Lifestyle Behaviors, Psychological Distress, and Well-Being: A Daily Diary Study

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Abstract

Rationale. Many lifestyle behaviors such as diet, exercise, and substance use are related to physical and mental health. Less understood is the day-to-day associations of these behaviors with both psychological distress, well-being, and with each other. *Objective.* This study investigated how several common lifestyle behaviors were associated with psychological distress and well-being using a daily diary study with multilevel modeling. Associations among behaviors were analyzed with multilevel mediation and network models. *Method.* An online participant pool consisting of 76 adults (age range: 19–64; mean age: 40.29; 58% female) completed daily diary surveys over 14 days and reported their engagement in lifestyle behaviors, their psychological distress, and their hedonic well-being and eudaimonic well-being. *Results.* Time spent in social interaction was the most consistent within-person correlate of psychological distress and well-being. The association between daily time in nature and well-being was mediated by social interaction and exercise. Network models found within-person associations among the lifestyle behaviors. *Conclusions.* The results indicate that social interaction may be an especially important lifestyle behavior to consider when promoting well-being. Future research should recognize that daily fluctuations in many lifestyle behaviors cluster together.

Keywords: Lifestyle behaviors; lifestyle medicine; psychological distress; well-being; clustering; network model; social interaction; nature

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Highlights

- Meaningful social interaction is the strongest predictor of same day well-being and psychological distress
- Daily fluctuations in fruit and vegetable intake predicts well-being and psychological distress
- The relationship between time in nature and well-being is mediated by social interaction and exercise
- Daily fluctuations in lifestyle behaviors demonstrate clustering

Introduction

Depression, anxiety, and substance use are among the top 20 contributors to global disability with depression ranked as first (Friedrich, 2017). Lifestyle interventions have been traditionally viewed as an important approach to managing chronic physical illness, but recent reviews have suggested that lifestyle factors are important contributing factors in overall psychological distress (Hoang, Kristoffersen, & Li, 2019; Lopresti et al., 2013; Walsh, 2011) and to depressive disorders specifically (Sarris et al., 2014). Important lifestyle behaviors include exercise, nutrition, substance use, social interaction, time outside, and meditation or relaxation. The quality of evidence for the links with psychological outcomes varies by behavior, but all have been associated with psychological distress in multiple studies. Despite the evidence linking lifestyle behaviors with psychological distress, there is not enough known about the daily processes relating these behaviors to psychological distress and well-being.

Most research in this area relies on traditional long-term longitudinal data to assess aggregated trends in variables over time. Daily diary studies can reduce recall biases and improve measurement accuracy regarding lifestyle behavior benefits (Iida et al., 2012). Daily diary studies can also reveal within-person relationships between the lifestyle behaviors and psychological distress and well-being whereas cross-sectional and most large-interval longitudinal research focuses on analyzing aggregated between-person associations. Pemberton and Tyszkiewicz (2016) reviewed studies of within-person associations between lifestyle factors and depressive symptoms and noted that most studies include only one or two lifestyle behaviors, making it impossible to compare the relative influence of the various behaviors on psychological distress and well-being. They argued that research can be enhanced by the simultaneous assessment of multiple lifestyle behaviors, which can reveal the relative association

of the behaviors with psychological distress. Other theory indicates that lifestyle behaviors may influence each other (Egger, 2018), and, in some cases, there may be mediational relationships linking lifestyle behaviors to psychological distress and well-being. This project investigated multiple healthy and risky lifestyle behaviors simultaneously to assess their relative association with each other and with multiple psychological distress and well-being outcomes.

Psychological Distress and Well-Being

Whereas medical and mental health treatment has historically focused on symptom reduction, scholars have recently incorporated positive functioning or well-being into conceptions of health (Huppert & Whittington, 2003). Hedonic well-being, which is based on satisfaction with life, positive emotions, and low negative emotions, is one example. In contrast, Ryff (1989) advocated for assessing richer elements of well-being, such as purpose, meaning, and personal growth, which is often described as eudaimonic well-being. Some research indicates that hedonic well-being and eudaimonic well-being are substantially statistically correlated but distinct (Joshanloo, 2016). Although several experience sampling studies have found associations between lifestyle behaviors and either psychological distress or one form of well-being (e.g., Flueckiger et al., 2017), these studies do not typically assess both psychological distress and well-being. This study aims to assess how lifestyle behaviors may be differentially linked to psychological distress and well-being in the same sample.

Lifestyle Behaviors

Although many lifestyle factors and behaviors have been associated with health and well-being (Nudelman et al., 2019 measured 37 lifestyle behaviors/factors in a cross-sectional study), this study included a focused set of behaviors that have both theoretical and empirical support. Egger (2018) described an organizing framework for understanding the roles of lifestyle

behaviors and other influences on health and well-being. He identified categories of determinants of chronic disease called anthropogens, which are "man-made environments, their by-products, and/or lifestyles encouraged by these environments" (p. 397). A subset of these categories are expected to influence mental health (nutrition; (in)activity; inadequate sleep; environment; meaninglessness; alienation; loss of culture/identity; drugs, smoking, alcohol; relationships; social inequity). The lifestyle behaviors used in this study map onto most of those categories with fruit and vegetable intake accounting for nutrition, exercise with in(activity), time spent enjoying nature with environment, social interaction with relationships and alienation, mindfulness with meaninglessness, and tobacco use and heavy alcohol use with drugs, smoking, alcohol. The remaining three categories of sleep, loss of culture/identity, and social inequity are less likely to be embodied by specific behaviors, but are more dependent on environmental factors, and, especially for sleep, on other lifestyle behaviors (Mastin et al., 2006).

The selection of lifestyle behaviors for this study also relied on four literature reviews that identified several lifestyle behaviors that have substantial empirical support (Boehm & Kubzansky, 2012; Lopresti et al., 2013; Sarris et al., 2014; Walsh, 2011). Drawing from Boehm and Kubzansky's (2012) model, behaviors were classified as either restorative (exercise, nutrition, social interaction, mindfulness meditation, and time spent in nature) or deteriorative (heavy alcohol use and tobacco use) in relation to psychological distress and well-being. Restorative behaviors contribute to emotion regulation and both biological and cognitive functioning, while deteriorative behaviors impair those factors.

