Examining Links Between Individual Depressive Symptoms, Indicators of Socioeconomic Status, and Stressors

Platania, Noemi

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Noemi Marianna Platania

Supervisor: Dr. Eiko Fried

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Abstract

Individuals with a lower socioeconomic status (SES) are at an increased risk for developing depressive symptoms. However, it has not been investigated whether this link is homogenous, or whether specific depressive symptoms relate to SES differentially. In this thesis, I explored (1) which individual symptoms of depression are related to subjective social status (as a proxy for SES); (2) how specific indicators of SES are related to specific symptoms of depression; and (3) how the addition of stressors impacts the relations between SES indicators and depressive symptoms. I used data previously gathered from 448 students aged ≥18 at institutions of higher education in the Netherlands, as a part of the WARN-D study. Variables were assessed through a questionnaire that was administered online. I estimated three regularised partial correlation networks to explore shared variances among nine symptoms of depression, five indicators of SES, and seven stressors. The network analyses revealed that (1) subjective social status (as a proxy for SES) was negatively associated with guilt/worthlessness, depressed mood, anhedonia, trouble concentrating, and feeling tired, meaning that participants with higher scores on subjective social status had, on average, lower scores on these symptoms; (2) educational level (as one of multiple indicators of SES) was negatively associated with appetite disturbances, and the ability to get by financially was negatively associated with depressed mood, guilt/worthlessness, and appetite disturbances; (3) these associations diminished considerably or disappeared altogether when controlling for the stressor variables. Overall, all SES-depression associations were small in magnitude. The results suggest that patterns of depressive symptoms might differ between high-SES and low-SES individuals. Future research should explore the mechanisms behind these differences to guide prevention and intervention. My findings are consistent with previous research showing that symptom composite scores obscure important differences between individuals.

Keywords: depression; socioeconomic status; individual depressive symptoms; network analysis

Layman's Abstract

Previous research has shown that people with a lower socioeconomic status (SES; meaning people with fewer resources such as income) are more likely to be depressed than those with a higher SES. However, depression can show up as many different symptoms, and it has not been researched which specific symptoms of depression are more common among people with a lower SES. To explore this, I used a method called network analysis. This method allows us to find the relationships between many different variables at once. I used data gathered from 448 students aged 18 and over at institutions of higher education in the Netherlands. The variables I examined were measured with a questionnaire that participants filled in online. In total, I calculated three networks. In the first network, I wanted to find out how the way in which participants judge their own social status (known as subjective social status) relates to nine different symptoms of depression. In the second network, I included four more measures of SES, to see whether they each had distinctive or similar relationships with the symptoms of depression. In the third network, I additionally included seven different stressors, such as participants' feelings of stress related to their finances. I did this to find out if part of the relationship between SES and depression could be explained by the increased stress that comes with having a lower SES. Overall, I found that some, but not all symptoms of depression had a relationship with some, but not all indicators of SES. For instance, I found that participants' educational level was negatively related to appetite problems, meaning that the lower a participant's level of education, the more likely they were to have appetite problems. These relationships were much smaller in the final network which included stressors. My results suggest that people with a lower SES might have different patterns of depressive symptoms than people with a higher SES. Future research should explore why this might be the case, and how this can be avoided.

Examining Links Between Individual Depressive Symptoms, Indicators of Socioeconomic Status, and Stressors

The association between socioeconomic status (SES) and depression has been found consistently, in a large body of literature (see e.g., Assari, 2017; Freeman et al., 2017; Lorant, 2017). Individuals with less income, lower educational attainment, and lower social standing are disproportionately affected by depressive disorders such as major depressive disorder and dysthymia. However, both SES and depression are complex, multifaceted constructs, which makes the underlying causal associations of this relationship difficult to identify and target.

Thus far, research investigating the link between SES and depression has operationalised depression as a single composite score. However, various authors have proposed that the use of such composite scores obscures relevant information, such as differences between individuals, and that depressive symptoms should be analysed individually (see e.g., Borsboom & Cramer, 2013; Fried & Nesse, 2014; Fried & Nesse, 2015). Establishing how SES interacts with specific depressive symptoms might help to clarify the mechanisms behind the SES-depression link, which is an essential step in the quest of designing both psychosocial and political/economic interventions for the prevention of mental health disparities.

The term "depression" is an umbrella term that is often used to refer to specific disorders, such as major depressive disorder. However, evidence suggests that rather than being categorical, depression exists on a continuum from healthy to critically depressed (Fried et al., 2022). As such, I will consider the full range of this continuum in this paper. Additionally, there can be sizable variations in the symptom presentation of individual patients (Fried & Nesse, 2015), as well as differences in the psychometric properties of depression questionnaires across groups defined by e.g., age (Nguyen et al., 2004) and SES (Williams et al., 2007). When attempting to disentangle the SES-depression link it may therefore be worthwhile to focus on a specific population, such as students.

The SES-Depression Link in Students

Students in higher education are at substantial risk for developing depressive symptoms (Auerbach et al., 2016). This risk is significantly higher for students with a more disadvantaged SES, even in high-income countries (Van de Velde et al., 2021). In the Netherlands, where we collected the data for this study, the introduction of the so-called “social loan system” in 2015, abolished the basic monthly grant that all students in higher education used to receive. This has had detrimental effects on students’ financial security, especially for students from low-income families (van den Berg & van Gaalen, 2018; van den Berg, 2020). Such financial difficulties

might lead to vicious cycles, in which symptoms of depression exacerbate students' financial situation, which in turn exacerbates their symptoms of depression (Richardson et al., 2015).

