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# Exploring the longitudinal clustering of lifestyle behaviors, social determinants of health, and depression

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## Abstract

Lifestyle behaviors such as exercise, sleep, smoking, diet, and social interaction are associated with depression. This study aimed to model the complex relationships between lifestyle behaviors and depression and among the lifestyle behaviors. Data from three waves of the Midlife in the United States study were used, involving 6898 adults. Network models revealed associations between the lifestyle behaviors and depression, with smoker status being strongly associated with depression. Depression, smoker status, age, time, and exercise were some of the most central components of the networks. Future lifestyle intervention research might prioritize specific behaviors based on these associations and centrality indices.

## Keywords

adults, depression, health behavior, lifestyle, physical activity, protective factors, sleep, smoking, social interaction, socio-economic status

Lifestyle behaviors are an important contributor to both physical and mental health (Murray et al., 2013; Sarris et al., 2014; Walsh, 2011). Systematic, meta-analytic, and narrative reviews demonstrate that there are consistent associations between mental health and behaviors such as exercise, diet, social interaction, time spent in nature, relaxation or meditation and substance use (Ashdown-Franks et al., 2020; Hoang et al., 2019; Lassale et al., 2019). Further, trials involving lifestyle interventions indicate that lifestyle change can improve mental health (Firth et al., 2019; Schuch et al., 2016), suggesting directional or causal relations. However, the direction of the relationships between these major lifestyle behaviors and mental health conditions are complex because theory and empirical work indicate that mental health conditions, particularly depressive disorders, have an apparently reciprocal

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effect on many lifestyle behaviors (e.g. exercise predicts reduced depressive symptoms, while depressive symptoms predict reduced exercise; Bao et al., 2017; Pereira et al., 2014). Further complicating the interpretation of previous findings, theory has argued that lifestyle behaviors influence each other and there is evidence that lifestyle behaviors cluster together (e.g. physical activity promotes healthy diet; Anderson & Fowers, 2020; Egger et al., 2019; Meader et al., 2016). Social determinants of health such as income and racial discrimination also impact health behaviors and outcomes as well (Braveman and Gottlieb, 2014). Regression models, with their inherent directional emphasis may fail to account for the complexity of these associations and may not be able to identify the most influential variables in the model. As such, the objective of this study is to build on previous research by looking at simultaneous associations among multiple lifestyle behaviors, social determinants of health, and depression using network models and longitudinal data.

## *Bidirectional relationships between depression and lifestyle behaviors*

Theoretical and empirical research demonstrate bidirectional relationships between depression and four lifestyle behaviors relevant to this study: physical activity, sleep, social interaction, and smoking.

*Depression and physical activity.* Depression has been theorized to lead to reduced physical activity via the anhedonia, slowed cognition, and low energy that characterize depression (Jerstad et al., 2010; Roshanaei-Moghaddam et al., 2009). Alternatively, exercise has been theorized to have positive impacts on mental health through a variety of biological (e.g. neurogeneration, inflammation, oxidative stress, endocrine functioning) and psychological mechanisms (e.g. self-esteem, social support, self-efficacy; Kandola et al., 2019). In general, longitudinal studies found bidirectional relationships between physical activity and depression (e.g. Azevedo Da Silva et al., 2012; Pereira et al., 2014), although the evidence is mixed (e.g. Choi et al., 2019).

*Depression and sleep.* Depression and sleep impairment are both characterized by impaired Hypothalamic-pituitary-adrenal (HPA) axis and neurotransmitter functioning (Bao et al., 2017; Wulff et al., 2010). In fact, sleep impairment is one of the symptoms of major depressive and other mood disorders (American Psychiatric Association [APA], 2013). The comorbidity of depression and insomnia may have common underlying factors such as increased arousal, which is implicated in both conditions (Staner, 2010). Sleep deprivation and depression are also both associated with similar daily patterns of cortisol levels (Adam et al., 2017). Low levels of serotonin, as well as a shared genetic basis related to the 5' regulatory region of the serotonin transporter gene, further supports the associations between depression and sleep disturbance (Cowen and Browning, 2015; Deuschle et al., 2010). Another conceptual model linking depression and insomnia frames dopamine dysregulation as a central factor such that depression may lead to dopamine dysregulation which impacts arousal and sleep (Finan and Smith, 2013). There is no consensus on the mechanisms or directions by which incident depression or insomnia might lead to the other disorder, although there is longitudinal evidence from meta-analyses showing bidirectional associations between depression and sleep in older adults (Bao et al., 2017) and college students (Dinis and Bragança, 2018).