Exercise. Exercise is well known for reducing medical risk, and its benefits for mental health and well-being have also received attention. Biologically, exercise may contribute to improved brain functioning by facilitating brain plasticity, reducing inflammation, reducing

oxidative stress, and regulating the hypothalamic-pituitary-adrenal (HPA) axis (Kandola et al., 2019). Physical activity may also promote self-esteem, self-efficacy, and social support (Kandola et al., 2019). A recent meta-analysis of randomized controlled trials indicated that exercise interventions have a moderate to large impact on psychological distress (Schuch et al., 2016). In Boehm and Kubzansky's (2012) review, a consistent link between hedonic well-being and physical activity emerged, with more mixed associations between eudaimonic well-being and exercise. Choi et al. (2017) explored the within-person associations between a set of lifestyle behaviors and happiness and meaning among Korean adults and exercise was one of the strongest predictors. Flueckiger et al. (2017) also found within-person associations between physical activity and components of hedonic well-being (positive and negative affect) in two student samples.

Nutrition. Recent research supports the protective effects of a diet that has fruits, vegetables, nuts, fish, and low amounts of pro-inflammatory foods such as processed meats (Firth et al., 2019; Lassale et al., 2019). Randomized trials generally support the association between nutrition and psychological distress (e.g. Firth et al., 2019). Longitudinal studies with large representative samples found that fruit and vegetable intake predicted hedonic well-being and eudaimonic well-being in Australia (Mujcic & Oswald, 2016) and mental health and hedonic well-being in the United Kingdom (Ocean et al., 2019). Within-person studies such as Conner et al.'s (2015) found within-person associations between fruit and vegetable intake with curiosity, eudaimonic well-being, creativity, positive affect, and (only for vegetables) negative affect. Purported mechanisms of a diet's influence on well-being include the repair of oxidative stress, the support of brain plasticity, and the influence of diet on the microbiota-gut-brain axis (Parletta et al., 2013).

Social Interaction. There is strong evidence linking social relationships to health, with social integration strongly predicting mortality (Holt-Lunstad et al., 2015), with purported mechanisms including inflammation and immune functioning (Hawkley & Cacioppo, 2010). Feeney and Collins (2015) argued that close relationship supports well-being by assisting with adversity and encouraging the pursuit of positive opportunities. Social interaction, social integration, social support, and quality relationships are negatively associated with cognitive decline, depression, and anxiety (Cacioppo & Hawkley, 2009; Schwarzbach et al., 2014). Studies have also found within-person associations between positive social events and happiness and meaning (Choi et al., 2017; Machell et al., 2015).

Alcohol Use. Although heavy alcohol use predicts psychological distress in many studies (Sarris et al., 2014), light to moderate alcohol use has been negatively associated with depression (Gea et al., 2013). Depression and alcohol use disorders have high comorbidity with the presence of either predicting a two-fold increase in having the other disorder, with pathways from alcohol use to depression being potentially mediated by neuroendocrine functioning and folate metabolism (Boden & Fergusson, 2011). At the daily level, alcohol use has been associated with positive mood in one study, but not for those who tend to drink to cope with difficulties (Steptoe & Wardle, 1999). Very heavy drink sessions predicted lower positive affect on the next day in a sample of college students who filled out daily diary surveys (Polak & Conner, 2012). Heavy alcohol has been negatively associated with eudaimonic well-being in cross-sectional studies, but relatively untested in intensive longitudinal designs (Boehm & Kubzansky, 2012).

Tobacco Use. Nicotine use and dependence were associated with mood and anxiety disorders in a 10-year study of a representative sample of U.S. adults (Swendsen et al., 2010). In a randomized trial, people who quit smoking reported decreased negative affect and increased

positive affect at one-year post-quitting, whereas those who continued to smoke reported increased negative affect and decreased positive affect (Piper et al., 2012). Impairments in the dopamine, serotonin, and norepinephrine systems may act as biological mechanisms in these associations (Morisano, Bacher, Audrain-McGovern, & George, 2009). Cross-sectionally, life satisfaction and eudaimonic well-being have been negatively associated with smoking in large national samples in the U.S. and England (e.g. McCann, 2010; Stranges, et al., 2014).

Mindfulness Meditation. Mindfulness, a popular technique for reducing psychological distress, has been described as attending to present-moment experiences with acceptance, curiosity, and non-judgmental awareness (Kabat-Zinn, 1990). Mindfulness may influence psychological distress by supporting healthy engagement (as opposed to over- or under-engagement) with both positive and negative emotions, supported by changes in brain structure, strength of synaptic connections, and immune functioning (Chambers, et al., 2009). Several meta-analyses have revealed moderate positive effects for meditation and mindfulness interventions on psychological distress (e.g., Khoury et al., 2015, Strauss et al., 2014). A meta-analysis of 47 randomized trials revealed that mindfulness interventions reduced stress and improved quality of life (Goyal et al., 2014). A daily diary study found that mindfulness predicted next-day positive and negative affect, but the reverse relationships were not found (Snippe et al., 2015).

Time Spent in Nature. Walsh (2011) suggested that nature plays an important role in emotion regulation, sleep, attention, and psychological distress. For example, using comprehensive administrative and geolocation data, near-by green space was negatively associated with anxiety and mood disorders in New Zealand (Nutsford et al., 2013) and antidepressant use across the Netherlands (Helbich et al., 2018). Density of street trees was

linked to reduced anti-depressant usage in London, controlling for important confounding variables (Taylor et al., 2015). A systematic review (Mygind et al., 2019) of controlled trials revealed that exposure to a natural environment had positive effects on mental health. Kuo (2015) and Hartig et al., (2014) theorized that the influence of nature experiences on mental health are partially mediated by physical activity and social interaction (along with other mechanisms such as immune functioning, inflammation, and blood glucose levels). Their models describe long-term, rather than moment to moment associations.

Behavior clustering. In conjunction with the expected associations between time in nature, physical activity, and social interaction, Egger's (2018) model indicates that most lifestyle behaviors are expected to not just influence health and well-being outcomes, but they are also expected to influence each other. Cross-sectionally, behaviors often cluster together, with healthy behaviors such as exercise and proper eating being associated, while smoking and heavy drinking tend to occur together (Fleary & Nigg, 2019). Among the various methods for assessing clustering, cross-sectional network analyses have recently shown that lifestyle behaviors cluster and that some (e.g., diet) are especially highly connected to the other lifestyle behaviors (Nudelman et al., 2019). One recent study found evidence of within-person clustering, relying on long-interval data collection with three time points over a year (Chevance et al., 2020).

Present Study

This project was designed to build on previous research on lifestyle behaviors and psychological distress and well-being with three central aims. First, this study included a relatively larger number of lifestyle behaviors in multilevel regression models to investigate their relative associations with both psychological distress and well-being. Second, this study tested

competing multilevel mediation models involving three of the lifestyle behaviors (time in nature, social interaction, and exercise). Third, this study explored the interrelations among lifestyle behaviors and potential behavior clustering using network analyses.