In the following, I first discuss how conceptualising depression as a network might further our understanding of the SES-depression link, before examining how to best measure SES in students and identifying potential mechanisms and confounders behind this link.

Depression as a Network

The practice of measuring depression as a composite score is based on the common cause theory, according to which psychological disorders drive the manifestation of symptoms and are thus the reasons why these symptoms covary (Caspi & Moffitt, 2018). When using composite scores, we assume that depressive symptoms are interchangeable indicators of depression. However, unlike the more widely applied common cause theory, the network theory of psychopathology posits that symptoms are not manifestations of a latent cause, but that disorders arise from interactions between symptoms themselves (Fried & Cramer, 2017). In other words, symptoms covary because of the network of relationships between them, much like organisms in an ecosystem. According to the network theory, such networks can be activated by external conditions (Borsboom, 2017). For instance, SES-related worry might bring about insomnia, which might lead to tiredness and concentration problems, triggering low mood and further worry.

When examining the SES-depression link using a composite score of depression, such processes remain unexplored. Instead, network theorists can use statistical network models to investigate the relationship between SES and each individual depressive symptom, while controlling for the relationships of the symptoms with each other. This method is called network analysis, and its application could give a clearer insight into the possible driving mechanisms behind the SES-depression link in students.

Measuring Student SES

Much like depression, the construct of SES is by no means unambiguous. It is a broad term encompassing an individual's access to economic, social, and cultural resources (Cowan et al., 2012). SES is usually operationalised as a composite score of income, occupation, and educational attainment (Braveman et al., 2005). When measuring SES in students, their parents tend to be used as proxies for these three variables (Rubin, 2012). This indirect approach has been criticised because it is more informative about students' parents than about students themselves. For instance, it does not account for students who are independent of their parents, or who do not know their parents' income, educational attainment, and/or occupation (Rubin et al., 2014).

Although such traditional measures of SES provide important information about students' social class, supplementing them with other types of measures could provide a more comprehensive and nuanced assessment of students' SES. For instance, subjective social status (SSS) assesses individuals' sense of position in the social hierarchy. SSS likely involves a combination of reflected appraisals and social comparisons (Aneshensel et al., 2013). Measures of SSS can provide more contextual insight into students' social class than objective measures of SES, and they relate more directly to students than measures relating to their parents' income, education, or occupation (Rubin et al., 2014). Lower SSS was found to be associated with depressive symptoms in Germany (Hoebel et al., 2017), a country that is socioeconomically similar to the Netherlands (Alvarez-Galvez, 2016).

Neighbourhood characteristics such as air pollution have also been suggested as a supplemental measure of student SES (Rodriguez-Hernandez et al., 2020). Research indicates that individuals with a lower SES face higher concentrations of air pollutants in most of the world (Hajat et al., 2015). Results in Europe are more mixed, suggesting the need for a more rigorous examination of the SES-air pollution link (Hajat et al., 2015). In the Netherlands, low-SES neighbourhoods appear to have higher levels of air pollution on average (Fecht et al., 2015). Higher levels of air pollution are associated with a higher prevalence of depression in the Netherlands (Generaal et al., 2019; Helbich et al., 2020), but this relationship has not been investigated in students.

Different indicators of SES appear to reflect different phenomena in mental health inequalities, as evidenced by their independent association with mental health outcomes (Saegert et al., 2006; Schlax et al., 2019). Consequently, assessing these different indicators simultaneously might be more informative than merging them into a composite score or operationalising SES as a single indicator. To my knowledge, there are no existing papers examining various indicators of (student) SES as a system using network analysis.

Potential Mechanisms and Confounders Behind the SES-Depression Link

The exact mechanisms of the relationship between SES and depression are still unclear, but stress exposure has emerged as a leading contender of a principal mechanism (Miech & Shanahan, 2000; Swartz et al., 2017). According to Pearlin's (1989) social stress theory, having a lower SES leads to higher stress exposure, which in turn increases the risk of subsequent mental illness. There is considerable evidence to support these two relationships. Individuals with a lower SES are exposed to more stressors and experience those stressors as more distressing than individuals with a higher SES (Businelle et al., 2014; Cohen et al., 2006; Lantz et al., 2005); increased stress exposure is an important predictor of depression (Van Praag et

al., 2012); and stress has been identified as a partial mediator of the relationship between SES and depression in various populations (Businelle et al., 2014; Foubert et al., 2021). Accordingly, stressors might be valuable additions to network models of SES and depression, given that they might explain some of the variance in both SES indicators and depressive symptoms.

According to Crenshaw's (1991) intersectionality theory, the interrelationships between SES and various other measures of social stratification and identity, such as gender or race, need to be considered to accurately investigate how systems of power influence the lives (and mental health) of marginalised groups. For instance, among women living in Germany, lower SES was associated with greater emotional distress in Turkish immigrants, but not in native Germans (Aichberger et al., 2012). Such mental health disparities appear to be primarily a result of identity-related stressors such as discrimination and structural inequalities, rather than of the identities themselves (Seng et al., 2012). Therefore, when examining the SES-depression link in students, it could be important to account for measures of identity-related stress.

Present Study

In this study, I aim to identify which specific symptoms of depression are related to SES by estimating three network models. In the first model, subjective social status (SSS) is used as a proxy for SES. In the second model, multiple indicators of SES are used to detangle the relationship between the symptoms of depression and the following aspects of SES: subjective (SSS), neighbourhood-level (air pollution), parental (parental education), educational (highest completed level of education), and financial (ability to get by financially). Finally, in the third model, I explore how the addition of stressors impacts the relations between indicators of SES and symptoms of depression.

