Risk factors for depression in Pacific adolescents in New Zealand: a network analysis

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Abstract

Background: Network analysis provides opportunities to gain a greater understanding of the complex interplay of risk factors for depression and heterogeneous symptom presentations. This study used network analysis to discover risk factors associated with both depression severity and depression symptoms amongst Pacific adolescents in New Zealand.

Methods: Mixed graphical models with regularization were fitted to data from a community sample of New Zealand born, Pacific adolescents, (n=561; 51% male; Mean age (SD) = 17 (0.35)) and associations between a wide range of potentially explanatory variables and depression severity and depression symptoms investigated. The associations identified were then tested for reliability, using resampling techniques and sensitivity analysis.

Results: In the networks, the explanatory variables associated with both depression severity and depression symptoms were those related to quality of the relationships with mother or friends, school connectedness, and self-assessed weight, but the symptoms they were associated with varied substantially. In the depression severity networks, impulsivity appeared to be a bridging node connecting depression severity with delinquency and negative peer influence.

Limitations: The data were analysed cross-sectionally, so causal inferences about the directions of relationships could not be inferred and most of the data were self-reported.

Conclusions: The results illustrate the varied way that adolescent depression can manifest itself in terms of symptoms and suggest specific items on the depression inventory that might be suitable targets for prevention strategies and interventions, based on the risk factor - depression symptom profiles of individuals or groups.

Keywords: depression; symptoms; adolescent; Pacific; network analysis; risk factors

Introduction

Adolescent depression is a serious and growing health issue and is one of the leading causes of illness and disability amongst adolescents (World Health Organisation, 2020). As with many countries worldwide, the prevalence of youth depression in New Zealand is increasing. Between 2012 and 2019, rates of depressive symptoms amongst New Zealand adolescents rose from 13% to 23% (Fleming et al., 2020). A recent report on youth mental health in New Zealand found it was declining and its impact on certain groups, including female, Māori and Pacific youth was disproportionate. The report called for a greater sense of urgency to deal with this mental health crisis (Menzies, Gluckman, & Poulton, 2020). Around 25% of Pacific adolescents in New Zealand report significant depressive symptoms compared with 20% for their Pākehā[2] (Caucasian) peers and these inequities are primarily gender driven. Around 33% of Pacific female adolescents reported significant depressive symptoms, compared with 15% for Pacific male adolescents (Fleming et al., 2020). Pacific youth are also more likely to attempt suicide, 12% compared to 3% of Pākehā and other European youth[3] (Fleming et al., 2020). Nevertheless, despite evidence of higher prevalence of depression, very few adolescent and youth studies have been conducted on Pacific wellbeing (Tucker-Masters & Dr Tiatia-Seath, 2017).

The Pacific population in New Zealand comprises those whose heritage traces back to various Pacific islands, with the largest groups from Samoa (48%), Tonga (22%), and the Cook Islands (21%), but also including Fiji, Niue, and Tokelau. This population is highly urbanized, with around two thirds living in the Auckland region, and young, with a median age of 23 years compared with 38 years for New Zealand as a whole (Statistics New Zealand, 2018). Pacific people in New Zealand are also more religious than New Zealanders generally, with only 23% of Pacific New Zealanders stating they have no religion, compared to the national average of 48%. Pacific people in New Zealand suffer disproportionate socioeconomic deprivation compared to New Zealanders generally; for example, they are disproportionately located in the Auckland's poorest suburbs (Ministry of Health, 2021b) and a recent survey found that 37% of Pacific children live in severe to moderate food insecure households compared to 19% for New Zealand children overall (Ministry of Health, 2019).

Heterogeneity of cause and symptom presentation makes full understanding of depression in adults and younger people challenging (Mullarkey, Marchetti, & Beevers, 2019; Thapar, Collishaw, Pine, & Thapar, 2012). That is, depression is multifactorial and contextually driven and thought to result from complex interactions between several risk factors and causal pathways (Maughan, Collishaw, & Stringaris, 2013). Network analysis is a visualization tool suitable for displaying such complex relationships (Haslbeck & Waldorp, 2018; McNally, 2016; Van Borkulo et al., 2014; Van Borkulo. et al., 2017). Following pioneering work by researchers in this field (Borsboom, 2008; Borsboom & Cramer, 2013; Boschloo, Schoevers, van Borkulo, Borsboom, & Oldehinkel, 2016; Fried & Nesse, 2015; Fried et al., 2017; McNally, 2016) psychological network analysis is being increasingly used to investigate depression at the symptom level rather than measuring depression as a single item construct, calculated by summing the symptom scores. According to this network model of psychopathology, depression is inadequately described by summing symptom scores to create a single latent construct, rather the symptoms are the disorder (Borsboom, 2008; Borsboom & Cramer, 2013; Fried & Nesse, 2015; Fried et al., 2017). Depression symptom networks provide valuable information about symptom importance that could be used to guide the design of symptom specific interventions and therapies (Fried & Nesse, 2015; Fried et al., 2017; McNally, 2016).