For the first aim, we hypothesized that the restorative lifestyle behaviors would be positively associated with eudaimonic and hedonic well-being, and negatively associated with psychological distress (and vice versa for the deteriorative behaviors). Because these behaviors have ties to distress and well-being through various, at least partially independent, purported mechanisms, we expected all behaviors to have unique significant associations with the dependent variables. Also, in accordance with our interpretation of the literature, the order in which the behaviors are described follows the expected size of effects between the behavior and the outcome variables. Because daily diary studies can assess the association of variables on next-day outcomes, we assessed the association between lifestyle behaviors and next day psychological distress and well-being, while controlling for well-being on the day of the behaviors. also, as demonstrated by previous research linking well-being and distress with later health behaviors (e.g., Schultchen et al., 2019), the study tested whether previous day psychological distress and well-being are associated with health behaviors (see supplemental materials).

For our second aim, we tested two competing sets of mediation models. Kuo (2015) and Hartig et al., (2015) argued that the association between time in nature and well-being is mediated by social interaction and exercise in a parallel fashion. Eime et al. (2013) argued that the benefits of engagement in sport exercise has a direct influence on social functioning, indicating a potential serial mediation. As such, parallel and serial mediation models were compared to see which model was better supported by the data.

For the third aim, we examined relationships among the lifestyle behaviors using network models. Networks are increasingly being used to model complex psychological and behavioral phenomena (Costantini et al., 2019). Network nodes represent the elements of the network system (in this case the lifestyle behaviors) while network edges represent the interactions between the nodes. The edges are based on partial correlations, which indicate associations between two variables, after controlling for all other variables in the network. Edges are conceptualized by both the strength of the association between nodes as well as the direction of association (Epskamp & Fried, 2018). Collecting daily reports of lifestyle behaviors allows for an exploration of within-person associations regarding day-to-day fluctuations in behaviors.

Method

Participants

The sample for this study was obtained through the online platform used for research participant recruitment, www.prolific.ac. Users of Prolific sign up to knowingly participate in research studies and can expect to be compensated for their participation according to minimum payment rates (Palan & Schitter, 2017). Online participant pools like Prolific provide similar quality data to offline samples, are more diverse than college student samples, but not completely representative of the adult U.S. population (Peer et al., 2017); 104 adult users clicked on the link to the baseline survey. Three individuals did not proceed past the consent form and one person missed an attention check item. 22 individuals completed less than seven usable daily surveys. An additional two individuals' responses appeared invalid, lacking variation in item responses. After excluding these participants, the sample consisted of 76 adults.

Exclusion criteria included pregnant women, anyone under the age of 18, those residing outside of the United States, and individuals who could not understand English. The sample was

57.9% female and 40.8% male with one participant who selected "other" for sex (1.3%). One participant identified as transgender. Participants' average age was 40.29 years (*SD* = 13.69, Range = 19–64). The sample was predominantly White (85.5%), with other participants identifying as Black, African American (9.2%), Latinx (5.3%), Chinese (1.3%), Vietnamese (1.3%), "Other" (1.3%), and bi-racial (1.3%). The participants' relationship status was reported as single (34.2%), married (32.9%), in a relationship (22.4%), divorced (9.2%), or separated (1.3%).

Procedure

A description of the study was listed on the Prolific website for potential participants to review. Interested participants were directed to an online survey via Qualtrics software. Participants provided consent, then completed a baseline survey including demographic items. For the next 14 days, the participants were sent an email through Prolific at 8 PM EST to remind them to complete the daily survey. They had until 2 AM EST to complete the study and were not able to complete the items if they missed submitting them within the time window. At the end of 14 days, participants were paid $12-$26 according to their level of completion.

Measures

The procedures described by Bonito et al., (2012) were used to calculate reliability estimates at the within-person level. Psychological distress was assessed with Kessler et al's (2002) 6-item Scale for Psychological Distress, which assesses common psychological symptoms (e.g., "During the past day how often did you feel hopeless?") with a 5-point response format ranging from 1 "All of the time" to 5 "None of the time." The internal consistencies (αs) were .75 for day-level reliability and .96 for person-level reliability. The items from this scale were summed.

The 5-item Satisfaction with Life scale was used to assess hedonic well-being (Diener et al., 1985). The 7-point response format ranged from 1 “Strongly disagree” to 7 “Strongly agree.” This measure has strong reliability and validity, and it was modified to ask about the day of reporting, following Maher et al. (2013; e.g., “I was satisfied with my life today”). The internal consistencies were calculated as .90 for day-level reliability and .92 for person-level reliability. The items from this scale were summed for descriptive statistics.

The 8-item Flourishing scale was modified to assess eudaimonic well-being (Diener et al., 2010; e.g., “I was engaged and interested in my daily activities”). It uses a 7-point Likert scale ranging 1 “Strongly disagree” to 7 “Strongly agree.” This measure has demonstrated internal consistency and convergent and divergent validity (Diener et al., 2010). The internal consistencies for the Flourishing scale were .80 for day-level reliability and .93 for person-level reliability. The items were summed for descriptive statistics.

Three items from the modified Godin Leisure-Time Exercise Questionnaire (Godin & Shepard, 1985; Flueckiger et al., 2017) were used to measure physical exercise. The participants reported on the number of minutes they spent engaging in mild (e.g., easy walking, golf), moderate (e.g., fast walking, volleyball), and intense (e.g., running, vigorous swimming) exercise. Each report of exercise greater than 15 minutes was given a metabolic unit (3 for mild exercise, 5 for moderate exercise, and 9 for strenuous exercise), which were summed to create a daily activity value ranging from 0 to 17. Previous research found good test-retest consistency (Godin & Shepard, 1985), and the measure has demonstrated adequate concurrent validity with actigraph measurement (Jacobs et al., 1993).

To assess nutrition-related lifestyle behaviors, participants reported the number of servings of fruits and vegetables consumed that day. Conner et al. (2015) used similar questions,

and in the present study they were combined with the images used by Mujcic and Oswald (2016) to demonstrate serving sizes. Participants reported on a scale with values ranging from none to ≥6 servings. The number of servings of each food type were summed to create the fruit and vegetable consumption variable.

Participants rated how much time they spent having meaningful interactions with close others in one item with responses ranging from 0 to 480 minutes. Close others could be "family, friends, coworkers, peers etc." Tobacco use was assessed by asking how many occasions the participants used tobacco that day. Alcohol use was assessed by asking the participants how many drinks they had in the previous 24 hours. An image displaying serving sizes from the National Institute on Alcohol Abuse and Alcoholism (n.d.) was provided. Alcohol use was coded as a binary variable indicating moderate or no alcohol (coded as 0) versus heavy use (2 or more drinks for women; 3 or more drinks for men; coded as 1) based on recommendations by the U.S. Department of Health and Human Services (2015). Mindfulness meditation was assessed by asking "How many minutes did you engage in formal mindfulness practice (sitting/breathing meditation, body scan meditation, or open-awareness meditation)?" Time spent in nature was assessed with one item asking how many minutes participants spent enjoying natural spaces that day (Kuo & Taylor, 2004; "a park, a farm, or just a green backyard or neighborhood space").