To this end, I analyse data collected as a part of the WARN-D study, a research project aiming to predict depression in students before it occurs. During the baseline survey, students in the Netherlands (*N* = 448) provided detailed information about themselves, including their mental health and their financial situation. Using this data, I model three regularised partial correlation networks, which were designed to uncover unique shared associations in multivariate data (Epskamp & Fried, 2018). To my knowledge, the topics presented above are largely uninvestigated thus far. Therefore, the present study is primarily exploratory in nature.

Methods

Participant Characteristics

Participants (N = 448) were recruited through advertisements on social media, email newsletters, posters, and word-of-mouth. Participants were included if they were students who (a) were enrolled at Dutch institutions of higher education (MBO, HBO, or WO degrees), (b)

were at least 18 years old, (c) were fluent in reading English or Dutch, (d) had a European bank account with an IBAN, and (e) owned a smartphone with an iOS or Android operating system. The exclusion criteria were current (a) schizophrenia, psychosis, or thought disorder, (b) major depressive disorder, (c) (hypo)mania/bipolar disorder, (d) primary substance use disorder, and (e) moderate or severe suicidal ideation. Additionally, participants were excluded if they (f) indicated that seeing an estimate of their daily calories burnt would be stressful to them (likely in the context of eating disorders).

The study protocol was approved by the ethics committee of the European Research Council and by the Psychology Research Ethics Committee at Leiden University (No. 2021-09-06-E.I.Fried-V2-3406). All participants provided written informed consent.

Design

The data used in this study were gathered as part of WARN-D, a five-year research project aiming to predict depression in students before it occurs. The project consists of four cohorts and three stages per cohort: a 90-minute baseline survey, three months of ecological momentary assessment, and two years of follow-up surveys. Data in the present study were collected during the first cohort's baseline survey, which was administered online using the Qualtrics survey software. Participants had the choice to complete the survey in Dutch or in English. They will be compensated up to 90€ for their participation, proportional to the number of surveys completed.

Measures

All measures used in this study are listed in full in the Supplementary Materials. The WARN-D team is currently building a repository of open measures, which will also include the Dutch translations of all measures.

Depressive Symptoms

The Patient Health Questionnaire (PHQ-9) assesses the frequency of the symptoms of depression using nine scales from 0 (not at all) to 3 (nearly every day; Spitzer et al., 1999). The PHQ-9 has good psychometric properties, with high criterion validity and test-retest reliability (Kroenke et al., 2010), and was validated in university settings (Keum, 2018). In the WARN-D baseline survey, an adapted version of the PHQ was used, which splits some of the items into two, for a total of 15 items: "Poor appetite or overeating" was separated into "Poor appetite" and "Overeating"; "Feeling down, depressed or hopeless" was separated into "Feeling down or depressed" and "Feeling hopeless"; "Trouble falling asleep, staying asleep, or sleeping too much" was separated into "Trouble falling asleep or staying asleep" and "Sleeping too much"; and "Moving or speaking so slowly that other people could have noticed. Or, the opposite –

being so fidgety or restless that you have been moving around a lot more than usual" was separated into "Moving or speaking so slowly that other people could have noticed" and "Being so fidgety or restless that you have been moving around a lot more than usual". For the purposes of this thesis, these items were transformed back into their original format by taking the maximum score of each split pair. The goal of this was to minimise the total number of nodes in the networks since the sample size in this study limited the number of parameters that could be reliably estimated.

Indicators of SES

Subjective Social Status. The MacArthur Scale of Subjective Social Status (Adler et al., 2000) is a single-item measure assessing an individual's perceived status (in terms of income, jobs, and education) in relation to other members of society. This scale is face-valid, intuitive, and has good convergent validity with objective measures of SES (Adler et al., 2000) and good predictive validity in relation to depression (Hoebel et al., 2017). It has been shown to be reliable and valid across various populations (Cundiff et al., 2011; Giatti et al., 2012; Goodman et al., 2001), including university students (Rubin, 2020). Participants were presented with a picture of a ladder representing the social ranking of society, with the highest rung (10) representing "people who are the best off" and the lowest rung (1) representing "people who are the worst off". Then, they were asked to select the rung that best represents where they stand on the ladder, on a scale from 1 to 10.

Highest Completed Level of Education (Own). Participants were asked about their highest completed level of education. There were seven response categories, ranging from "secondary school diploma" (3) to "doctoral degree" (9). This item was conceived by the WARN-D team.

Highest Completed Level of Education (Parents). Participants were asked about the highest completed level of education that their parents or the people who raised them obtained. There were 9 response categories, ranging from "none" (1) to "doctoral degree" (9). This item was conceived by the WARN-D team.

Ability to Get By Financially. Participants were asked about their usual financial situation at the end of the month. Response categories were "I usually don't have enough money to get by" (1), "I usually have just enough money to get by" (2), and "I usually have some money left over " (3). This item was adapted from the Netherlands Study of Depression and Anxiety (Penninx et al., 2008).