Several previous studies have modelled preadolescent or adolescent depression data using network analysis (Bodner, Kuppens, Allen, Sheeber, & Ceulemans, 2018; Boschloo, Schoevers, van Borkulo, Borsboom, & Oldehinkel, 2016; Fritz, Fried, Goodyer, Wilkinson, & Van Harmelen, 2018; Hukkelberg & Ogden, 2018; Jones, Mair, Riemann, Mugno, & McNally, 2018; Kim, Kwon, Ha, Lim,

[2] Pākehā is a Māori language term used to describe the inhabitants of New Zealand with European heritage.
[3] Māori are also disproportionately likely to report significant depressive symptoms and attempt suicide and whilst this is also of concern Māori are not the focus of the present research.

& Kim, 2021; McElroy, Shevlin, Murphy, & McBride, 2018; Mullarkey et al., 2019; Schweren, Van Borkulo, Fried, & Goodyer, 2018), but none, to the authors' knowledge, with Pacific adolescents. Given that network analyses are sensitive to culturally specific results (Kim, Kwon, Ha, Lim, & Kim, 2021; Wasil, Venturo-Conerly, Shinde, Patel, & Jones, 2020), the applicability of network results across cultures and ethnicities cannot be assumed. Thus, if network analysis is to fulfil its potential as an aid to clinical decision making, more culturally and ethnically specific network analyses are needed. The veracity of this technique is also influenced by the number and quality of the variables in the analysis and rich data are likely to provide more informative results.

To address this gap in network literature, this study used network analysis to model the cross-sectional associations between depression and a particularly rich multidimensional set of variables in a sample of Pacific adolescents in New Zealand, including variables covering socio-demographics, health, school, lifestyle, and a number of internalizing and externalizing behaviours, such as relationships (parents and friends), resilience, Pacific cultural identity, negative peer influence, substance use, impulsivity, and delinquency. Past research has shown that these variables could have an impact on depression (Barcaccia et al., 2020; Boers, Afzali, Newton, & Conrod, 2019; Bukowski, Pizzamiglio, Newcomb, & Hoza, 1996; Carbonell et al., 2002; Carlson & Cantwell, 1980; Clayborne, Varin, & Colman, 2019; Lundervold, Breivik, Posserud, Stormark, & Hysing, 2013; Paterson, Iusitini, & Taylor, 2014; Piko & Pinczés, 2014; Remes et al., 2019; Tang, Tang, Ren, & Wong, 2019). To the authors' knowledge, this is also the first study to investigate such a wide range of possible risk factors for depression severity and depression symptoms amongst adolescents, using network analysis.

This current research builds on important work, conducted by the Pacific Islands Families (PIF) Study team, that investigated risk and protective factors for child and adolescent depression up to the age of 14 amongst Pacific youth (Paterson et al., 2014; Paterson, Tautolo, Iusitini, & Sisk, 2018).

Methods

Source of data and participants

The data used in this study were collected as part of the PIF Study, an ongoing longitudinal study of a birth cohort of 1398 Pacific children born at a South Auckland hospital in New Zealand in the year 2000. Eligibility criteria for the PIF Study included having at least one parent who identified as being of a Pacific ethnicity and was a permanent resident of New Zealand. The PIF study has been guided by the Pacific People's Advisory Group and approved by Auckland University of Technology Ethics Committee (AUTEC) (references 17/26 and 19/364 apply). To date, data have been collected at regular intervals from 6 weeks to 20 years of age. The current cross-sectional analysis used data collected from 2017 to 2018, when the youth cohort turned 17. In the 17-year wave, 632 participants took part, but there were issues with missing data. Therefore, the final analytic sample included 561 participants (see Results section for more details of participant removal and missing data strategies). Further details on the PIF Study and characteristics of the cohort are available elsewhere (Paterson et al., 2008).