*Depression and social interaction.* Various mechanisms may link depression with social interaction. In their review, Cruwys et al. (2014) argued that "depression is a fundamentally social disorder, with reduced social connectedness implicated as a cause, symptom, and target for treatment of depression" (p. 215). Depressed individuals have an underlying dysfunction in avoidance and approach activity patterns and as a result fail to engage positive activities such as social interaction (Trew, 2011). Behavioral activation, an efficacious treatment for depression, focuses on increasing approach behaviors and reducing avoidance goals in an effort to help the

person have positive experiences which will lead to increased approach motivations (Jacobson et al., 2001). While perceived social integration (i.e. social support, a sense of belonging) seems to be more closely tied to depression than objective social interactions (i.e. social contacts, social network size), both are associated with depression (Wade and Kendler, 2000). Notably, social interactions have been associated with later social support, which in turn was associated with depressive symptoms (Peirce et al., 2000). Bidirectional, longitudinal associations between social disconnectedness and depression/anxiety (mediated by perceived isolation) were found in a sample of adults (age 57–85; Santini et al., 2020), underscoring the need to consider bidirectional interactions

*Depression and smoking.* Some research has shown that depression and smoking also have strong positive associations across a range of research designs (e.g. Chaiton et al., 2009; Weinberger et al., 2017). It has been argued that depression, which often involves negative mood, might lead to smoking as a form of self-medication given that smokers often report mood enhancing effects while smoking (Munafò and Araya, 2010). At the same time, smoking may affect neurotransmitter functioning and involve mood-related withdrawal symptoms, which can contribute to depressive symptoms (Picciotto and Mineur, 2014). Some longitudinal research supports the argument that smoking leads to later depression (Boden et al., 2010), but findings from a systematic review indicate that the current understanding of direction of causation is not clear (Fluharty et al., 2017).

## *Lifestyle behavior clustering*

Both theory and previous research posit that lifestyle behaviors influence each other and there is evidence that lifestyle behaviors cluster together, meaning that individuals who engage in a particular lifestyle behavior tend to engage in other behaviors. For example, exercise and smoking can predict sleep quality (positively for exercise and negatively for smoking; Brook et al., 2015; Kishida and Elavsky, 2016) while insomnia can in turn negatively affect social interaction (Hom et al., 2017), and chronic loneliness can positively predict smoking (Kobayashi and Steptoe, 2018). A systematic review demonstrated further associations of relationships among lifestyle behaviors, with alcohol and tobacco co-occurring with the greatest frequency (Meader et al., 2016).

Looking beyond paired associations, past research indicates that multiple lifestyle behaviors cluster together, meaning that they tend to co-occur with each other and are thus not independent. One theoretical model argues that "anthropogens"–man-made environments and lifestyle behaviors that can affect health and well-being–are also expected to impact engagement in other behaviors (Egger et al., 2019). Studies have shown that behaviors do cluster together, with some behaviors, including sleep, being more central within the network of behaviors (Nudelman et al., 2019). A systematic review also found evidence of clustering among four common lifestyle behaviors (smoking, nutrition, alcohol, and physical activity; Noble et al., 2015). Almost universally, research on lifestyle clustering occurs at the between-person level (variations/associations across individuals), without regard to the within-person level (variations/associations within individuals over time). One notable exception is Chevance et al. (2020) who explored within-person associations in some health behaviors following a weight management intervention. This study found that when people consumed less sugar than their average, they also consumed less fat than their average. Another exception was (Anderson & Fowers, 2020) who identified lifestyle clustering at the daily level across 14 days, where higher-than-average time spent in nature was associated with higher-than-average social interaction and exercise. In sum, the theoretical and empirical research indicate that lifestyle behaviors are associated with each other, and that multiple behaviors often cluster together, but there is less support at the within-person level.