Air Pollution. In 2009, the concentration of air pollutants in the Netherlands was measured by the European Study of Cohorts for Air Pollution Effects (Cyrys et al., 2012). This

data was used to predict pollution concentrations at the address level. In the present study, I used the annual concentration of the mean blackness of $PM_{2.5}$ filters (in 10^{-5} /m) as a proxy for air pollution. The data is from 2009, but there is evidence that $PM_{2.5}$ levels remain stable over periods of 10+ years (Cesaroni et al., 2014). Air quality data was retrieved from the Geoscience and Health Cohort Consortium. This information was linked to participants' four-digit postal codes for those participants who consented to this and who resided in the Netherlands (95.09%).

Stressors

Struggle with Gender identity and Sexual Orientation. These two constructs were measured with the following items conceived by the WARN-D team: "Has your [sexual orientation/gender orientation] led to significant struggles in your life? Struggles are broadly defined, including both internal struggles (e.g. self-discovery, identity issues) and external struggles (e.g. stigma, negative reactions)". Both items were measured on a Likert scale from 1 (not at all) to 7 (extremely).

Subjective Integration into Dutch Society. Participants were asked how well integrated they feel into Dutch society and culture, on a scale from 1 (not at all) to 7 (completely). This item was conceived by the WARN-D team.

Global Stress. Participants were asked how much stress they currently experience in their "life overall", on a scale from 0 (none) to 4 (very severe). This item was adapted from the Caring Universities Project (2022).

Financial Stress. Participants were asked how much stress they currently experience in their "financial situation", on a scale from 0 (none) to 4 (very severe). This item was adapted from the Caring Universities Project (2022).

Perceived Discrimination. The Everyday Discrimination Scale (EDS) attempts to capture routine, chronic, experiences of discrimination in nine items (Williams et al., 1997). For example, items include "You are treated with less courtesy than other people are" and "People act as if they think you are not smart". The response categories range from 0 (never) to 5 (almost every day). In this study, frequency-based coding was used, meaning that each response was given a value based on the Likert scale, before being summed across items. This produced a final EDS score per person, ranging from 0 to 45, with higher scores relating to more experiences of discrimination. The relationship between EDS scores and depressive symptoms is robust to this kind of frequency-based coding (Michaels et al., 2019). The EDS exhibits good construct validity for race-based discrimination (Clark, 2004; Krieger et al., 2005), but to my knowledge, its validity for other types of discrimination has yet to be investigated.

Feelings of Safety. Participants were asked how safe they feel in their daily lives, on a scale from 1 (not at all) to 7 (extremely). This item was borrowed from the World Health Organisation Quality of Life BREF (World Health Organisation, 1998).

Data Analyses

All statistical analyses were performed using the open-source statistical software R (v4.1.2). Prior to conducting the analyses, all variables were standardised. After excluding variables not relevant to the analyses, only 0.91% of data were missing in total. For demographic and psychometric variables, 1.33% and 0.64% of data were missing, respectively. For the item assessing air pollution, 4.91% of data were missing, mostly because air pollution data for participants who indicated a non-Dutch address were not available. All networks were estimated using pairwise complete observations, which deals well with small amounts of missing data (Burger et al., 2022). All analyses were planned a priori.

I estimated three regularised Gaussian Graphical Models (GGMs), one for each research aim (see Table 1 for an overview), using the R-package *bootnet* (Epskamp et al., 2018). Regularisation involves estimating models while balancing parsimony and fit, meaning that edges are only included if they improve the fit of the model to the data. To regularise the models, I used the graphical least absolute shrinkage and selection operator (LASSO). This LASSO results in small edge estimates being set to exactly zero. When using the graphical LASSO, the sparseness of a network is controlled by the tuning parameter λ. Higher values of λ result in fewer edges being removed from the model, and thus in a less sparse network. I selected the value of λ using the Extended Bayesian Information Criterion (EBIC). The EBIC, in turn, uses a hyperparameter γ that controls how much the EBIC prefers sparser models. γ is usually set between 0 and 0.5, with higher values indicating that sparser models are preferred. To ensure more parsimonious and interpretable models, I set γ to 0.5. Since most of the variables were measured on ordinal scales and many of the distributions were heavily skewed, Spearman correlations were used to estimate the networks (Epskamp & Fried, 2018).

In order to visualise the network structures, I used the R-package *qgraph*, which uses the *glasso* package in combination with EBIC model selection (Epskamp et al., 2012). The layout of the networks was calculated by the Fruchterman-Reingold algorithm, which ensures that nodes with more and stronger connections are placed closer together, whereas those with fewer and weaker connections are placed further apart (Fruchterman & Reinhold, 1991).

For descriptive purposes, I estimated node predictability (R^2), which quantifies how well a node can be predicted by its neighbours in the network (Haslbeck & Fried, 2017). After estimating the networks, I employed a nonparametric bootstrap using 1000 samples to examine

the precision of the edge weight parameters, which results in bootstrapped confidence intervals for each edge (Epskamp et al., 2018). Specificity can be lower than expected in the exploratory estimation of regularised GGMs (Williams & Rast, 2018). Therefore, I conducted a sensitivity analysis using the network estimation method *ggmModSelect*, an unregularised model selection using stepwise estimation.