Because socioeconomic status has an important role in influencing lifestyle behaviors, health, and well-being, the participants completed the MacArthur Scale of Subjective Social Status (Adler et al., 2000). This scale assessed individuals' overall socioeconomic status using a single item ranging from 1 to 10. The item presents the participants with an image of a ladder with ten rungs and the participants mark where they would rank themselves relative to others in the United States in terms of money, education, and occupation. This item has predicted health

and well-being across countries and is significant even when controlling for objective indicators of socioeconomic status (Präg et al., 2016).

<Insert Table 1 about here>

Data Analysis

Aim one. For the first aim, multilevel modeling was utilized to explore both within- and between-person associations (Iida et al., 2014). The initial goal was to have a single multivariate multilevel model that simultaneously analyzed all three dependent variables (hedonic well-being, eudaimonic well-being, and psychological distress). However, a histogram revealed that the psychological distress data followed a zero-inflated distribution with 0 being the modal response. A negative binomial multilevel model was used with a log link function to more appropriately study psychological distress with a separate multivariate multilevel linear model that included both hedonic well-being and eudaimonic well-being. SPSS 25 was used to calculate descriptive statistics and run the multilevel models with the GENLINMIXED and MIXED commands. Additional details on the multilevel linear models are available in the supplemental materials.

Multilevel models were analyzed with full information maximum likelihood estimation and the model building process followed the recommendations of Nezlek (2012; see supplemental information). The study involved person-mean centering for the lifestyle variables to allow parsing out the associations of the individual's daily fluctuations in lifestyle behaviors from their averages of those lifestyle behaviors. Each participant's means of the lifestyle behaviors, centered on the grand mean, were entered into the model to assess the between-person associations.

Unconditional two-level models were created for each dependent variable (DV) to obtain the intraclass correlation coefficient (*ICC*), which represents the amount of variance accounted

for by between-person differences. We intended to analyze tobacco use as a within-person independent variable, but due to its very high *ICC* (.95), there was virtually no within-person variance. It was entered as a between-person variable, coded as 1 for smoker and 0 for non-smoker.

To compare the relationships between the lifestyle variables and the DVs in a multivariate model, the items from the eudaimonic and hedonic well-being scales were rescaled. The mean of the scale across all days was subtracted from each item and the resulting value was divided by the scale standard deviation. The within-person lifestyle behaviors were also standardized for these analyses to facilitate comparison across behaviors.

Aim 2. To test the competing mediation models, Mplus software was utilized with maximum likelihood estimation (Muthén & Muthén, 2017). First, enjoying nature was entered into two multilevel models, predicting eudaimonic and hedonic well-being to assess for baseline associations. Then, for the parallel mediation models, both exercise and social interaction were added as mediators, allowing for covariance between them. Indirect effects through each mediator, the total indirect effect, and the direct effect from nature to each dependent variable were calculated. Serial mediation models, with nature predicting exercise, exercise predicting social interaction, and social interaction predicting the dependent variables were assessed. The indirect effects of the serial mediation were calculated and compared to the effects of the parallel mediation models. All the other lifestyle behaviors and socioeconomic status were entered as covariates.

Aim 3. For the network analyses, person centered variables were used in the models. The R package QGRAPH was used to compute and create a visual chart of the graphical least absolute shrinkage and selection operator (lasso) network (Epskamp et al., 2018). The

EBICglasso function uses the Extended BIC (*EBIC*) to select the tuning parameters, which determine how sparse or dense the resulting network is. While temporal (lagged) effects can be computed in network models, only contemporaneous network effects were calculated due to the present sample size and measurement intensity. The resulting graphical representations of the network allowed for visual inspection of the associations, which is particularly helpful for small networks (Costantini et al., 2018). For further analysis of the individual nodes, centrality estimates were calculated including strength centrality (rate of direct connections with other nodes) and closeness centrality (direct and indirect paths to other nodes are short). To assess the accuracy of the centrality estimates, the correlation stability coefficient was calculated using the R package Bootnet with a value of around .5 or greater being recognized as having sufficient stability (Epskamp, Borsboom, and Fried, 2018). Because this method was designed for continuous variables, alcohol was analyzed on a continuous scale rather than the binary of heavy vs light/no alcohol.

Results

After data collection, there were 894 days of data from 76 participants. Descriptive statistics and correlations at each level of analysis was calculated to evaluate multicollinearity (See Table 1 and supplemental information for more details). The correlations in Table 1 were indicative of a basic form of pairwise clustering, as some of the behaviors were correlated at the within- and/or between-person levels. In relation to the mediation model that was tested, time enjoying nature was correlated with both exercise and social interaction at the within-person level.

Main effect models

The results from the psychological distress and the hedonic well-being/eudaimonic well-being models are in Table 2 and the variance-covariance matrices are available as supplementary materials. Random slopes were calculated between time spent in social interaction and eudaimonic well-being and time spent meditating and psychological distress, meaning that the slope of those relationships varied from person-to-person. One random slope in the hedonic well-being/eudaimonic well-being model and one from the psychological distress model were retained due to their impact on model fit and significance values.

Psychological distress. The psychological distress model indicated that psychological distress was negatively associated with within-person social interaction (b = -0.12, 95% *CI* [-0.17, -0.08]) and fruit and vegetable intake (b = -0.05, 95% *CI* [-0.09, -0.01]), while positively associated with alcohol use (b = 0.44, 95% *CI* [0.13, 0.76]). The other within-person variables were not associated with psychological distress. Between-person minutes of social interaction was negatively associated with psychological distress (b = -0.25, 95% *CI* [-0.45, -0.05]).

Hedonic well-being. The multivariate model (with both hedonic well-being and eudaimonic well-being included) indicated that hedonic well-being was positively associated with within-person social interaction (b = 0.10, 95% *CI* [0.07, 0.13]), exercise (b = 0.02, 95% *CI* [.00, .03]), and fruit and vegetable intake (b = 0.04, 95% *CI* [0.01, 0.07]). There was a marginally significant negative association between hedonic well-being and alcohol use at the within-person level as well (b = -0.17, 95% *CI* [-0.35, 0.01]). At the between-person level, hedonic well-being was positively linked to social interaction (b = 0.13, 95% *CI* [0.06, 0.21]), perceived socioeconomic status (b = 0.22, 95% *CI* [0.09, 0.36]), and marginally associated with exercise (b = 0.05, 95% *CI* [0.00, 0.10]).