### Social determinants of health

Social and economic factors also play a role in lifestyle behaviors, with socioeconomic status being negatively associated with positive health behaviors. In Nudelman et al.'s (2019) study on behavior clustering, there were some differences in the most central behaviors between males and females and between low SES and high SES individuals. At the environmental level, there is a linear relationship between socioeconomic depravation and the geographic clustering of businesses or outlets that support unhealthy behavior such as establishments providing fast food, tobacco, gambling, and alcohol (Macdonald et al., 2018). Systematic reviews have also found consistent associations between risk behaviors and both occupational status (Meader et al., 2016) and SES (Noble et al., 2015). Further, in one large longitudinal study, risk factors for all-cause mortality were disproportionately harmful to individuals who were of lower SES (Foster et al., 2018). Thus, the economic factors that might underly any behavior clustering must be accounted for. In light of the complexity of these relations, observational research seeking to explore how lifestyle and mental health are associated should account for the impact of social determinants of health.

### The present study

While there is significant evidence for bidirectional associations between lifestyle behaviors and depression, as well as clustering among the lifestyle behaviors, research which accounts for all of these relationships simultaneously is needed. Following the approach of Chevance et al. (2020) who investigated changes in behavior over a 1-year period as part of a weight-loss intervention, this study sought to build off of previous research by utilizing network models (Epskamp and Fried, 2018) to explore simultaneous associations between the behaviors and depression at the within- and between-person levels using three waves of surveys across two decades in a large sample of adults in the U.S. As such, this study builds on previous research by looking at the clustering of all of these factors in a national longitudinal dataset.

## Methods

### Data

Participants for this study were drawn from the Midlife Development in the United States (MIDUS) longitudinal panel study. This was a high-quality probability sample of adults in the contiguous United States, aged 25–74 years old ($M = 47$) at the first of three waves of data collection. The first wave of data collection occurred between 1995 and 1996, with a second wave occurring between 2004 and 2006 and a third wave between 2012 and 2014. Random digit dialing was used to recruit a representative sample, which was also accompanied by a selection of siblings, oversamples of five urban cities, and a national sample of twins (total $N = 7108$). Seventy 5% ($n = 4963$) of the Wave 1 sample completed the Wave 2 phone survey, adjusted for mortality (Radler and Ryff, 2010). And 78% of Wave 2 completers also participated in Wave 3 ($n = 3924$) and of those, 2425 completed the self-administered questionnaire, which included many of the relevant variables for this study. A screening of the smoking variables showed discrepancies in 210 participants responses, wherein they reported a history of smoking at one wave and no history of smoking at a later wave. As such, these participants were excluded from the analysis, resulting in a sample of 6898 participants.

### Measures

Trained interviewers, who received 20 hours of general and study-specific training, administered the depression measure and smoker status item by phone, while the other items being collected by self-administered questionnaires. For the variables that were measured at each time point, the person mean centered values were included in the within-person analyses while the person means were included in the between-person analyses. Descriptive statistics are listed in Table 1.

**Table 1.** Participant characteristics.

| | Available data | | Imputed data ($n = 6898$ per imputation) | Completers' data (n = 2005) |
|---|---|---|---|---|
| | % | *n*= | % | % |
| Female | 51.49 | 6896 | 51.50 | 53.17 |
| Minority status | 9.50 | 6062 | 9.82 | 4.67 |
| Depression W1 | 13.25 | 6898 | 13.25 | 11.99 |
| Depression W2 | 10.58 | 4753 | 10.69 | 10.33 |
| Depression W3 | 9.90 | 3132 | 9.44 | 8.41 |
| Smoker status W1 | 23.24 | 6898 | 23.24 | 16.11 |
| Smoker status W2 | 16.05 | 4753 | 15.52 | 13.19 |
| Smoker status W3 | 9.74 | 3132 | 9.91 | 9.09 |
| | *M* (SD) | | *M* (SD) | *M* (SD) |
| Age | 46.38 (12.98) | 6895 | 46.35 (13.00) | 44.52 (10.60) |
| Income W1 | $73,303 ($64,868) | 5921 | $73,248 ($64,821) | $84,944 ($66,697) |
| Income W2 | $71,494 ($60,434) | 3690 | $73,451 ($63,200) | $81,052 ($61,323) |
| Income W3 | $87,843 ($73,508) | 2591 | $83,496 ($69,607) | $93,148 ($73,142) |
| Exercise W1 | 43.03 (15.56) | 6073 | 43.66 (17.70) | 45.42 (13.85) |
| Exercise W2 | 74.03 (47.01) | 3501 | 69.06 (44.08) | 77.36 (44.22) |
| Exercise W3 | 77.37 (48.06) | 2561 | 81.34 (46.59) | 78.51 (47.57) |
| Social W1 | 3.05 (1.26) | 6035 | 3.04 (1.26) | 2.95 (1.21) |
| Social W2 | 3.02 (1.28) | 3817 | 3.02 (1.27) | 2.91 (1.23) |
| Social W3 | 2.98 (1.27) | 2742 | 3.01 (1.27) | 2.93 (1.25) |
| Sleep problems W1 | 1.38 (1.66) | 6059 | 1.39 (1.66) | 1.31 (1.58) |
| Sleep problems W2 | 2.10 (1.77) | 4006 | 1.99 (1.77) | 2.01 (1.73) |
| Sleep problems W3 | 2.25 (1.77) | 2759 | 2.32 (1.79) | 2.19 (1.74) |