Table 1

Overview of the Network Models

Model	Nodes	Depression	SES	Stressors
1	10	9 items PHQ	SSS	-
2	14	9 items PHQ	SSS, highest completed education (own), highest completed education (parents), ability to get by financially, air pollution	-
3	21	9 items PHQ	SSS, highest completed education (own), highest completed education (parents), ability to get by financially, air pollution	Struggle with gender identity, struggle with sexual orientation, subjective integration into Dutch society, financial stress, global stress, perceived discrimination, feelings of safety

Note. SES: socioeconomic status; PHQ: Patient Health Questionnaire; SSS: subjective social status

Results

Descriptive Statistics

Of the total sample (*N* = 448), 360 participants (80.4%) identified as female; 71 participants (15.8%) identified as male; 16 participants (3.6%) identified as genderfluid, gender non-conforming, and/or non-binary; and 1 participant (0.2%) did not share their gender identity. The mean age was 22.7 years (SD = 4.0), with an age range of 18 - 53 years. Furthermore, 387 participants (86.4%) were enrolled at research universities (WO); 47 participants (10.5%) were enrolled at universities of applied sciences (HBO); and 14 participants (3.1%) were enrolled at vocational institutions (MBO). About half of the participants were Dutch (50.4%); the other half (49.6%) were non-Dutch and/or had multiple nationalities. The means and standard deviations of all variables included in the models are shown in Table 2.

Table 2

Summary Statistics of all Variables

Variable	*M*	*SD*	Range
SES indicators			
Subjective social status	6.9	1.5	1 (lowest status) - 10 (highest status)
Highest completed education (own)	5.3	2.0	3 (secondary school diploma) - 9 (doctoral degree)
Highest completed education (parents)	6.2	1.9	1 (none) - 9 (doctoral degree)
Ability to get by financially	2.5	0.6	1 (not enough money at the end of the month) - 3 (money left over at the end of the month)
Address-level air pollution	1.5	0.2	0.9 (least air pollution) - 2.2 (most air pollution)
Depressive symptoms			
Guilt/worthlessness	0.8	0.9	0 (not at all) - 3 (nearly every day)
Psychomotor retardation/agitation	0.1	0.3	0 (not at all) - 3 (nearly every day)

Variable	*M*	*SD*	Range
Depressed mood	0.7	0.7	0 (not at all) - 3 (nearly every day)
Anhedonia	0.7	0.8	0 (not at all) - 3 (nearly every day)
Suicidal ideation	0.9	0.6	0 (not at all) - 3 (nearly every day)
Fatigue	1.5	0.9	0 (not at all) - 3 (nearly every day)
Concentration problems	1.1	1.1	0 (not at all) - 3 (nearly every day)
Appetite disturbances	0.5	0.8	0 (not at all) - 3 (nearly every day)
Insomnia/hypersomnia	0.9	1.1	0 (not at all) - 3 (nearly every day)
Stressors			
Subjective integration into Dutch society	5.0	2.0	1 (not at all) - 7 (completely)
Struggle with sexual orientation	2.0	1.5	1 (not at all) - 7 (extremely)
Struggle with gender identity	1.8	1.3	1 (not at all) - 7 (extremely)
Perceived discrimination	5.6	6.0	0 (none) - 45 (very severe)
Feelings of safety	5.7	1.2	1 (not at all) - 7 (extremely)
Financial stress	1.4	1.2	0 (none) - 4 (very severe)
Global stress	1.7	0.9	0 (none) - 4 (very severe)

Note. SES: socioeconomic status.

