Network analysis as an emerging method in adversity research – a reflection on Pollman et al. (2022)

Abstract

In this issue, Pollman and colleagues (2022) apply network analyses to childhood and adolescent adversity data. They use the rich, longitudinal data from the Avon Longitudinal Study of Parents and Children. By applying network analyses, they draw-out clusters of adversities and the strength of relationships between these clusters and individual adversities with later mental health, substance use and wellbeing. The authors additionally look at adversity clusters in two developmental stages – childhood and adolescence. This commentary discusses how adversity clustering has typically been captured in studies in the past, what network analyses might offer this area of research, and the contribution of the study by Pollman et al (2022). The commentary concludes with some reflections and recommendations for the future of adversity clustering research.

We have long known that adverse childhood experiences (ACEs) are associated, at a population average level, with poorer health outcomes e.g.(Felitti et al., 1998). We have also known for some time that ACEs tend to cluster or co-occur e.g.(Dong et al., 2004). In recent years, researchers have applied a few different statistical methods to capture ACEs clustering, with the aim of drawing out which ACEs tend to co-occur and to determine the ACEs clusters that are most harmful for people's health. This commentary piece will briefly consider how adversity researchers have typically dealt with this clustering in their work, the strengths and limitations of these methods, and what network analysis (as applied by Pollman et al (2022) in the present issue) might offer as an emerging statistical method for adversity clustering. The piece will then conclude with a set of reflections and recommendations for future adversity research.

What are the frequently used methods for considering ACEs clustering in research?

Many researchers interested in associations between ACEs and outcomes, have applied an "ACE score" approach. This approach simply involves adding up the number of adversities experienced or reported into a total score. The total ACE score is then typically categorised as: no ACEs, 1 ACE, 2 ACEs, 3 ACEs and 4+ ACEs (Felitti et al., 1998). The hypothesis is that the more adversities experienced, the poorer the outcome is likely to be, at least on a population average level. ACE scores are a simple but crude way to deal with adversity clustering. Consequently, several researchers have criticised the use of ACE scores in research but also in practice (Lacey & Minnis, 2020). The main criticisms of the ACE score approach are that it fails to recognise that each adversity may be differentially associated with the outcome of interest, that the mechanisms involved in translating ACEs experience into poorer outcomes are the same, and that the specific patterning or clustering of ACEs is ignored. The recognition of these limitations has led researchers to seek out other, more complex, statistical methods which recognise and draw-out the clusters of ACEs that exist in a population.

One alternative statistical method that has greatly increased in popularity in ACEs research in recent years is latent class analysis (also called person-centred mixture modelling). Latent class analysis allows researchers to investigate and derive groups (classes) of people who co-report similar ACEs. These groups are then named by the researcher to reflect their composition and a categorical variable can be derived for further analysis. This variable can then be used as an exposure (independent variable) or outcome (dependent variable) in subsequent analyses. For example, a frequent line of inquiry is which classes of people have the poorest outcomes. Again, latent class analysis is not without its limitations (Lacey & Minnis, 2020; Weller et al., 2020). One limitation is "naming fallacy" in that the names that researchers apply to the groups may not accurately reflect their composition. Second, class membership is probability based and it is therefore not possible to determine the exact number of people or proportion of people in each class. Third, as a data-driven method the results may be dataset specific and therefore findings may be difficult to translate across settings.

Network analysis as an emerging method in ACEs research

Network analysis is emerging as a potentially useful method for ACEs clustering research. The method has been used by a handful of studies to date, including by Pollman et al (2022) in the present issue. Network analysis is a very visual method for illustrating the correlations between different adversities. The goal of this method, as applied here, is to determine the clusters of adversities present in a sample, to depict the nuanced relationships between different adversities, and finally to illustrate the relationships between adversities and adversity clusters with mental health and wellbeing outcomes.

In previous work, network analysis was first applied to a clinical sample of children and young people aged 4-18 years, with the aim of illustrating the clustering between a broad range of different adversities and trauma (Hodgdon et al., 2019). The authors identified four adversity clusters in their sample. The first was termed "overt individual trauma" and was comprised of psychological maltreatment, physical abuse and assault, and sexual abuse and assault. The second was termed "environmental family" trauma and was comprised of neglect, impaired caregiving and forced displacement. The third was termed "environmental community" trauma with school, domestic and community violence. And the fourth, "acute" trauma, included traumatic loss, medical trauma and injuries or accidents. This study demonstrated the utility of network analysis for adversity research, although the method was yet to be applied in a broader population sample. Breuer et al (2020) applied network analysis to a sample of adult psychiatric inpatients and their ACE experiences. As might be expected, abuse and neglect demonstrated the strongest interrelations, although all ACEs were associated with a range of mental health disorders (e.g.

depression, eating disorders and personality disorders). The authors drew out two clusters of ACEs. The first was a maltreatment cluster comprising physical and emotional neglect and abuse. The second was an “adverse circumstances” cluster including maternal-directed domestic violence, parental substance misuse, and parental separation. The main limitations of this study were its reliance on retrospective reports of ACEs, adhering to the Kaiser Permanente ACEs study adversities (Lacey & Minnis, 2020) and restriction to a clinical sample.