*Depression.* As part of the telephone interview, the participants completed a version of the World Health Organization's Composite International Diagnostic Interview Short Form (Kessler et al., 1998), which was based on the third edition of the Diagnostic and Statistical Manual of Mental Disorders (APA, 1987). Participants were asked if, over the past 12 months, they had a period of 2 weeks where they felt sad or blue for all or most of the day for all or most days. If they screened positive, they then reported on anhedonia and depressed affect during those 2 weeks. If they reported feeling either of those symptoms at least most of the day on almost every day or more, they were then screened for other symptoms such as feeling down, changes in appetite, or low energy. If the participant reported anhedonia or depressed affect and four other symptoms, they were coded as having had a depressive episode. The short-form version was shown to have high sensitivity and specificity relative to the full Composite International Diagnostic Interview (Kessler et al., 1998), which itself has demonstrated high interrater reliability, but has received some criticism for potentially resulting in false positives (Kurdyak and Gnam, 2005).

*Physical activity.* As part of the self-administered questionnaire, participants reported on how often they engaged in moderate or vigorous physical activity. In Wave 1, this included a total of four items, asking about each intensity of physical activity in summer and winter. In

Waves 2 and 3, physical activity was measured with twelve items: moderate or vigorous activity related to work, leisure, or chores, in both summer and winter. These 12 items were reduced to four items by summing the three domains of physical activity (work, leisure, or chores) for both vigorous and moderate exercise. Then for all waves, the summer and winter vigorous activity variables were averaged and then multiplied by a metabolic value (7), while the summer and winter moderate activity variables were averaged and then multiplied by a different value (5) to represent metabolic units (Buchner, 2010). Finally, these weighted values were summed to represent average physical activity. The values were standardized within each wave for the network models to aid in cross-wave comparisons.

*Smoking.* Participants were asked if they currently smoke cigarettes. Cigarette smoker status was listed as either 1 (current smoker) or 0 (current non-smoker) for each wave. These values were person-mean-centered for within-person analyses and the person means were included for between-person analyses.

*Sleep complaints.* Participants reported on how often they had trouble getting to sleep or staying asleep during the past 30 days. The response options included "Almost every day," "Several times a week," "Once a week," "Several times a month," "Once a month," and "Not at all." Responses were coded such that values ranged from 0 ("Not at all") to 5 ("Almost every day").

*Social interaction.* Two items were used to measure social interaction behaviors. The two items are "How often do you have any contact, even something as simple as saying 'hello', with any of your neighbors?" and "How often do you have a real conversation or get together socially with any of your neighbors?." Responses were on a 6-point continuum (1 = almost every day; 6 = never or hardly ever). Previous research used this composite variable to demonstrate longitudinal associations between social interaction and eudaimonic well-being (Greenfield and Reyes, 2014).

*Income.* Participants reported their total household income at each wave.

*Racial/ethnic minority status.* All participants reported on their racial and ethnic status. White, non-Hispanic participants were the reference group (coded as 0) and participants who were racial or ethnic minorities were coded as 1.

