	0.12	0.25	–					
10	93 (9.04)	0.18	0.25	0.40	0.24	0.18	0.15	0.09	0.11	0.28	–				
11	37 (3.6)	−0.16	0.05	−0.08	−0.09	−0.12	0.12	0.26	0.36	−0.10	0.05	–			
12	43 (4.2)	0.28	0.26	−0.03	0.19	0.08	0.15	0.12	0.08	−0.07	0.07	-[a]	–		
13	40 (1.6)	0.25	0.28	0.18	0.17	0.14	0.17	0.03	0.02	0.11	0.14	0.18	0.29	–	
14	101 (9.8)	0.12	0.14	0.17	0.35	0.12	0.30	0.03	0.03	0.13	0.20	0.19	0.10	0.71	–

Notes: 1 = Bullied, 2 = Peer rejected, 3 = Parental divorce, 4 = Familial conflicts, 5 = Parental unemployment, 6 = Financial difficulties, 7 = Sibling illness, 8 = Parental illness, 9 = Parental mental health problems, 10 = Parental addiction, 11 = Familial death, 12 = Sexual abuse, 13 = Physical abuse, 14 = Emotional abuse. [a] The correlation coefficient between parental death and sexual abuse could not be computed due to an absence of cases.

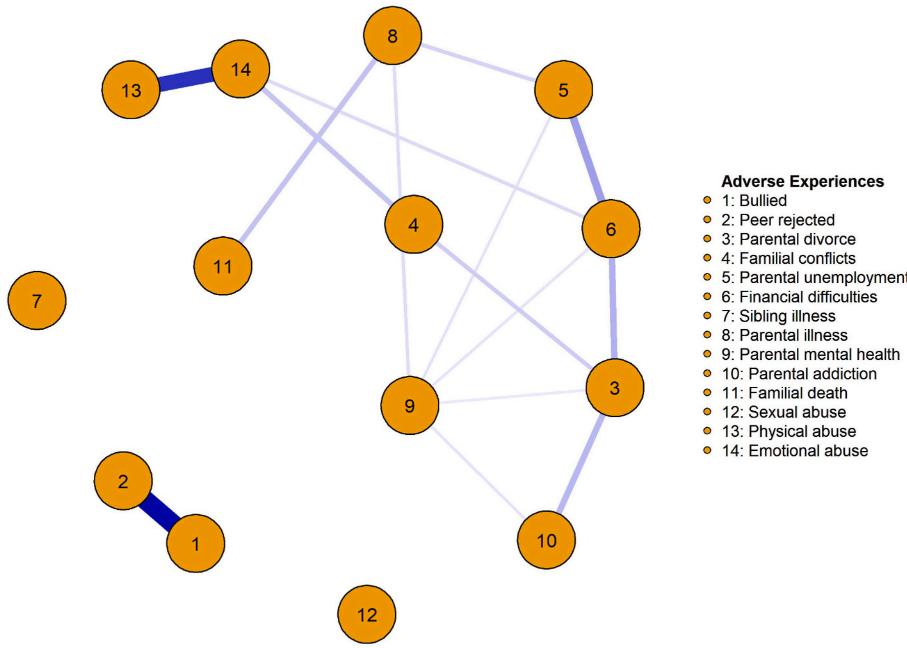

Fig. 1. Undirected network model of Early Life Adversity. The network model contains 14 adversities. Edge thickness represents the strength of the associations between AEs; thicker edges represent stronger associations (depicted by stronger color saturation). All edges have positive signs. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

provide some insight into potential pathways, some of which perhaps more likely than others given theoretical considerations.