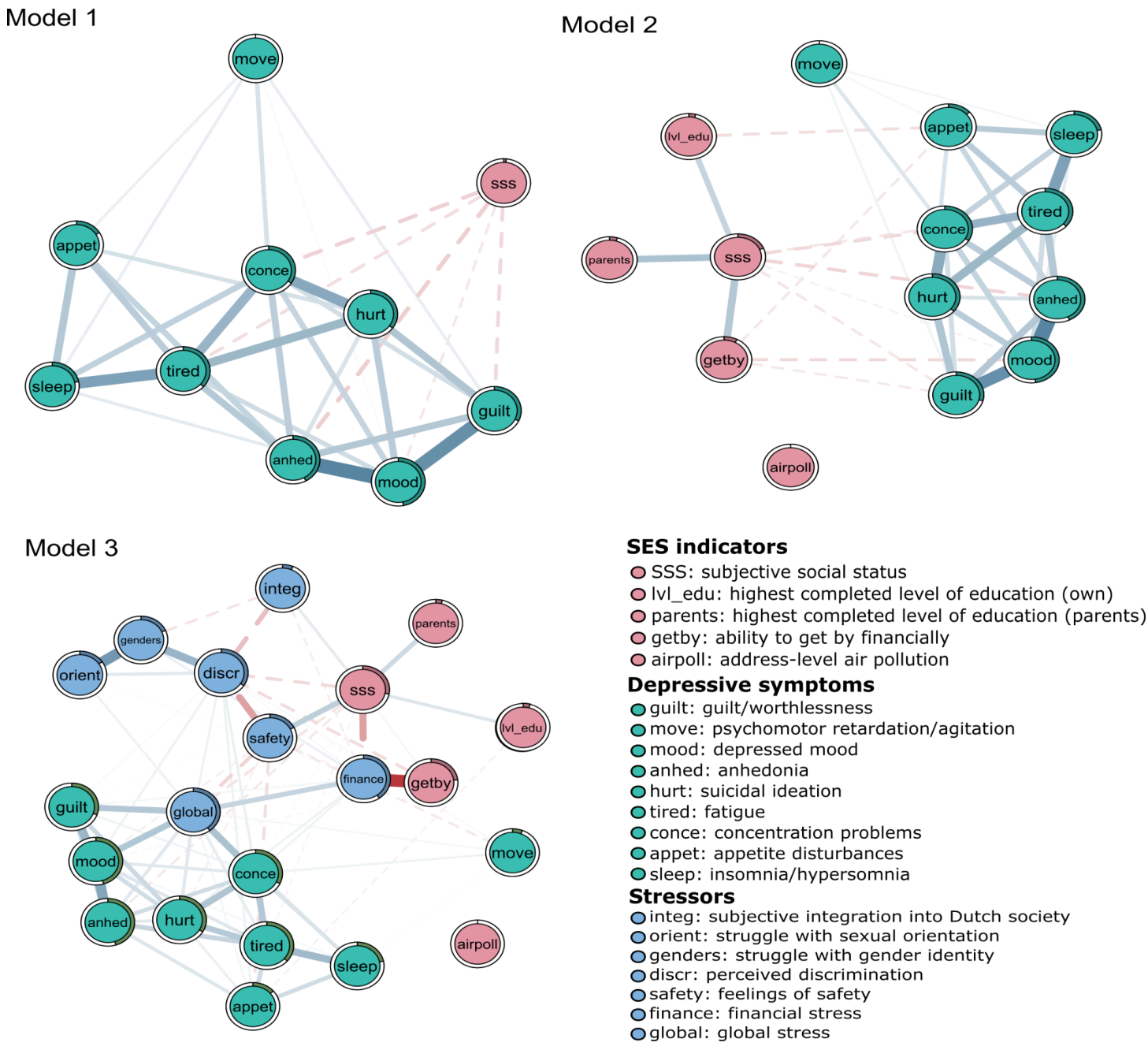
Model 1

The networks for all models are shown in Figure 1. In Model 1, the symptoms of depression were positively correlated amongst each other, the strongest partial correlation being between depressed mood and anhedonia (0.30). SSS was negatively associated with guilt/worthlessness, depressed mood, anhedonia, trouble concentrating, and feeling tired. This means that people with higher SSS scores had, on average, lower scores on those specific depressive symptoms, after controlling for all other variables in the model. These partial

correlations were small, ranging from -0.03 to -0.07, and bootstrap routines revealed that their sizes did not differ significantly from each other (see Supplementary Materials). The mean node predictability was 27%, with depressed mood having the largest shared unique variances with the other variables (47%). SSS had a predictability of 1.6%, meaning that it shared overall little variance with the rest of the nodes.

Figure 1

Illustration of the Network Models



Note. The three models described in this paper. Model 1 portrays the SES-depression link using subjective social status as a proxy for SES; Model 2 disentangles SES into five sub-dimensions; and Model 3 displays the SES-depression link with the addition of stressor variables. Edges represent regularised partial correlations (positive in blue; negative in red and dashed). Thicker edges represent stronger partial correlations. The coloured proportion of the circle around each node represents the amount of variance explained by its neighbours (i.e., predictability).

Model 2

In Model 2, the associations between SSS and the depressive symptoms were attenuated slightly (see Figure 1). This is expected given that (a) adding more variables generally reduces power, and (b) the newly added SES indicators that share variance with SSS may have accounted for part of the SSS-depression link. Of these other indicators, the ability to get by financially was negatively associated with depressed mood, guilt/worthlessness, and appetite disturbances; educational level was negatively associated with only appetite disturbances. All partial correlations between SES indicators and depressive symptoms were small (ranging from -0.02 to -0.05) and did not differ significantly from each other (see Supplementary Materials). Education, getting by financially, and parental education shared positive edges with SSS, with correlations ranging from 0.10 to 0.14. The sizes of these edges also did not differ significantly from each other (see Supplementary Materials). The mean predictability across all nodes was 21.1%. Predictability for SSS increased to 18.9%, which was by far the highest among the SES indicators.

Model 3

With the addition of stressors, the edges between the SES indicators and depressive symptoms were greatly attenuated further (see Figure 1). The sizes of these edges did not differ significantly from each other (see Supplementary Materials). The link between SSS and depressed mood, as well as the links between the ability to get by financially and guilt/worthlessness and appetite disturbances, disappeared. The strongest negative edge was between financial stress and getting by, with a partial correlation of -0.36. This edge had a significantly more negative edge coefficient than all other edges. The strongest positive edge was between struggle with gender and struggle with sexual orientation (0.30), which was significantly stronger than all other edges, except for the five next strongest edges: anhedonia and depressed mood (0.26); struggle with gender identity and discrimination (0.21); guilt/worthlessness and depressed mood (0.21); low energy and sleep problems (0.20); and global stress and concentration problems (0.18). Of the stressors, global stress was the most

connected to the depressive symptoms. Its strongest positive associations were with trouble concentrating (0.18), guilt/worthlessness (0.16), and depressed mood (0.16). These edges differed significantly from the weaker edges in the model (see Supplementary Materials). The mean predictability was 26%. Of the SES indicators, SSS had the highest predictability (28%), followed by the ability to get by financially (23%). Of the stressors, financial (40%) and global stress (39%) had the highest predictability.

Robustness and stability analyses

Estimating the networks via the alternative procedure *ggmModSelect* yielded similar results to the regularised estimation (Spearman correlations among the adjacency matrices ranged between .90 and .77; see Supplementary Materials). Consequently, I only described the results of the regularised GGM here. The stability analyses revealed that 95% confidence intervals (CIs) for most of the edge weights in all three models were of moderate size (for details, see Supplementary Materials). Notably, many of the CIs overlapped, meaning that many of the edge weights probably only differed slightly from each other and their order in the figure must be interpreted with care. Since the networks are regularised, using bootstrapped CIs to test whether edge weights are significantly different from zero is not applicable (Fried, 2018).