<Insert Table 2 about here>

Eudaimonic well-being. The multivariate model also indicated that eudaimonic well-being was positively linked to the within-person level of social interaction (b = 0.12, 95% CI [0.09, 0.15]) and fruit and vegetable intake (b = 0.04, 95% *CI* [0.01, 0.06]). There was a marginally significant negative association between eudaimonic well-being and alcohol use (b = -0.14, 95% *CI* [-0.30, .02]). At the between-person level, eudaimonic well-being was significantly positively related to social interaction (b = 0.14, 95% *CI* [0.07, 0.20]), exercise (b = 0.05, 95% *CI* [0.00, 0.09]), and perceived socioeconomic status (b = 0.14, 95% *CI* [0.03, 0.27]), with an unexpected positive association with smoking status (b = 0.34, 95% *CI* [0.06, 0.80]).

Lagged models. To assess the influence of lifestyle behaviors on next day psychological distress and well-being, controlling for the distress and well-being on the day of the behaviors, we conducted a set of lagged analyses. The results of those analyses indicated that there were no significant within-person associations between lifestyle behaviors and next-day well-being. However, social interaction (b = 0.10, 95% *CI* [0.05, 0.14]) and fruit and vegetable intake (b = 0.07, 95% *CI* [0.00, 0.14]) were positively associated with next-day psychological distress (See supplementary materials for all results).

Coefficient comparisons. Comparisons of the within-person coefficients for the various associations between the lifestyle behaviors and the well-being dependent variables resulted in social interaction having a stronger association with hedonic well-being relative to exercise (b = 0.08, 95% *CI* [0.02, 0.14]), fruit and vegetable intake (b = 0.08, 95% *CI* [0.02, 0.14]), which both had significant associations (See Figure 1). Social interaction also had a stronger association with eudaimonic well-being relative to fruit and vegetable intake (b = 0.10, 95% *CI* [.05, .15]) which was significant. There were no significant differences in coefficient sizes across the

hedonic well-being and eudaimonic well-being dependent variables. The full results from these analyses are available as supplementary information.

Mediation Models

When nature was entered alone in a model, it had a significant baseline association with hedonic well-being (b = 0.09, 95% *CI* [0.02, 0.16]), but not with eudaimonic well-being (b = 0.06, 95% *CI* [-0.01, 0.13]). There were significant associations between nature and social interaction (b = 0.41, 95% *CI* [0.13, 0.69]) and exercise (b = 1.05, 95% *CI* [0.60, 1.49]). Figure 2 and supplemental figures describe the results of the mediation models with statistical tests. Overall, the parallel mediation models fit the data better as there was no significant association between exercise and social interaction. The time in nature and hedonic well-being association was fully mediated by both exercise and social interaction, while only social interaction mediated the association between time in nature and eudaimonic well-being.

<Figure 1 about here>

Network Models

Four network models were tested (see Figure 3). The first model contained the six lifestyle behaviors. The patterns observed in the first model represent the partial correlation networks of the six lifestyle behaviors. The correlation stability coefficients were .53 for edges and .59 for the strength centrality estimate.

The next three models included the lifestyle behaviors and one dependent variable each. Across the models, the general structure among the lifestyle behaviors remained the same. Further, the associations between the lifestyle behaviors and the dependent variables generally mirrored the multilevel regression analyses. The correlation stability was .54 for edges and .54 for strength centrality estimate in the hedonic well-being model, 0.65 and 0.66 for the

eudaimonic well-being model, and 0.46 and 0.58 for the psychological distress model. Centrality indices are available in the supplemental materials and indicate that exercise, time in nature, and social interaction were the most central behaviors in each of the four networks.

<Figure 2 about here>

Discussion

This study explored the daily associations between several lifestyle behaviors and three dependent variables: psychological distress, hedonic well-being, and eudaimonic well-being. Multilevel regression models indicated the relative strengths of the associations between the lifestyle behaviors and the dependent variables with social interaction having the strongest associations. Multilevel mediation analyses found that the relationship between time in nature and well-being variables was mediated by social interaction and exercise. Network models revealed clustering among the day-to-day fluctuation in lifestyle behaviors and the dependent variables, demonstrating contemporaneous associations among the lifestyle behaviors. The study was innovative in that it assessed a larger number of lifestyle behaviors, included both well-being and distress dependent variables, and was conducted in a multivariate multilevel framework.

Following Pemberton and Tyszkiewicz's (2016) recommendation that lifestyle factors be measured simultaneously in daily diary and experience sampling studies, to allow for relative comparisons, we were able to analyze the daily associations between six lifestyle behaviors and three dependent variables (See Table 2 and Figure 1). The most striking finding from the study is that fluctuations in social interaction have the largest association with same day distress and well-being. This aligns with previous research that has linked individual differences in, and daily fluctuations in social interaction with various outcomes (Choi et al., 2017; Machell et al., 2015).

The present study controlled for various healthy and risky lifestyle behaviors, indicating the consistency of the social interaction associations. Egger (2018) identified two lifestyle categories that are explicitly associated with social interaction (alienation and relationships), which are supported by the strong associations found in this study. Social interaction was not only more strongly associated with psychological distress and well-being than lifestyle behaviors without clear associations, but also fruit and vegetable intake, exercise, and alcohol use, which had significant associations. The size of the coefficient was large enough that, in practical terms, the association between a one standard deviation fluctuation in social interaction and eudaimonic well-being is about three times as large as the association between fruit and vegetable intake and eudaimonic well-being (See Figure 1). The association between social interaction and hedonic well-being is about two and a half times greater than that between exercise and hedonic well-being. Thus, while large fluctuations in other lifestyle behaviors or moderate fluctuations in a combination of lifestyle may be able to match associations with social interaction, fluctuations in time spent in social interaction was more strongly associated with distress and well-being. As highly social creatures (Tomasello, 2014), who depend strongly on others for support and belonging (Feeney & Collins, 2015), fluctuations in social interaction may have more immediate ties to human well-being than other obviously important lifestyle behaviors.

<Figure 3 about here>

Concerning the second aim of the study, we tested two sets of competing mediation models linking time spent enjoying nature to well-being, as mediated by physical activity and social interaction. The parallel mediation models following Kuo (2015) and Hartig et al., (2014) received greater support because controlling for time in nature, social interaction, and physical activity were unrelated. The models indicated that the positive associations of time in nature and

well-being are fully mediated by social interaction and physical activity (See Figure 2). Both previously mentioned models have multiple other potential mediators listed (e.g. sunlight and air quality), but because our focus was on lifestyle behaviors, we did not assess these environmental variables. The study cannot speak to whether average associations between time in nature and health and well-being can be fully explained by exercise and social interaction, but for day-to-day fluctuations, the mediation models were supported by the data.