*Time.* The wave number was also included in the analyses (scaled to 0, .5, and 1) to assess the influence of the passage of time on the other variables in the within-person network models. For example, a negative within-person association between physical activity and time would indicate that as people age, they exercise less.

## Analyses

This dataset included a mixture of variable types, with some dichotomous (smoking, depression) some continuous (income) and some ordinal (sleep problems). The variables were person centered for the within-person model and the person-means were calculated in the between-person model. Because most network model software is focused on one type of data (all dichotomous/binary or all continuous normal) we utilized the BGGM package (Williams and Mulder, 2020) in R (R Core Team, 2021) and RStudio (R Studio Team, 2020), which can analyze mixed data types. Similar to other software, the network models produced by BGGM are correlations controlling for the other variables in the model (partial correlations). The Bayesian approach of BGGM results in estimated posterior means, standard deviations, and credible lower and upper bounds.

To visualize the network models, partial correlation matrices obtained from BGGM were graphed with the package qgraph (Epskamp et al., 2012). When the percentile-based 95% credible interval of the edge estimates failed to include 0, they were represented as a line in the network model. Solid edges represent a positive association between pairs of variables while dashed edges represent negative associations. The thickness of the lines represent the size of

the association, with thicker lines representing larger partial correlations.

Two different models were run: a between-person network model and a within-person network model. The between-person network model represents the partial correlations between the averages of the lifestyle behaviors, depression, and other variables. To carry out this model, participant means of each variable were obtained by averaging the variables across the three waves of data. This model explored how average levels of variables, across a 20-year span, are associated with each other. For example, do people who have a history of smoking across those 20 years also tend to have a history of depression? The second model, the within-person network model, represents the associations between the study variables at each wave, after subtracting out the person-means from the three waves of data (see Costantini et al., 2019). This process results in three waves of person-centered variables for each participant. The within-person network model can, for example, can be used to examine whether fluctuations around each participant's mean of exercise in a given wave are associated with fluctuations in the participant's sleep – or in other words, if someone is exercising more than their average at a certain wave, do they also have better quality of sleep than their average?

Along with the direction and size of associations, it was also of interest to assess the centrality of the variables in the network. Strength centrality indices were calculated to observe which variables are most central within the networks, meaning that they have many connections to the other variables. Although there are many forms of centrality, strength has assumptions that fit psychological/behavioral network models better than other indices (Bringmann et al., 2019). Strength centrality is a calculation of the absolute edge weights for each node, such that the value is a composite of all associations (positive or negative) a node has with other nodes.

To handle missing data, multilevel multiple imputation was conducted with the mice package (van Buuren and Groothuis-Oudshoorn, 2011) using the available data. Sensitivity analyses were also completed using participants who provided complete data on all three waves of data. The network models described in the manuscript are based on fifteen imputed datasets, while the networks using the data from only participants who provided data at all three waves are provided in the supplementary materials. All analyses were conducted with the R statistical software and the statistical code can be obtained at https://osf.io/fhuqz/.

## Results

Demographic variables can be seen in Table 1, with summary statistics given for all available data, for the imputed data, and for completers only. Based off the imputed data participants were on average 46 years old (SD = 12.98), slightly more likely to be female (51.59%), mostly White (91.18%), and had an average salary at Wave 1 of $73,394 (SD = $65,023). At Wave 1, 13.25% of individuals reported being depressed and by Wave 3 that value was 9.67%. About 23% of participants smoked at Wave 1, while 15.52% smoked at Wave 2 and 10.12% smoked at Wave 3. In an investigation of the missing data, minority individuals, lower income individuals, and participants who smoked at Wave 1 were less likely to complete all three waves of data collection. This differential attrition supports the use of the multiple imputation technique.