Variables included in the analysis

Depression was measured in two ways, as a single latent construct and in terms of individual depression symptoms, using the shorter version of the Children's Depression Inventory (CDI:S) (Kovacs & Preiss, 1992). The CDI:S is a 10-item, self-rated symptom scale, suitable for youths aged 7 to 17 years and has been widely used in research and clinical practice. It has been shown to be a reliable measure of depressive symptoms (Klein, Dougherty, & Olino, 2005). In this study, items on the CDI:S were scored 1 to 3, and after reverse scoring relevant items, higher symptom scores corresponded to higher symptom severity. The symptom scores were then summed to create a single scale to measure *depression severity*, with higher scores corresponding to higher severity. The CDI:S is usually scored 0 to 2, not 1 to 3 as in this study, therefore, when comparing the CDI:S scores in this study with those in other studies, it may be necessary to add 10 to mean scores and one to symptom scores.

The socio-demographic variables of *gender*, *ethnicity*, and socio-economic deprivation were included in the study. The level of socio-economic deprivation was assessed with a self-reported measure of food security, *money for food*. To check data reliability, the data from the *money for food* variable were cross referenced with data from the New Zealand index of socioeconomic deprivation for individuals (NZiDep), collected at the 14-year wave from the primary carers, predominantly mothers, of the participants. The two measures were found to be significantly correlated (r_s=0.17 p<0.001)[4], providing confidence in the self-reported data from the youth participants. Data were collected when all participants were very close in age (M = 17.0, SD = 0.35), therefore age was not included as a variable.

The following variables were measured using psychometric inventories: *depression severity*, *relationship with mother*, *relationship with father*, *relationship with friends*, *impulsivity*, *delinquency*, *negative peer influence*, *gang involvement*, *resilience*, and Pacific identity, which was measured with the following subscales *Cultural Efficacy* (*CE*), *Group Membership Evaluation* (*GME*), *Religious Centrality and Embeddedness* (*RCE*), and *Pacific Connectedness and Belonging* (*PCB*). The 'mother' and 'father' figures in the variables measuring *relationship with mother* and *relationship with father* included biological parents or mother or father figures, such as a grandmother or grandfather, who had performed that role. Confirmatory Factor Analysis (CFA) was performed on the items making up each inventory, using R package Lavaan (Rosseel, 2012), to check whether they supported first a single factor solution, and if not then whether they could be used in terms of subscales. Single variables were then created by summing the scores of the inventory items, after any necessary reverse coding. See Table S1 in the online supplementary materials for the results of the CFA.

Other variables used in the analysis included *church attendance*, *binge drinking*, *smoke cigarettes, smoke marijuana, take legal highs,* (for example, party pills), *ever had sex, hours online, online bullying - victim*, *online bullying - perpetrator, attend school*, *part of school*[4], *get along with teachers*[5], *body mass index* (*BMI*), *health, energy levels,* and *self-assessed weight*. Weight and height measurements, used to calculate BMI, were taken by the study assessors, otherwise all data were self-reported. See Table 1 below for the summary characteristics of the both the full year-17 sample (N=632) and the analytic sample (n=561) and Tables S2 and S3 in the online supplementary material for a more detailed description of all the analysis variables, their distribution, and the psychometric inventories used.

Statistical Analysis

Statistical analysis was completed using statistical software R (R Core Team, 2020) augmented by various R packages.

The distributions of the analysis variables were explored using means and standard deviations for the continuous numeric variables, and cell counts and proportions for the categorical variables. Bivariate analyses were also conducted to measure the correlations between variables, using Spearman's rank correlation.

All continuous numeric variables showed skewed distributions and so were transformed using the non-paranormal transformation (Liu, Lafferty, & Wasserman, 2009) with the R package Huge (Zhao, Liu, Roeder, Lafferty, & Wasserman, 2012) before being entered into the network analyses. The distributions of the depression symptoms were very skewed with very small cell counts (< 5 in some

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[4] The two measures of socio-economic deprivation were not exactly the same, one measured the extent of food insecurity and the other the number of deprivations experienced. Therefore, the correlation coefficient between the two would not be expected to be very high. The aim was to test whether they were significantly correlated to provide confidence in the *money for food* deprivation measure, self-reported by the adolescents.