3.2.1. *Sensitivity analyses*

We re-estimated the network model using different hyperparameter settings, as well as a different ruleset for the inclusion of edges (the OR-rule). The model based on a hyperparameter of 0.0 and the AND-rule did not differ from the main model discussed previously. The other two models (based on the OR-rule, and a hyperparameter of 0.25 and 0.0, respectively) did differ from the main model in one notable way: the network models based on the OR-ruleset also included an edge between peer rejection and parental divorce. It is possible that this association only arose in the OR-rule based models because it is more likely for parental divorce to predict peer rejection than vice-versa. OR-rule based models are in general less conservative than AND-rule based models. As such, the findings from the AND-rule based models are likely more stable. In the following section we will focus on the stability of the network models in more detail.

3.2.2. *Stability of the network models*

The non-parametric bootstrap for the main network model presented in this study indicated that the majority of the edge weights were accompanied by relatively large CIs. As a result, it is not possible to reliably say that the strength of an edge weight between any pair of nodes is different than any other edge weight that connects any other pair of nodes on a population level. This does not have any implications for the presence of the edge in general. Only two edge weights, between nodes 1–2 (bullying and peer rejection) and 13–14 (physical abuse and emotional abuse), had bootstrapped CIs that did not overlap with the bootstrapped CIs of the other edges. This suggests that the strength of these edge weights are different from edge weights between any other pair of nodes. We also further inspected the absence of edges linking sibling illness and sexual abuse to other AEs, despite some associations in the correlational analyses. We found that for sexual abuse, the vast majority of the bootstrapped networks did not include an edge between sexual abuse and any other AE (>90% of networks), with the exception of a potential edge with familial conflicts (69.9% contained a zero edge). A similar pattern emerged for sibling illness, with the exception of potential edges with parental mental health problems, familial death and parental illness (69.6%, 66.9% and 60.1%). The non-parametric bootstrap for the models based on the OR-rule indicated similar patterns. The edge between peer rejection and parental divorce, which was not included in the main network model, appeared less stable than other edges included in the model as only 49% of the 1000 bootstrapped networks included this edge. This information indeed confirms that this edge is not very stable.

4. Discussion

We propose network analysis as an alternative statistical approach for modelling early life adversity (ELA). We modelled ELA using network analysis and compared the findings from the network model to findings based on correlation analysis, and showed that network analysis provides more detailed information on the interrelations between specific AEs than a simple correlation analysis. In the real-life application, the network of ELA, consisting of fourteen adverse experiences (AEs), comprised direct relationships between AEs in addition to more complex, indirect relationships. AE pairs characterized by a relatively strong correlation in the correlation analyses were also all directly connected in the network model. On the other hand, AE pairs characterized by weaker correlations in the correlation model were either not associated in the network model, or only indirectly through interactions with other AEs. The network model, and the included edges therein, therefore allow for insight into the potential pathways through which AEs may co-occur. The application of network analysis in this study showed how modelling ELA as a network of AEs allows capturing the complex nature of the ELA construct. The application also shows how network analysis can be used to answer research questions in the ELA domain.

4.1. *The application of network analysis in the field of ELA*

Applying network analysis to ELA can aid in addressing a variety of research questions (Table 2). First, like in our real-life application, an

Table 2
Examples of ELA research questions to be addressed with network analysis.

Research questions	Outcome
How do adverse experiences cluster together and how are they conditionally associated with each other?	Identify points for targeted intervention
How are adverse experiences conditionally associated with health outcomes?	Understand mechanisms linking early adverse experiences with health
Do conditional associations between AEs and outcomes depend on social support?	Identify mechanisms that may amend the harmful effects of early life adversity