### *Between-person network*

The between-person network model–based on the partial correlation matrices for person means of the relevant variables–is depicted in Figure 1. The larger effects involving the depression and the lifestyle behavior variables are discussed here, while the complete partial correlation estimates can be seen in the supplementary materials. Based on the weight of the edges, the models revealed that the association between smoking and depression was one of the stronger relationships ($r_p = 0.63$, 95% CI (0.61, 0.64)) – the proportion of waves of being a smoker was associated with proportion of

waves being depressed, controlling for other associations. Depression was also positively associated with sleep problems ($r_p$=0.26, 95% CI (0.24, 0.27)), being female ($r_p$=0.13, 95% CI (0.09, 0.24]) and surprisingly, exercise ($r_p$=0.06, 95% CI (0.04, 0.09)). Exercise was negatively associated with baseline age ($r_p$=−0.35, 95% CI (−0.36, −0.33)), being female ($r_p$=−.21, 95% CI (−0.23, −0.19)), and being a minority ($r_p$=−0.16, 95% CI (−0.18, −0.12)), while it was positively associated with social interaction ($r_p$=0.14, 95% CI (0.13, 0.16)). Social interaction was positively associated with baseline age ($r_p$=0.22, 95% CI (0.21, 0.24)) and racial minority participants tended to have fewer sleep problems ($r_p$=−.12, 95% CI (−0.15, −0.10)).

The strength centrality indices suggested that the most central nodes were depression (1.25), age (1.18), exercise (1.09), and smoker status (0.93). The other nodes, in descending order of centrality, were race (0.90), income (0.87), sleep (0.67), female gender (0.66), and social interaction (0.63).

### *Within-Person network*

As with the between-person network, depression and smoking were strongly positively related at the within-person level ($r_p$=0.54, 95% CI (0.53, 0.55)). This indicates that fluctuations in depression, around one's average chance of being depressed, was positively associated with fluctuations in smoking status. Time had some of the stronger relationships as well including positive associations with depression ($r_p$=0.23, 95% CI (0.22, 0.25)), sleep problems ($r_p$=0.19, 95% CI (0.16, 0.20)), and smoker status ($r_p$=0.14, 95% CI (0.12, 0.15)), indicating that as time progressed, participants were more likely to report depression, sleep problems, and transition to smoker status. Exercise surprisingly had a small positive association with depression ($r_p$=0.02, 95% CI (0.001, 0.04)), while it was also positively associated with social interaction ($r_p$=0.08, 95% CI (0.05, 0.09)), and income ($r_p$=0.05, 95% CI (0.03, 0.07)), and negatively associated with sleep problems ($r_p$=−0.03, 95% CI (−0.04, −0.01]). Besides these associations, there were other small associations which can be seen in the figure and supplementary materials.

The strength centrality indices were highest for depression (0.91) and lowest for social interaction (0.17). Falling between these values were smoker status (0.83), time (0.63), sleep problems (0.45), income (0.20), and exercise (0.19).

## Discussion

Consistent with the extensive prior research on lifestyle behaviors and depression that uses bivariate analyses, the current study's the network models revealed a number of associations between the network nodes. These findings represent an important initial step in exploring the complex ways in which behaviors may influence each other and mental health. Further, we found that certain variables – in particular, smoking – are related to other variables to a higher degree, while some variables – notably social interaction with neighbors–have weaker associations to other components in the network.

In both the between and within-person models, depression and smoking were some of the most central components in the network. Across the within- and between-person models, the centrality indices for the common variables were generally similar with depression and smoker status being high, while social interaction was the lowest. However, exercise was a more central variable in the between-person network model than in the within-person model.

The clustering of lifestyle behaviors in this and previous studies (e.g., Anderson & Fowers, 2020; Nudelman et al., 2019) has potentially useful clinical implications. For instance, if certain behaviors are strongly associated, controlling for all other associations, attempting to intervene on one may potentially bring about changes in the others. As such, this model indicates that smoker status may be the variable that is most highly linked to depression and may be the best target of lifestyle change if depression is the outcome of interest. Viewed from an alternative angle, some behaviors may be