[5] For those students that had left school, questions about school were asked in the past tense, for example, 'How well did you get along with your teachers when you were at school?' and the answers combined with those students that were still at school.

cases for the most severe symptom level), and so were entered into the networks as continuous numeric variables, after being transformed.

As the data contained categorical, ordinal and continuous numeric variables, mixed graphical models were used to fit the networks and estimate pairwise associations, using the R package *mgm*, which is suitable for the network modelling of data of different types (Haslbeck & Waldorp, 2015). In the networks, nodes represented the variables and edges the pairwise relationships between them (Borsboom & Cramer, 2013). The presence of an edge implied that two variables were associated, after conditioning on all other variables (Drton & Perlman, 2004). The networks were weighted and the edge weights, equivalent to partial correlation coefficients, calculated via nodewise regression (Haslbeck & Waldorp, 2015; Meinshausen & Bühlmann, 2006). To control for spurious edges, the networks were regularized using least absolute shrinkage and selection operator (LASSO) (Tibshirani, 1996), with model selection using Extended Bayesian Information Criterion (EBIC) (Foygel & Drton, 2010) plus a hyperparameter gamma (Chen & Chen, 2008; Foygel & Drton, 2010), all available through the mgm package (Haslbeck & Waldorp, 2015). Gamma was set at 0.25 for the main network models. For sensitivity analysis, network models were also fitted using a more conservative gamma value (0.5).

The mgm package integrates with the R package qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) to display the network as a graphical model. The package uses the Fruchterman-Reingold algorithm which places nodes with stronger connections closer together.

Network reliability was tested using 500 non-parametric bootstrap resamples (Haslbeck & Waldorp, 2015), to test how often an edge was recovered, that is how often an edge was estimated to be non-zero in the bootstrap samples. A rate of edge recovery at or close to 100% provides strong evidence that the association is reliable (Fried & Haslbeck, 2019; Haslbeck & Waldorp, 2015). Redundant nodes, nodes that are too topologically similar, can cause problems for network analysis. Therefore, the goldbricker function in R package NetworkTools (Jones, 2020) was used to identify redundant nodes.

The relative importance of the individual depression symptoms was tested using three common measures of node centrality: Strength, Betweenness, and Closeness. Strength is calculated by summing the edge weights for each node; Betweenness by counting the number of times a node lies on the shortest path between two other nodes; and Closeness by the average distance from a node to other nodes (Costantini et al., 2015). Nodes with high centrality are potentially influential in the network and action affecting them could affect other nodes (Borsboom & Cramer, 2013).

Results

At the PIF Study 17-year data collection wave, 632 participants took part, but there were problems with missing data, particularly with the CDI:S, the variable measuring *depression severity*, with 48% of participants having one or more items missing. After removing those participants with more than 30% of items missing on the CDI inventory, data were imputed using missForest (Stekhoven & Bühlmann, 2012). See Appendix 1 in the online supplementary materials for a more detailed description of the missing data analysis and imputation method. The final analytic sample included 561 participants. Participants excluded from the analysis had lower *impulsivity* (P=0.034) and spent less time online (*hours online*) (P=0.007) (P values calculated after adjusting for multiple testing using Holm) compared to those included, but there were no other significant differences between the two groups for the other explanatory variables. *Depression severity* scores were significantly lower in the analytic sample (P=0.002), compared with the full 17-year sample, as were symptom scores for *cry* (P=0.003) (P values based on the Wilcoxon rank-sum test). See Table 1 for the summary characteristics of both the full year-17 and analytic samples.

The analytic sample included 297 males (51%), 276 females (49%), with 400 (71%) identifying as either Samoan or Tongan. Gender and ethnicity were both self-identified. These gender and ethnicity proportions are representative of the national average for Pacific youth aged 15-19 in New Zealand, however, those identifying as Cook Islands Māori or Other Pacific Island were underrepresented (Statistics New Zealand, 2018). Around 8% of the analytic sample identified as being either New Zealand Pākehā, Māori, or all Pacific groups equally, as opposed to with one of the Pacific ethnic groups. Consistent with national statistics on food insecurity amongst Pacific families (see Introduction), this sample of Pacific adolescents suffered much higher food insecurity than New Zealand families generally, with 71% of this sample saying their parents worried about having enough money for food 'Sometimes', 'Often', or 'Always' compared with 22% of parents overall in New Zealand, based on data in a survey using a similar measure (Ministry of Health, 2019). The proportion of the sample still attending school at 17 was 87.9%, which was above the national average of 83.5% (Ministry of Education, 2020).