The findings from the second aim are also relevant for the third aim, with the time in nature, exercise, and social interaction having highly central positions within the network indicating that they had higher rates of associations with each other and the other lifestyle behaviors (See Figure 3). Time in nature seemed particularly central for its strong associations with exercise and social interaction, while the other two failed to have associations with each other. While other studies have found network structures and clustering in cross-sectional lifestyle behavior data, this study demonstrated that behaviors cluster at the within-person level as well – for example, on days when people spend more time in nature than their average, they also tend to socialize more and exercise more than their average, and these behaviors are associated with mindfulness, alcohol use, and fruit and vegetable intake.

The multilevel regression models found that fruit and vegetable intake was consistently associated with the dependent variables. In that way, our results were similar to Conner et al.'s (2015) findings that daily fluctuations in fruit and vegetable consumption were associated with eudaimonic well-being among young adults, although our sample included a much broader range of adults. Despite having consistent associations with the dependent variables at the daily level, fruit and vegetable intake did not have close associations with other behaviors, despite previous research showing clustering with exercise and other behaviors in cross-sectional and large-

interval longitudinal research (Chevance et al., 2020; Fleary & Nigg, 2019; Nudelman et al., 2019). This study demonstrates that fully understanding lifestyle behaviors' associations with each other and with psychological distress and well-being requires daily dairy or experience sampling designs because these behaviors occur in daily living and may not fully be conceptualized in aggregated data that includes significant recall demands.

While daily fluctuations in exercise and hedonic well-being were significantly related, there was unexpectedly no association between exercise and psychological distress or eudaimonic well-being. This finding indicates the wisdom of assessing multiple lifestyle behaviors simultaneously because, for example, when only exercise was entered into a multivariate multilevel model with hedonic and eudaimonic well-being, there was a small significant association between it and eudaimonic well-being (0.01, $p = 0.03$, 95% *CI* [0.00, 0.03]). These findings suggest that although exercise had a weak relationship with eudaimonic well-being, that link may have been swamped by the inclusion of other variables and examining the effects of lifestyle behaviors in isolation may overestimate their associations. At the same time, this finding is also hampered by questions about the measurement of exercise, discussed in the limitations section. It is also important to recognize that most experience sampling research on exercise that found associations between exercise and well-being used smaller measurement windows (e.g., Mata et al., 2012).

Lagged analyses generally did not find any associations between the dependent variable and next day lifestyle behaviors, although social interaction and fruit and vegetable intake was unexpectedly positively associated with next-day psychological distress. The interesting finding that greater than average social interaction is associated with increased psychological distress on

the next day may represent a rebound effect resulting from the energy expended on social interaction or the letdown after a day with higher than average socializing.

Limitations

There are limitations to this study, some of which are associated with measurement quantity and quality. In terms of quantity, some behaviors occur at different rates or have different temporal associations with the dependent variables and may be better measured more frequently. This study required participants to recall and estimate the degree to which they engaged in each lifestyle behavior across a whole day and may have introduced some error through recall. Also, the lagged analyses might have found stronger temporal effects had the behaviors and outcomes been measured more frequently. In terms of quality, objective assessments of physical activity may be important to consider because one study indicated that the correlation between self-reported and objectively measured physical activity was .37 (Prince et al., 2008). More thorough assessments of diet that includes more categories and more specific serving sizes might add nuance to the positive associations of fruit and vegetable intake with the DVs as well. Measurement of mindfulness or other spiritual practices may require more extensive assessments to capture their effects. Time spent in meaningful social interaction was measured, but not the quality of those interactions, which is an important factor (e.g., Machell et al., 2015). When designing daily diary studies , it is important to consider participant fatigue, which explains our emphasis on breadth, more than depth of measurement.

Repeated responses to questions about lifestyle behaviors and well-being could influence the participants' responses to those questions (Iida et al., 2012). When time was entered in this study it was not associated with the DVs and did not improve model fit. This study was somewhat modest in sample size due to funding constraints. Samples of this size have lower

power to detect effects at the person level, but having multiple days of assessment allowed for the detection of small associations between day-to-day fluctuations in the behaviors and the dependent variables. Further, with low power at the between-person level, the unexpected positive association between smoker status and eudaimonic well-being should be viewed tentatively considering previous research. The findings of this study may not be fully generalizable to the wider population because users of Prolific tend to be younger and more educated than the U.S. population (Peer et al., 2017). With a modal response of no psychological distress symptoms, the findings may not apply to clinical samples. Note that the distribution of the psychological distress variable from this study is similar to the distribution of negative emotional experiences in a larger, more representative daily diary study (Ryff & Almeida, 2018).

Conclusions

Lifestyle factors play an important role in health and well-being (Karunamuni, Imayama, and Goonetilleke, in press; Sarris et al., 2014; Walsh, 2011). This study suggests that certain lifestyle behaviors such as social interaction and fruit and vegetable intake are consistently associated with psychological distress and well-being at the daily level. One lifestyle behavior, time in nature, may be beneficial because of its strong association with social interaction and exercise. The study also demonstrates that lifestyle behavior clustering occurs not just cross-sectionally, but in day-to-day living (i.e., on a given day, spending more time in nature than one's personal average was associated with more exercise and social interaction than one's personal average). This study made it possible to compare the associations among lifestyle behaviors and well-being measures, clarifying the importance of social interaction and other lifestyle behaviors for well-being.