undirected network model for ELA can be used to investigate conditional associations between a set of AEs. This can provide more insight into how specific AEs are associated with each other. For example, our undirected network model showed that parental illness and financial difficulties were conditionally independent given parental unemployment, and that family-related AEs and peer-related AEs were not associated with each other. Second, outcomes of interest (e.g., mental health of the developing child or adolescent) can be incorporated into the network to investigate how AEs, conjunctively, are conditionally associated with such outcomes. In doing so, researchers can gain insight into potential pathways through which AEs are associated with outcomes of interest. In addition, it is possible to condition on the presence of specific nodes in the model (e.g., parental illness and familial death) to investigate how different combinations of nodes are associated with outcomes of interest (e.g., depressive symptom severity). This would allow researchers to understand synergies between AEs, which has recently been discussed by Briggs et al. (2021). For more information on this topic we refer to Lunanksy et al. (2021). Third, networks can be compared across sub-populations (e.g., sex, socio-economic background, history of mental health problems) to identify differences for example network structure, or whether differences exist in the strengths of edge weights. To that end, researchers can for example use the Network Comparison Test (NCT) to compare two networks that were estimated in different sub-populations (e.g., boys and girls) (van Borkulo, 2018). Lastly, protective factors (e.g., socio-economic resources, resilience, positive experiences) could be included in a moderated network model (MNM) (Haslbeck et al., 2019) to investigate whether such factors moderate the associations between individual AEs, or between AEs and outcomes of interest. It is worth mentioning that a few recent studies included a limited number of AEs, mainly maltreatment-related AEs, in network models of psychopathology (Betz et al., 2020; Isvoranu et al., 2017; Peel et al., 2021). In addition, Sheridan et al. (2019) investigated the clustering of a set of AEs with neurocognitive outcomes (Sheridan et al., 2019). Although these studies partially overlap with the example applications described here, network analysis has the potential for addressing several ELA-related research questions. A few examples of such research questions can be found in Table 2. We advocate for researchers, practitioners and policy-makers to work together in devising research questions of interest, as well as in the interpretation of findings (Lacey et al., 2020; Portwood and Lawler, 2021).