Depression severity ranged from 10 (the lowest possible score) to 27 (close to the highest possible score of 30) in the analytic sample. Females had a significantly higher mean *depression severity* (mean = 12.96, SD = 2.84) than males (mean=12.11, SD = 2.69) (t(554.89, t=-3.66, p<.001). Applying the scoring system used in another study, which set cut-off points at 6 and 7[6] for sum scores of symptoms on the CDI:S to identify potential cases (Meehan, Houghton, Cowley, Houghton, & Kelleher, 2008), 87 participants (15.5%) had *depression severity* scores of 16 or more and 59 (10.5%) of 17 or more in this study. The depression symptoms with the highest means were *looks* followed by *bothered*, and the lowest were *love* and *not enough friends*. See Table 1 for *depression severity* and symptom item means.

The bivariate analysis showed that many variables were very highly correlated, including *relationship with mother* and *relationship with father* (r_s =.57, P<.001). See Tables S10 to S11 in the online Supplementary materials.

<Table 1>

Network Estimation

PCB and *binge drinking* were identified by goldbricker in the R package NetworkTools (Jones, Mair, Riemann, Mugno, & McNally, 2018) as being redundant nodes, that is they were too topographically similar to other nodes in the networks, namely to *CE and GME* in the case of *PCB* and to *ever had sex* in the case of *binge drinking* (see Statistical Analysis section above). Therefore, *PCB* and *binge drinking* were removed from the network analysis. Networks were also fitted with the full set of analysis variables to test the impact of removing *PCB* and *binge drinking* and the results were unchanged. See Tables S4 to S9 in the online supplementary materials, for the weighted adjacency matrices for the depression severity and depression symptom networks and also for the full set of variables, with none removed.

Network associations with depression severity

The variables associated with *depression severity* in the main network model (gamma=0.25) were, with edge weights shown in brackets, *part of school* (0.28), *relationship with mother* (0.23), *relationship with friends* (0.13), *impulsivity* (0.14), *gender* (0.11), *energy levels* (0.16), and *self-assessed weight* (0.04). See Figure 1 for the depression severity network graph and Table 2 for the legend of node labels and explanatory variables. For *part of school, relationship with mother, relationship with friends,* and *gender*, the associations were negative, implying that a lack of school connectedness, lower scores on the relationship scales, or being female were independently associated with higher *depression severity*. *Impulsivity* was positively associated, meaning higher *impulsivity* scores were correlated with higher *depression severity* scores.

For *energy levels* and *self-assessed weight,* the signs were undefined in the network graphs, but post hoc testing indicated that the two highest levels of *self-assessed weight* ('a little overweight' and

[6] These scores of 6 and 7 corresponded to scores of 16 and 17 in this study as each depression symptom was measured from 1 to 3 and in the Meehan et al. (2008) study it was measured 0 to 2, as is more common.

‘overweight’) were associated with higher *depression severity* scores, and for *energy levels* the depression severity scores increased as *energy levels* decreased in a linear trend.

The edge *relationship with mother—depression severity* had the highest edge recovery rate. It was recovered in all the bootstrap samples (100% reliability), followed by *impulsivity—depression severity* (94%). The edges between *depression severity* and *energy levels, relationship with friends*, and *part of school* all had rates close to or over 80%, and so were estimated somewhat reliably. The edges *self-assessed weight—depression severity* and *gender—depression severity* were estimated much less reliably, being recovered in just over half of the bootstrap samples.

When gamma was raised to 0.5, all edges with depression severity remained, apart from the ones with *gender* and *self-assessed weight* which were shrunk to zero. See Table 3 for edge weights, direction of associations (where defined), and edge recovery rates of those explanatory variables associated with depression severity.

<Figure 1 colour version>

<Table 2>

<Table 3>

Network associations with individual depression symptoms

Relationship with mother shared an edge with the largest number of symptoms in the main network model (gamma=0.25), namely *alone* (0.07), *not work out* (0.09), *sad* (0.07), and *self-hatred* (0.10). *Relationship with friends* shared an edge with two symptoms: *not enough friends* (0.13) and *does things wrong* (0.04). *Delinquency*, *part of school*, *self-assessed weight*, and *hours online* shared an edge with one symptom (see Figure 2 for the depression symptom network graph). Edge weights between depression symptoms and explanatory variables were generally much lower in the depression symptom network, with most edge weights between 0.04 to 0.10, except for *part of School – not enough friends* (0.29), followed by *relationship with friends – not enough friends* (0.13).