Pollman’s (2022) study therefore represents an important extension to these prior two studies. Most importantly they use a rich, longitudinal birth cohort – the Avon Longitudinal Study of Parents and Children (ALSPAC). This cohort has followed the lives of babies born between 1991-1992 in the Avon area in the South-West of England. ALSPAC has rich, repeated measures of adversities over time. Most of these are prospectively collected but the authors also utilise some of the cohort members’ own retrospectively reported recollections of their childhood experiences. Further, the authors inspect a broader range of adversities, moving beyond the usual 10 ACEs in the Kaiser Permanente ACEs study – an aspect of adversity research that is becoming widely recommended (Lacey & Minnis, 2020). Finally, they consider the importance of the developmental stage at which adversities are experienced, and subsequently included pertinent adolescent adverse experiences (AAEs) (e.g. loneliness, educational failure and intimate partner violence). This study therefore is an important addition to the scientific literature on applying network analysis to the context of adversities.

Pollman et al (2022) first set out to explore the clustering of adversities and found two clusters in childhood representing “direct abuse” (emotional, physical and sexual abuse) and “adverse family factors” (parental substance misuse and intimate partner violence). In adolescence, they found three clusters of AAEs – again, “direct abuse” (although in adolescence this additionally included parental conflict, trouble with the policy and occupational problems), “adverse family factors” and an additional cluster of “educational and social factors”, which included bullying, loneliness, and educational issues. The clusters they found in these two different developmental stages therefore showed some consistency. The authors then examined how the clusters related to adolescent mental health and wellbeing. What stood out starkly in their findings was the importance of emotional abuse. Emotional abuse (experienced within or outside the household) was the most common adversity reported in this sample and related to most indicators of adolescent mental health and wellbeing. Interestingly, the authors found higher correlations between the examined AAEs and this is possibly due to greater temporal proximity to the outcomes. Finally, what the network analysis showed is the complexity between different adversities and mental health; all ACEs were associated with mental health outcomes via direct pathways. However, for AAEs, several showed indirect pathways to later mental health, for example parental substance misuse →carer criminality →poorer mental health. This finding suggests that the relationships between different adversities is complex and likely changes over time.

Where next for adversity clustering methods?

While Pollman et al (2022) adeptly demonstrate the application of network analysis to adversity clustering, there is still some way to go before we can be confident of how adversities truly cluster in the broader population. Like latent class analysis, network analysis is also a data-driven method and, as such, shares one of the same main limitations – that of dataset specificity. Hence replication of the method across different datasets is required, although it is noteworthy that Pollman et al (2022) find similar clusters to Breuer et al (2020). Further, network analysis should be applied on more diverse and representative longitudinal studies. Inclusion of participants with missing data would also be important as most current network analysis studies use pairwise deletion. Finally, we need an extended longitudinal focus, capturing how adversities persist or change in their nature and severity, and the relationship between different adversities over time. Such analysis would allow us to identify the patterns of the temporal ordering of adversities and identify which adversities tend to trigger others and consequently inform interventions. However, this type of analysis would require rich, repeated longitudinal data, ideally on a population representative sample – a real challenge for existing longitudinal datasets.

Conclusions

To conclude, there is mounting evidence using robust statistical methods that adversities do indeed cluster. However, it is clear that adversities cluster in complex ways and in ways which likely depend on developmental stage. Network analysis is an emerging but promising statistical method for drawing out the nuances in relationships between adversities, plus individual adversities, and potential outcomes.

References

Breuer, F., Greggersen, W., Kahl, K., Schweiger, U., & Westermair, A. (2020). Caught in a web of trauma: network analysis of childhood adversity and adult mental ill-health. *Child Abuse & Neglect*, *107*(104534).

Dong, M., Anda, R. F., Felitti, V. J., Dube, S. R., Williamson, D. F., Thompson, T. J., Loo, C. M., & Giles, W. H. (2004). The interrelatedness of multiple forms of childhood abuse, neglect, and household dysfunction. *Child Abuse & Neglect*, *28*(28), 771–784.

Felitti, V., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., Koss, M. P., & Marks, J. S. (1998). Relationship of Childhood Abuse and Household Dysfunction to Many of the Leading Causes of Death in Adults. *American Journal of Preventive Medicine*, *14*(4), 245–258.

Hodgdon, H., Suvak, M., Zinoviev, D., Liebman, R., Briggs, E., & Spinazzola, J. (2019). Network analysis of exposure to trauma and childhood adversities in a clinical sample of youth. *Psychological Assessment*, *31*(11), 1294–1306.

Lacey, R. E., & Minnis, H. (2020). Practitioner Review: Twenty years of research with adverse childhood experience scores – advantages, disadvantages and applications to practice. *Journal of Child Psychology and Psychiatry*, *61*(2), 116–130. https://onlinelibrary.wiley.com/doi/10.1111/jcpp.13135

Pollmann, A., Fritz, J., Barker, E., & Fuhrmann, D. (2022). Networks of Adversity in Childhood and Adolescence and Their Relationship to Adult Mental Health. *Research on Child and Adolescent Psychopathology*. https://doi.org/10.1007/s10802-022-00976-4

Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent Class Analysis: A Guide to Best Practice. *Journal of Black Psychology*, *46*(4), 287–311. https://doi.org/10.1177/0095798420930932