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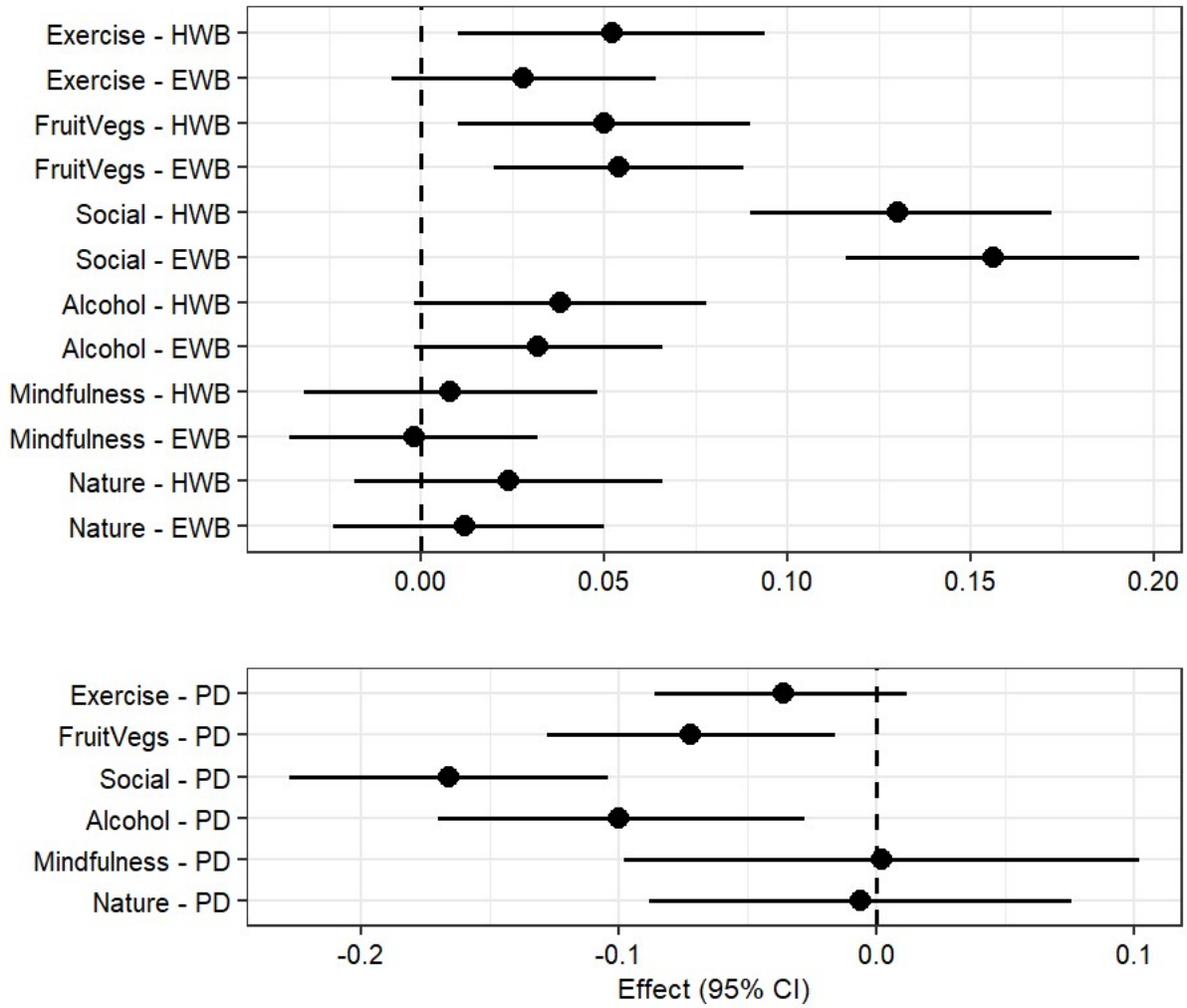

Fig.1. Forest Plot of Within-Person Lifestyle Behavior Coefficients.

Coefficients based on standardized values of the person-centered lifestyle behaviors. For example, a 1 *SD* increase in within-person social interaction is associated with a .13 SD increase in hedonic well-being and a .16 *SD* increase in eudaimonic well-being. The bars extending from the point estimates represent the 95% confidence intervals. Note that for making relative comparisons, heavy alcohol use was reverse coded with heavy alcohol use as the reference group. EWB = eudaimonic well-being; HWB = hedonic well-being; PD = psychological distress.

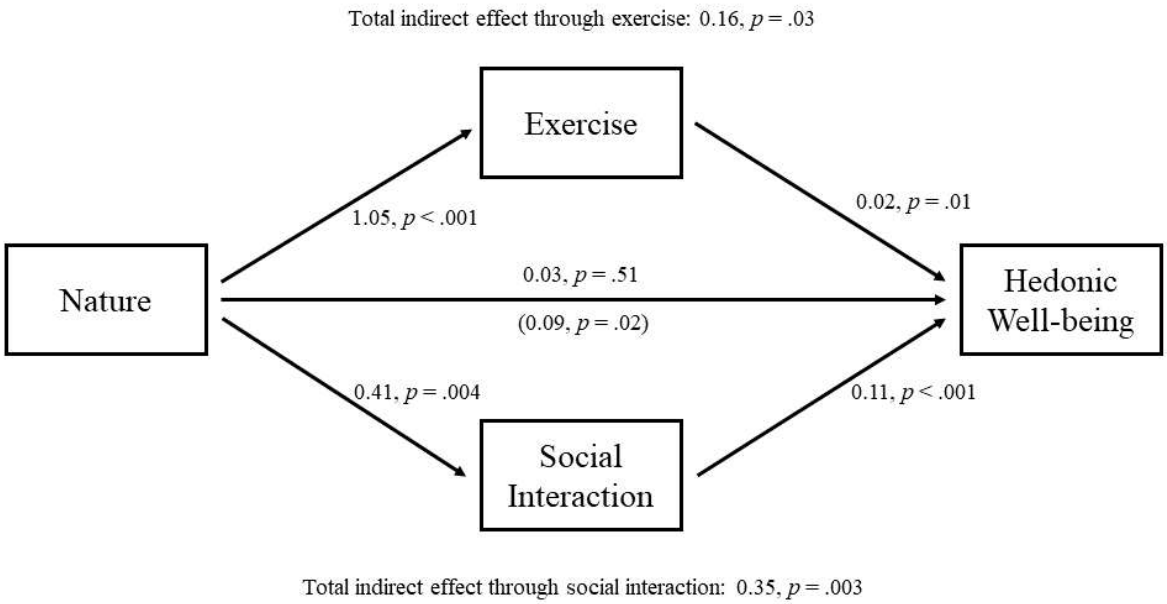

Fig. 2. Time in Nature Hedonic Well-being Parallel Mediation Model.