<Figure 2 colour version>

All associations between depression symptoms and *relationship with mother, relationship with friends*, and *part of school* were negative, implying that lower scores on the relationship scales or a lack of school connectedness were independent risk factors for the symptoms they shared an edge with. The association between *delinquency* and *does things wrong* was positive, implying higher *delinquency* scores were a risk factor for *does things wrong*. The signs for *self-assessed weight—looks* and *hours online—self* were undefined in the network graphs, but post hoc testing indicated that the two highest levels of *self-assessed weight* (‘a little overweight’ and ‘overweight’) were risk factors for the symptom *looks* and spending 7 or more hours online was a risk factor for *self-hatred*.

In terms of reliability, the highest edge recovery rate was for *self-assessed weight – looks* (92%), followed by *relationship with mother—self-hatred (78%), relationship with friends – not enough friends* (78%). See Table 4 for edge weights and recovery rates of those variables associated with at least one depression symptom.

<Table 4>

Centrality

Centrality measures were calculated for the depession symptoms. *Alone* had the highest centrality score by far, for all three measures (Strength, Betweenness, and Closeness) followed by *self-hatred* and *sad*, whose scores were almost identical for Strength. *Self-hatred* had a slightly higher Betweenness score and *sad* a slightly higher Closeness score. See Figure S1 in the online supplementary materials for the centrality plot.

Discussion

This study was conducted with a community (non-clinical) sample and the mean scores for *depression severity* and depression symptoms are comparable with those from other studies into adolescent depression with community samples. The mean *depression severity* scores for males and females were similar to those in another study, based on a subsample of 13-year-olds in Ireland (Meehan et al., 2008). Comparing the mean depression symptom scores of *alone*, *sad*, *cry*, *self-hatred*, *love*, and *not enough friends*, these were lower in this study compared with a study of US adolescents (Mullarkey et al., 2019), and higher compared with a study of adolescents in the Netherlands (Gijzen et al., 2021), with the exception of *not enough friends*, which was about the same in the Netherlands study.

Relationship with mother, relationship with friends, part of school, delinquency, self-assessed weight, and *hours online* were all associated with at least one depression symptom, but the symptoms they were associated with varied substantially. Some symptoms, for example, *cry* or *love* were not associated with any explanatory variables. These findings support the network model of psychopathology that depression symptoms are not all equal in terms of their impact on depression and that potentially clinically valuable information is lost in terms of possible symptom specific interventions when depression is measured as a sum score (Borsboom, 2008; Borsboom & Cramer, 2013; Fried & Nesse, 2015; McNally, 2016). Variable associations between depression symptoms and risk factors have been shown in other studies with adults (Lux & Kendler, 2010), including in a network analysis with young adults (Fried, Nesse, Zivin, Guille, & Sen, 2014), but to the author's knowledge this is the first study to show this amongst adolescents.

A poor-quality mother-child relationship was arguably the highest risk factor for depression for this group of Pacific adolescents. In the depression severity network, *relationship with mother* was the only explanatory variable to have an edge recovery rate of 100%. Other studies have also found that the quality of parental relationships and level of family functionality are important determinants of childhood and adolescent depression (Nishikawa, Sundbom, & Hägglöf, 2010; Paterson et al., 2014). In the depression symptom networks, *relationship with mother* was associated with four symptoms, but only two of these associations were reliable (based on edge recovery rates), *relationship with mother—self-hatred* and *relationship with mother—alone*. These two symptoms also had the highest centrality scores (along with *sad*). Based on the network model of psychopathology, that depression symptoms are likely to be causally related and reinforcing and triggering each other, it has been argued that designing interventions aimed at symptoms with high centrality could have many beneficial knock-on effects for other symptoms (Borsboom & Cramer, 2013). *Relationship with father* was indirectly negatively associated with both *depression severity* and depression symptoms, through its positive correlation with *relationship with mother*, and so was also important in terms of depression risk. The findings from this study and others emphasize the importance of quality parental (or primary caregiver) relationships at all stages of a child's life.