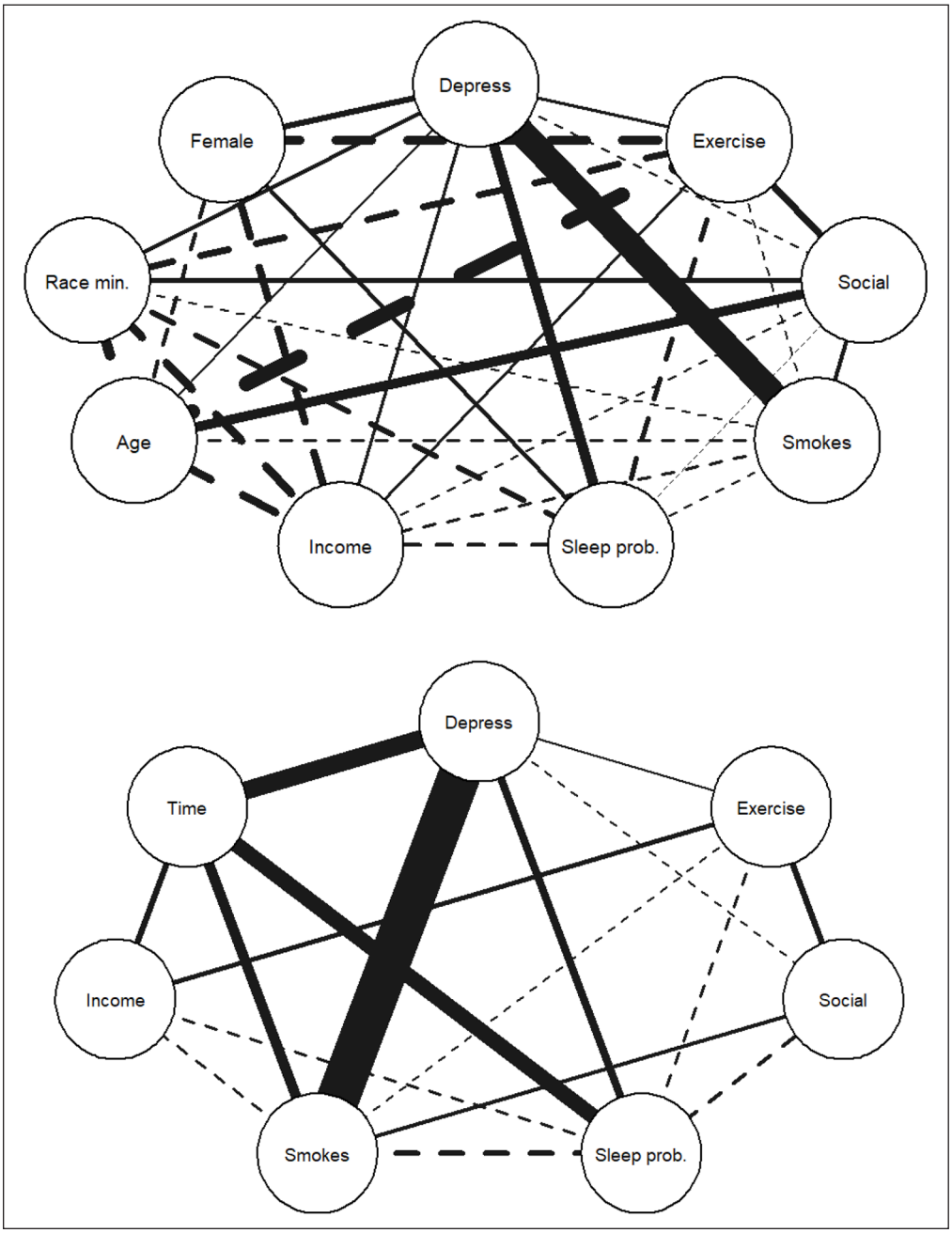


**Figure 1.** Between-person and within-person network model. Nodes (circles) in the top figure represent the between-person variables (averaged across all waves for variables measured more than once). Nodes in the bottom figure represent the within-person variables (person-centered). Edges (lines) represent partial correlations among the variables. The type of the lines indicate the direction of association: solid = positive; dashed = negative. The width of the lines represent the size of the associations: thicker = larger; thinner = smaller. Color versions of these plots are available at https://osf.io/bm3nu/.

resistant to change unless the other highly related variables are also targeted, meaning that if smoker status is the target of change, seeking to directly intervene on smoking might be more effective if depressive symptoms are also treated (Brown et al., 2001). Thus, future research could test whether highly associated nodes can support change in untargeted variables (e.g. smoking cessation treatment leads to reduced depression) or create resistances to change in targeted variables (e.g. smoking cessation will not be successful unless depression is also targeted).