Discussion

This study was the first to examine the links between SES and specific symptoms of depression, contrasting prior research based on composite scores. Specifically, I explored (1) which specific symptoms of depression are related to SSS; (2) how specific indicators of SES are related to specific symptoms of depression; and (3) how taking stressors into account impacts the relations between SES indicators and symptoms of depression. My results can be summarised as follows.

When operationalising SES as SSS, the construct was negatively related to guilt/worthlessness, depressed mood, anhedonia, trouble concentrating, and feeling tired, all measured over the past two weeks. In other words, participants with lower SSS scores had higher average scores on those specific symptoms, and those with higher SSS scores had lower average scores. All SSS-depression links were small. The differences between the relations were not significant, so we cannot say which symptoms of depression had the strongest link with SSS.

Splitting the measurement of SES into multiple indicators revealed a more complicated picture: the ability to get by financially was negatively related to depressed mood, guilt/worthlessness, and appetite disturbances; educational level was negatively related to appetite disturbances. The associations between SSS and depressive symptoms became

somewhat smaller. This may have been a result of the difference in the number of variables between the first and the second model. Since the second model included more variables, its power to detect relationships was smaller. Additionally, the added variables shared variance with SSS, which may have accounted for part of the associations between SSS and the depressive symptoms.

With the addition of stressors into the model, the relationship between SSS and depressed mood, as well as the relationships between the ability to get by financially and appetite disturbances and guilt/worthlessness, disappeared. All remaining SES-depression links diminished considerably. Instead, relations emerged between SES and stressors, and between symptoms and stressors.

The results of this study are consistent with prior research showing that symptoms of depression differentially relate to diverse variables (e.g., Aalbers et al., 2018; Fried et al., 2019; Skjerdingstad et al., 2021). This underlines the importance of modelling the symptoms of depression separately rather than as a composite score in future investigations (Fried & Nesse, 2015). Furthermore, this study provides more evidence for the previously established link between SES and depression in students (Ibrahim et al., 2013). In our sample, this link was non-homogenous: the symptoms of depression had differential relationships with different indicators of SES, and some were not associated with any of the indicators.

The current study was the first to examine the interrelationships between intersectional stressors, SES indicators, and depressive symptoms. The finding that the links between SES and depression attenuated substantially or disappeared altogether when stressors were added into the analysis is consistent with the social stress hypothesis, according to which increased stress among those with a lower SES partially explains the SES-depression link (Pearlin, 1989). However, it is important to note that this finding could also be due to the fact that the addition of the stressor variables reduced the power of the final analysis. Presumably, the relationships between indicators of SES, symptoms of depression, and stressors are highly multicausal and multivariate, so more research is needed to investigate them, particularly when it comes to their causality (see limitations).

The question remains where SES-symptom links come from. It could be that depression influences SES, or vice-versa, or that both influence each other. Furthermore, it could be that a third variable, such as stress, influences both SES and depressive symptoms. The cross-sectional nature of my analyses limits the conclusions that can be drawn about this (see limitations). However, we must consider that the depressive symptoms were measured over the past two weeks, whereas the indicators of SES were measured globally. Additionally, most

students have limited control over their SES, since they tend to be dependent on their parents (Rubin, 2012). These two details imply that it is unlikely that the depressive symptoms influenced SES unidirectionally.

It is more likely that the SES-symptom links found are a result of the adversities that accompany living with financial difficulties. For instance, it has been suggested that financial hardship imposes a cognitive load (Mani et al., 2013), which could affect the ability to concentrate. Similarly, low SES is associated with increased hunger (Dykes et al., 2003; Hill et al., 2016). This might be due to an accumulation of (SES-related) stress, which can cause neurobiological changes in appetite (Adam & Epel, 2007). It is possible that such symptoms resulting from financial difficulties act as bridge components between low SES and depression, activating an interconnected network of depressive symptoms and explaining why depressive disorders are more common among individuals with a lower SES. Future research should seek to understand these mechanisms and how they might be averted.

The specific relationships different SES indicators had with distinct depressive symptoms suggest that various aspects of SES could have varying consequences for the manifestation of depression. This also implies that using SES sum scores when investigating the SES-depression link may obscure relevant information. Notably, of the SES indicators, SSS had the most associations with depressive symptoms, which is in line with the idea that much of the SES-depression link can be explained by individuals' subjective SES (Mehravar et al., 2021). However, it could be that these associations are a partial result of endogeneity. In other words, it is possible that SSS captures not only subjective social status but also aspects of mental health (Collins & Goldman, 2008).

Measuring Student SES

This study is the first to explore (student) SES as a network, and my results have several implications for future research on SES in students. First off, I used SSS as a proxy for SES for my first research question. This decision appears to have been justified. SSS shared edges with all other SES indicators, except for air pollution, and it had the highest predictability among the SES indicators. These findings support previous notions that SSS may be a more comprehensive way of assessing SES than objective measures (Hoebel et al., 2017), especially in students (Rubin et al., 2014). This could be because when students rank their SSS, they consider their entire financial context, including e.g., debts, inheritances, and social support, which is difficult to measure and usually remains unassessed.

To my knowledge, this study was also the first to use air pollution data as a measure of SES in students. Air pollution was not associated with any of the other variables in the models.