High quality relationships with friends and school connectedness came through consistently and reliably as protective factors against depression, and vice versa, that is poor quality or lack of friendships or absence of school connectedness were risk factors. Other research into adolescent depression has also found similar links between the strength of close friendships and more positive outcomes, including more resilience and less depression symptoms (Bukowski et al., 1996; Narr, Allen, Tan, & Loeb, 2019). The association between school-related factors and adolescent depression supports findings from other studies (Kim et al., 2021; Paterson et al., 2014), including in recent meta-analyses (Clayborne et al., 2019; Finning et al., 2019; Tang et al., 2019). What is perhaps more noteworthy in this study is how important friends were to feeling part of school and the strength of the associations between school connectedness, friends, and depression. *Relationship with friends* and *part of school* were both negatively associated with *depression severity* and the symptom *not enough friends*. *Not enough friends* was the only symptom to be reliably associated with two explanatory variables. The edge weights for *part of school–depression severity* and *part of school–not enough friends* were the highest in their respective networks. Another school related variable, *get along teachers*, was not associated with either *depression severity* or any depression symptoms. A network analysis of symptoms of depression amongst Korean preadolescents found a strong association between school dislike and lack of friendship (Kim et al., 2021), yet a network study with US adolescents using the same symptom items did not (Mullarkey et al., 2019). The authors of the Korean study theorised that, compared to their American peers, Korean children may be more likely to develop depression because of a fall out with friends or lack of friendships because of the more collectivist culture in East Asian countries (Kim et al., 2021). There is some empirical evidence that Pacific people hold more collectivist views than NZ Europeans (Podsiadlowski & Fox, 2011), and this could be, at least in part, responsible for the strong relationships between school connectedness, friendships and depression. Depression was indirectly negatively associated with *attend school* through the positive association between *attend school* and *part of school*, The results from this study imply that maintaining positive friendships could be an important factor in continuing to attend secondary school and so could be a focus for any programmes aiming to keep adolescents at school for longer; although this study was cross-sectional, so causality cannot be assumed.

Impulsivity was positively associated with *depression severity* for both gamma values and with a high level of reliability and this supports findings from other adolescent depression studies (Piko & Pinczés, 2014; Regan, Harris, & Fields, 2019), plus a recent meta-analysis that found that self-regulation (similar to impulsivity) in childhood was a predictor of depressive symptoms in adulthood (Robson, Allen, & Howard, 2020). Furthermore, in the depression severity networks, *impulsivity* was the bridging node between *depression severity* and *delinquency* (and *negative peer influence).* Based on evidence that has shown that targeting bridging nodes may cut connections with undesirable outcomes (Jones et al., 2018; Solmi et al., 2020), planning interventions that reduce impulsivity could potentially have many beneficial consequences, including reducing the risks for the development of depression and engaging in delinquent behaviours. In the depression symptom networks, *delinquency* was a risk factor for the depression symptom *does things wrong* and *impulsivity* was indirectly associated with this symptom through its positive association with delinquency. Encouraging more self-reassurance and less self-criticism has been found to be protective against depressive symptomatology for adolescents (Barcaccia et al., 2020). However, this study was cross-sectional, so the direction of the association is unknown, also the reliability of the *delinquency—does things wrong* edge was low. Future longitudinal studies could help identify causality, with respect to impulsivity, delinquency, and depression.

Gender was weakly associated with depression severity: the edge recovery rate for *gender–depression severity* was low, and this edge disappeared in the gamma=0.5 network model. *Gender* was also not directly associated with any depression symptoms but was indirectly associated with the symptom *not enough friends*. Based on results of past studies (Carlson & Cantwell, 1980; Ivarsson, Svalander, & Litlere, 2006; Kandel & Davies, 1982; Maughan et al., 2013; Paterson et al., 2018) and results from New Zealand surveys, (see Introduction) (Fleming et al., 2020), the expectation may have been for a stronger association between *gender* and depression in the networks. The relatively weak association (between *gender* and the depression measures) in this study could be the result of the conditional dependencies the network models are based on. Some of the explanatory power of *gender* appears to have been reduced due to *gender*'s shared variance with other factors, several of which were very significantly correlated with *depression severity* and depression symptoms. See Tables S10 to S13 in the online supplementary material for the zero-order correlation matrices of the analysis variables in the depression networks and the associated P values (unadjusted for multiple testing).