A parallel argument can be made for the centrality indices. If a behavior or condition is highly central, as depression and smoking were, then that behavior or condition may have a disproportionate effect on the rest of the network. As such, future research questions center on whether targeting change in that central behavior or condition may have especially beneficial impact on overall lifestyle profile. Alternatively, it may be better to work on peripheral nodes, which may be more amenable to change because they are less tied to other change-resistant behaviors or disorders. In moving forward to test these hypotheses, the literature on multiple behavior change indicates that focusing on a moderate number of behaviors (e.g. 2–3), rather than too few (1) or too many ($\geqslant$4) tends to have the greatest outcomes (Wilson et al., 2015). The findings from network studies, especially for individualized networks, might guide practitioners in focusing on those two or three behaviors that are core to the network of health.

Income, as one indicator of socioeconomic status, had a positive association with depression at the between person level, but fluctuations in income at the within-person level was not associated with depression. At the within-person level, income was also less central in the network, potentially indicating that change in income, by itself, may not have large effects on this network of behaviors and conditions, but it is important to recognize that even small effects are important in behavior change and health (Paulus and Thompson, 2019). At the between-person level, females were more likely to be depressed, less likely to exercise, more likely to have sleep problems, and tended to have lower incomes. When making sense of the disparities in depression diagnoses across gender (Van de Velde et al., 2010), these models indicate that some of these gender-associated lifestyle behaviors and determinants of health need to be accounted for.

This large-interval longitudinal study shows some of the between-person associations with lifestyle behaviors as well as within-person fluctuations across 8 or 9 years at a time. The within-person data analysis perspective is essential for understanding changes over time, which is missed in analyses focused on between-person associations (Hamaker, 2012). Future research could focus on how to individualize behavior change targets by conducting intensive experience sampling studies to measure lifestyle behaviors and conditions of interest, such as depression, anxiety, and pain. An adequate ($>$40–50, depending on model complexity; Epskamp et al., 2018) number of measurements allows for the creation of personalized network models, showing unique edge weights and node centrality for each person. Using this information, providers could be informed as to what behaviors are most influential within the person's life or potentially, which are more amenable to change. Integrating this form of measurement into personalized lifestyle interventions would be especially enlightening to show changes in the individualized networks over time.

There were some limitations to this study. First, in terms of measurement, many epidemiological studies such as the MIDUS study assess numerous constructs and as such, the measurement of specific constructs may be limited. This was especially the case for sleep problems, which was measured with a single item. Second, the MIDUS surveys involved a significant amount of attrition. The imputation appears to have been generally effective, but there may be some sources of bias in the findings due to loss of participants over the two decades. Self-reported physical activity was measured somewhat differently in Waves 2 and 3 relative to Wave 1, which raises some

concerns. However, longitudinal measurement invariance analyses (available at https://osf.io/fhuqz/) provide evidence that the items performed similarly across waves. Despite efforts to specifically recruit minority participants, the sample was mostly white, with higher household income than the average family. As such, the findings may not be fully generalizable to the U.S. population. Lastly, there were a number of important lifestyle factors that were not assessed in this study (e.g. dietary patterns, sedentary time, and alcohol consumption). If future studies include those variables, we may see changes to the observed network structure, including novel associations and modifications of the associations demonstrated in this study.

Overall, this study elucidates the complex networks of lifestyle behaviors, social determinants of health, and depression. Studies often consider unidirectional relationships between these variables, but a thorough review of the literature commonly reveals bidirectional associations. The use of network models in this study allowed for an examination of how all of these factors are related at the between-person and within-person levels over about two decades, in a large sample of U.S. adults. With certain behaviors having strong bivariate partial correlations and high centrality in the networks (e.g. depression and smoking), future research should examine how lifestyle interventions can be personalized to account for these variables' place within networks of lifestyle and health.

## Data sharing statement

The de-identified individual participant data is available (including data dictionaries) from the Inter-university Consortium for Political and Social Research (https://www.icpsr.umich.edu/web/ICPSR/series/203). All of the individual participant data collected during the study were made available, after de-identification. The author's script for running the data cleaning and analysis in R, analyses output, and an overview of the supporting documentation (https://osf.io/fhuqz/). These files are available in the Figshare repository and as Supplemental Material on the SAGE Journals platform.

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