This is surprising because higher air pollution has been shown to be linked to elevated levels of depression (Generaal et al., 2019; Helbich et al., 2020) as well as lower SES (Hajat et al., 2015) in the Netherlands. This inconsistency might be because the variance in air pollution was relatively low. Furthermore, air pollution was measured using participants' current postal code, but students are less likely to have a permanent residence than average individuals. Additionally, the data for this study were gathered during the COVID-19 pandemic. The address that participants provided may not have been the place in which they had spent most of their time in the months prior to data collection, especially because about half of our sample consists of international students. Due to the extraordinary circumstances of this study, future research should investigate whether air pollution is indeed an invalid measure of student SES when examining the SES-depression link.

The finding that there were differential relationships between the various SES indicators and the depressive symptoms demonstrates the value of measuring student SES multidimensionally in mental health research. Further investigations into which other dimensions of student SES may be relevant to include when exploring the SES-depression link are necessary.

Implications

This paper adds to the amassing evidence for the link between economic inequality and mental health disparities. Such evidence suggests that if we are serious about the prevention of depression, reducing inequality must be one of our primary targets. Downstream psychological approaches like psychotherapy and medication must be complemented with upstream interventions which might involve targeting e.g., structural racism, the medicalisation of mental illness, and the current economic paradigm (Macintyre et al., 2018). Additionally, further research on the prevention of poor mental health, which currently receives low levels of funding (Wykes et al., 2015), is imperative.

The results of this study suggest that the SES-depression link is more complex than previously assumed. The relationships between the indicators of SES and various depressive symptoms were non-homogenous. This implies that individuals with a lower SES might have different patterns of depressive symptoms than those with a higher SES, with different underlying mechanisms. By lumping all individuals displaying certain symptoms together under the broad diagnosis of "depression", we assume that SES-related distress can be corrected through the same therapeutic or medical interventions as any other distress. Instead, an awareness of the complexity of both depression and SES should contribute to treatment decisions. For instance, psychotherapists could assist clients in the realisation that many

psychopathological symptoms may have societal origins; Smail (2016) terms this fostering "outsight" rather than insight.

Strengths and Limitations

The results of this study must be interpreted in light of several limitations. The sample was relatively homogenous, with most participants being female research university students with few financial worries on average. This means that the generalisability of my findings may be limited, but also more defined for the specific population described in this paper. The fact that even the relatively slight differences in SES in this sample resulted in mental health disparities raises the question of how much stronger this relationship might be in more socioeconomically diverse and/or clinical samples.

This study was also limited by the participant sample size. Depending on the number of parameters included, network models require a large sample size for reliable estimation. Since the number of participants available for this study was relatively modest, I had to make some decisions to limit the number of variables in the models. Firstly, I aggregated some of the depressive symptoms in bidirectional items (e.g., increased and decreased appetite). This obscured insight into the detailed relationships with those symptoms. Secondly, I only included five indicators of SES in the models, even though other indicators, such as work status, sources of income, and satisfaction with finances, were available in the dataset. This might be problematic because when a variable with strong connections to two or more nodes in a network is left out of a model, the remaining associations in the network may be considerably changed (Epskamp et al., 2018). Despite these two decisions, Model 3 in this study is underpowered, meaning that smaller effects may not have been detected. Future investigations with larger sample sizes might benefit from including a larger variety of both SES indicators and depressive symptoms in their network models. Since the dataset used in this study included only the first of four cohorts in the WARN-D project, the analyses in this paper could be repeated at the end of the WARN-D data collection phase.

Furthermore, there are limitations that come with attempting to capture a construct as ambiguous as depression. The PHQ-9, which was used as a measure of depressive symptoms, consists of nine items that correspond to the nine symptoms of major depressive disorder as listed in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013). However, there are many other symptoms, such as anger or anxiety, which are common among individuals diagnosed with major depressive disorder (Judd et al., 2013). Including such symptoms in my analyses may have provided a more complete portrayal of the SES-depression link but was not possible due to the small sample size.

Moreover, PHQ-9 symptoms like sleep problems or suicidal ideation are complex and would warrant assessment with more than a single item each (Fried et al., 2022).

All analyses in this paper were based on cross-sectional data, limiting inferences that can be drawn. As discussed above, the findings of this study alone cannot determine whether targeting socioeconomic inequality could reduce depressive symptoms. However, we can interpret these findings in light of previous research suggesting that the relationship between SES and mental health disparities may be causal (e.g., Diaz et al., 2014; Ridley et al., 2020; Schubert et al., 2016). On the other hand, there is also evidence that the relationship between health and SSS arises from effects operating bidirectionally (Nobles et al., 2013). For instance, it is plausible that depressive symptoms affect SSS since they might lead to a worse subjective appraisal of socioeconomic status. Longitudinal research applying network approaches to the SES-depression link is needed to confirm my findings and to establish the direction(s) of effects.

Notwithstanding these limitations, this study is the first to apply network methodology to the SES-depression link. As such, its results are primarily exploratory, but can be used to generate future hypotheses about the SES-depression link. The data were gathered using an online questionnaire, meaning that social desirability bias was likely low since such bias occurs primarily when interviewers are involved (Hoebel et al. 2014). Additionally, the symptoms of depression were assessed over the previous two weeks, limiting recall bias.

Conclusion

In a global political environment of growing inequalities in wealth, education, and income, SES has emerged as a crucial determinant of depression, but the mechanisms of this association have not been explored in detail. With this paper, I aimed to contribute to this by beginning to detangle the SES-depression link. I hope that my results encourage further efforts to approach this link from more complex angles, and ultimately, to build an economic system in which mental health is prioritised over profit.

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