Energy levels had a relatively strong relationship with *depression severity,* in terms of edge recovery rates and edge presence for both gamma values (0.25 and 0.5). Associations between fatigue and depression are supported in other studies (Lundervold et al., 2013) and it is a common presenting symptom of those with Major Depressive Disorder (Targum & Fava, 2011). It was not associated with any depression symptoms, however, which was most likely because of the variance it shared with a number of other variables, reducing its explanatory power. For example, in the zero order correlation matrices, *energy levels* was significantly associated with every depression symptom. See Tables S10 to S13 in the online supplementary material for the zero-order correlation matrices of the analysis variables in the depression networks and the associated P values (unadjusted for multiple testing).

Self-assessed weight was weakly associated *depression severity*, but had a more reliable and consistent relationship with the depression symptom *looks*: it had the highest edge recovery rate amongst the associations with symptoms (92%) and the edge was maintained when gamma was raised to 0.5. Interventions targeting dissatisfaction with body image have been proven to decrease depressive symptoms in both sexes (Bearman, Stice, & Chase, 2003).

Online hours was associated with the symptom *self-hatred*, and other studies have also found screen time (Boers et al., 2019) or social media use (Riehm et al., 2019) are risk factors for adolescent mental health, but the edge recovery rate for this association was low, so this finding is not really interpretable without replication.

Neither *money for food*, the deprivation indicator, or *resilience* were found to be associated with depression severity or any depression symptoms, which goes against findings from other studies (Carbonell et al., 2002; Lorant et al., 2007; Ostler et al., 2001; Poole, Dobson, & Pusch, 2017; Remes et al., 2019; Skrove, Romundstad, & Indredavik, 2013) including New Zealand health statistics (Ministry of Health, 2021a). The lack of association in this study could be because the sample was relatively homogeneous, both in terms of area and individual deprivation (see Methods section, subhead Source data and participants, and Results section, subhead Summary characteristics). A study by Fagg et al (2006) also found no significant associations between material deprivation and mental illness and thought the reason might lie in the low level of socio-economic disparity in their sample (Fagg, Curtis, Stansfeld, & Congdon, 2006). It is not clear why *resilience* was not associated with any depression measures. It was associated with *depression severity* in the zero-order correlation matrix (see Tables S10 to S13 in the online supplementary material), but even then, only weakly. Perhaps the inventory used to measure *resilience* did not capture the true variability of this construct across the sample, but more investigation would be needed before any conclusions drawn.

Limitations

One of the main limitations of the current study was its cross-sectional design, meaning causality could not be established. It was also largely exploratory and was not testing any hypotheses, but it did have clear aims. Most of the variables were self-reported and there were issues with missing data. These issues were partially overcome by removing participants with too much missing data and imputing with a suitable multiple imputation method, but the participants removed from the analysis had, on average, lower impulsivity, and spent less time online. The *depression severity* scores and scores for the symptom *cry* were higher in the full year-17 sample (N=632) compared to the analytic sample (n=561). Data on other mental disorders, such as anxiety spectrum disorder and post-traumatic stress disorder, were not available for this study, and the physical health data were self-reported, other than BMI. Depression is often comorbid with other mental and physical health conditions (Mimura, 2001), and it is possible that the associations with depression found in this study could be the result of such comorbidity. The community sample was relatively homogeneous in terms of age, socio-economic status, ethnicity, and location (all lived in Auckland), so may not generalize to other populations or clinical samples.

Conclusion

This study used network analysis to discover the risk factors for depression amongst a sample of Pacific adolescents. It measured depression both as a single latent construct and in terms of individual symptoms. The results showed that there was much variation in terms of how risk factors presented in terms of symptoms. Measuring depression in terms of a single construct is still important for diagnostic purposes, for example, but much potentially useful information is lost if only the sum of depression symptom scores is used. Most of the associations with depression identified in this study, such as *relationship with mother*, *relationship with friends*, *school connectedness*, and *impulsivity*, support those from other studies (Bukowski et al., 1996; Narr et al., 2019; Nishikawa et al., 2010; Paterson et al., 2018; Piko & Pinczés, 2014; Regan et al., 2019; Tang et al., 2019), but this study identified associations with these risk factors at the symptom level, and this additional information could be useful in helping to shape treatment strategies and tailor make intervention programmes, for individuals or groups based on their risk factor - depression symptom profiles.

Supplementary materials
See folder Supplementary material PIF Study 17

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Declaration of interests

☐ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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