4.2. Important considerations for future research using network analysis

Several pitfalls ought to be considered when applying network analysis to address ELA-related research questions. First, there is currently no consensus on what constitutes ELA (Lacey and Minnis, 2019). As such, it is very likely that future studies in which network analysis is applied include a varying set of AEs. Due to the fact that edges between nodes are highly dependent on the variables that are included in the model (Borsboom et al., 2021), results might differ drastically between studies and thus hamper comparisons (Lacey and Minnis, 2019). Future studies on ELA using network analysis should consider including conceptually similar AEs wherever possible, especially when performing replication studies. Second, network analysis is, like any other statistical approach, affected by sample size. There are currently no clear guidelines for sample size requirements in network analysis. In general, larger sample sizes lead to easier recovery of edges in the model (Epskamp et al., 2017). The prevalence of certain AEs is generally relatively low. For example, the prevalence of physical abuse in this study population was 1.6%. Similar prevalence rates were found for several other AEs in this study, including familial death, peer rejection, and sexual abuse. Given the low prevalence rates of these AEs it is difficult to obtain a large absolute number of cases for these AEs. As a result, it becomes more difficult to obtain precise estimates regarding edges between them. In larger databases (e.g., the DANLIFE cohort), where the absolute number of cases of AEs (e.g., physical- and emotional abuse, and familial death) is larger despite low prevalence rates, such associations will be more easily uncovered (Bengtsson et al., 2019). Sample size requirements also differ between model estimation and selection procedures. In this study we made use of LASSO regularization, an often used model estimation and model selection approach in the network literature (Epskamp et al., 2017; van Borkulo et al., 2014). LASSO regularization is used specifically for relatively small data sets, as it has shown to lead to adequate recovery of network structures especially in lower sample size settings (Epskamp et al., 2017; Foygel Barber and Drton, 2015; van Borkulo et al., 2014). LASSO leads to a conservative network model, where only a few edges explain the structure in the data. This allows for good recovery of the overall network structure, but it might lead to exclusion of adversities that are rare, and are less likely to have a strong connection with other adversities. To illustrate: although physical abuse is rare, it was so strongly associated with emotional abuse (zero-order correlation of 0.71) that an edge between these AEs was included in the network model. Familial death, which was also very rare, only had a relatively weak association with illness of a sibling (zero-order correlation of 0.26). It is possible that this edge was not included in the network model for that reason, despite the fact that an edge between these two AEs is likely given theoretical grounds. Similar patterns emerged for sexual abuse and peer rejection. The sensitivity analyses and stability and accuracy analysis also confirmed that there was variation in potential inclusion of edges between sexual abuse, sibling illness and peer rejection with other AEs across the bootstrapped network models. To gain more insight into these issues, future studies should conduct simulations to assess how well a simulated network structure is retrieved across various sample sizes to understand how network analysis performs in different study settings and with different model estimation and selection techniques (e.g., maximum-likelihood based estimation with model search algorithms or Bayesian approaches). Third, researchers ought to be aware of the impact of noisy data in network analysis. Missing data, especially in sub-groups of individuals whom are more likely to experience more adversity (e.g., from a lower socio-economic background), may lead to smaller and less precise estimates for associations between pairs of AEs. This may lead to the exclusion of edges when in reality, such an edge does exist in the population. It is possible that certain edges were not included due to missing data in this study. Besides missing data, heterogeneity within AEs might pose problems in network analysis specifically, but also for research on ELA in general. There is often marked heterogeneity in the ways studies operationalize AEs. For example, parental mental health problems in this study included depression, anxiety and psychotic experiences of either the mother or the father. Studies exist that for example only include parental depression, or variations thereof (Bevilaqua et al., 2021; Bussemakers et al., 2019). Heterogeneity within AEs might impact study findings because it leads to masking of potential associations. For example: parental depression, which was collapsed into a parental mental health variable together with psychotic complaints and anxiety complaints, might be associated with parental physical illness, whereas parental psychotic complaints might not be. This heterogeneity could lead to lower overall effect estimates for edges between for example parental mental health problems with other AEs. Fourth, much attention has recently gone out to the importance of timing, frequency and severity of AEs (Lacey and Minnis, 2019; Lopez et al., 2021; Portwood and Lawler, 2021). Detailed information on severity and frequency of AEs can be readily incorporated in undirected network models. This merely has consequences for the type of statistical model one would use to estimate such a network (e.g., including count variables to represent the frequency that an AE has occurred in a network with dichotomous variables would require a MGM). Incorporating the timing of AEs, however, would require models that allow for incorporating repeated measurements (e.g., time-varying MGMs) as well as study designs that include repeated measurements on the occurrence of AEs. The use of network models on longitudinal data is an endeavor that should be further explored in the future. Last, more and more attention has gone out to the replicability of findings using network analysis (Borsboom et al., 2021). To that end, Burger et al. (2020) have devised a structure that researchers may use to assure that all necessary details of the network analysis (e.g., sample selection, estimation techniques, stability analysis, and software usage) are adequately reported (Burger et al., 2020). We recommend that researchers who apply network analysis in the field of ELA take note of the reporting structure laid out by Burger et al. (2021) to facilitate standardization and reproducibility of findings.

5. Conclusion

Using network analysis for modelling the ELA construct allows capturing the complex nature of interrelated AEs. We recommend researchers to apply network analysis when they are interested in investigating associations between specific AEs and, conjunctively, with outcomes of interest, to identify targets for intervention or understand underlying mechanisms. As mentioned previously by Lacey and Minnis (2019) and Portwood and Lawler (2021), insight into such mechanisms is much needed to move the field forward in terms of developing theoretical frameworks as well as for the development of policies or interventions aimed at reducing the occurrence of early life adversity, or the consequences thereof. All in all, network analysis provides researchers in the field of ELA with a valuable new tool that allows to further elucidate the complexity of ELA.

Declaration of interest

The authors declare no conflicts of interest.

Credit statement

Tjeerd Rudmer de Vries: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Visualization, Project administration. Iris Arends: Conceptualization, Writing – original draft, Supervision. Naja Hulvej Rod: Writing – review & editing. Albertine J. Oldehinkel: Conceptualization, Writing – review & editing. Ute Bültmann: Conceptualization, Writing – original draft, Supervision, Funding acquisition.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.114784.

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