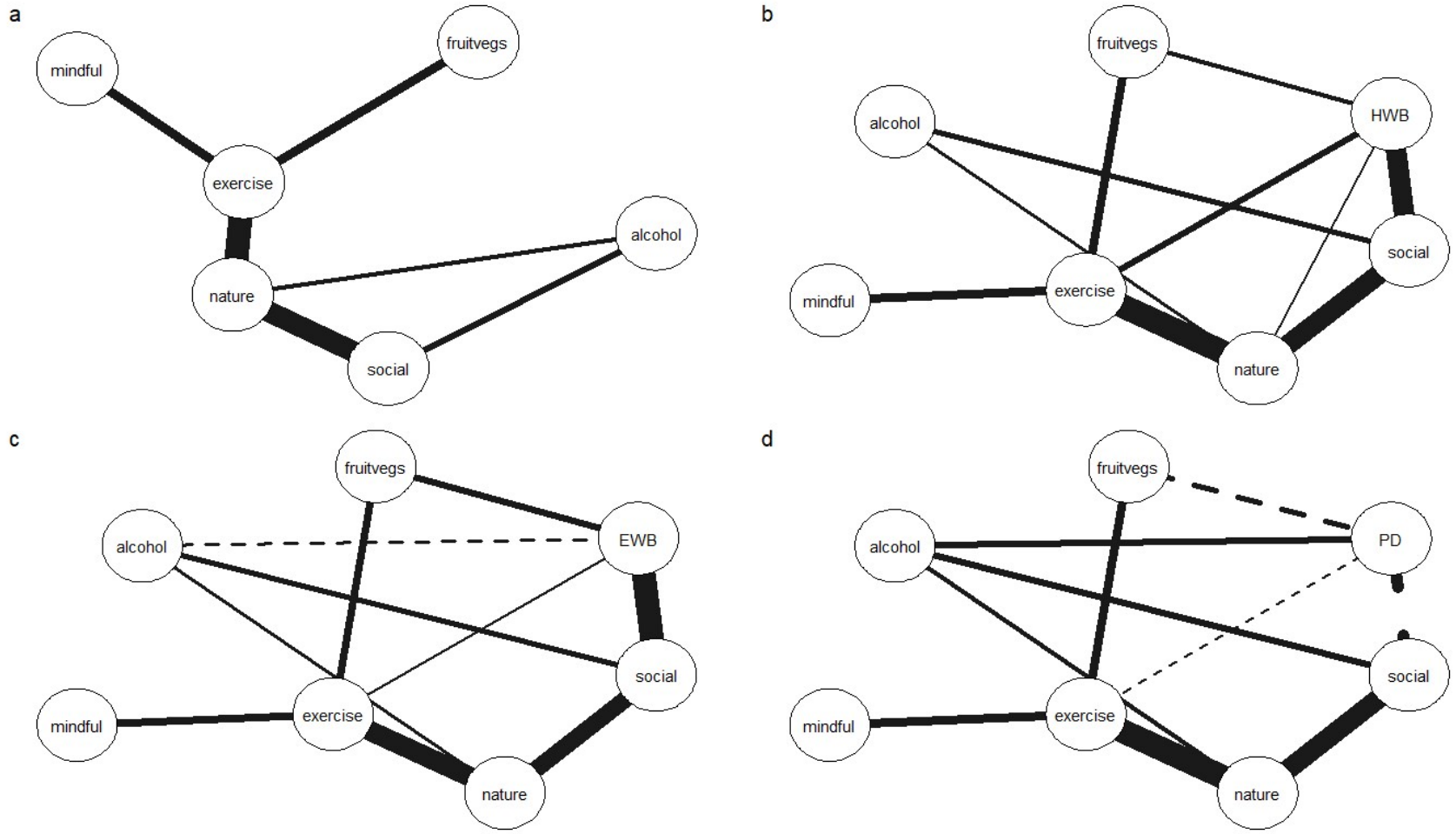

Fig. 3. Network Models

a) Behaviors only model; b) behaviors and hedonic well-being (HWB); c) behaviors and eudaimonic well-being (EWB); d) behaviors and psychological distress (PD). The structure of networks b, c and d are constrained to equal an average of their network structures to facilitate comparison. Edge width represents magnitude of the association. Solid lines represent a positive association while dashed lines represent a negative association.

Table 1

Within- and Between-Person Correlations of Daily Variables.

	M	*SD*	*ICC*	1	2	3	4	5	6	7	8	9	10
1. Exercise	3.32	4.06	.37	-	.37**	.09*	.02	.23**	.39**	-.12**	.26*	.28**	.03
2. Fruits and vegetables	3.33	2.53	.67	.12**	-	-.11*	-.14**	.02	.24**	.03	.02	.15**	-.04
3. Social interaction	1.98	2.24	.59	.04	-.01	-	.00	-.18**	-.06	-.24**	.41**	.44**	.19**
4. Alcohol	0.10	0.30	.37	.07*	.04	.10*	-	-.11**	-.10**	-.10**	.17**	.12**	-.15**
5. Mindfulness meditation	0.04	0.12	.42	.11**	-.01	.03	-.02	-	.32**	-.01	-.12**	-.03	-.07*
6. Time in nature	0.46	0.84	.21	.25**	-.01	.22**	.05	.02	-	.01	.13**	.22**	.03
7. Psychological distress	10.72	4.69	.68	-.07	-.09**	-.14**	.11**	.00	-.04	.75/.96	-.45**	-.50**	-.18**
8. Hedonic well-being	21.92	5.97	.52	.11**	.08*	.22**	-.04	.03	.11**	-.43**	.90/.92	.85**	.36
9. Eudaimonic well-being	41.04	7.23	.55	.07*	.10**	.29**	-.03	.01	.08*	-.44**	.67**	.80/.93	.29**
10. Perceived SES	4.64	1.72											

M = Mean; *SD* = Standard deviation; *ICC* = Intra-class correlation; *SES* = Socioeconomic Status

Within-person correlations are on the lower half. Between-person correlations are on the upper half. For the three dependent variables, the within-person reliabilities are listed first on the diagonal, followed by the between-person reliabilities.

**$p < .01$ level (2-tailed)

*$p < .05$ level (2-tailed)

Table 2

Multilevel Models of Within- and Between-Person Fixed Effects.

Variable	Psychological Distress[a]			Hedonic Well-being			Eudaimonic Well-being		
	B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*
Intercept	0.19	0.50	.71	0.53	0.31	.09	0.28	0.28	.32
Within									
Social Interaction	-0.12	0.02	<.001	0.10	0.02	< .001	0.12	0.02	< .001
Exercise	-0.01	0.01	.15	0.02	0.01	.02	0.01	0.01	.12
Fruit and Vegetables	-0.05	0.02	.01	0.04	0.01	.02	0.04	0.01	.002
Alcohol	0.44	0.16	.01	-0.17	0.09	.07	-0.14	0.08	.07
Meditation	0.01	0.52	.99	0.09	0.23	.70	-0.03	0.19	.89
Nature	-0.01	0.06	.88	0.03	0.03	.27	0.02	0.03	.51
Between									
Smoker	-0.36	0.36	.32	0.28	0.20	.18	0.43	0.19	.02
Social Interaction	-0.25	0.09	.02	0.13	0.04	.001	0.14	0.03	<.001
Exercise	-0.10	0.05	.07	0.05	0.02	.06	0.05	0.02	.03
Alcohol	-0.58	0.52	.29	0.62	0.33	.06	0.37	0.29	.21
Socioeconomic Status	-0.19	0.15	.21	0.22	0.07	.001	0.15	0.06	.02
AIC	2545.49			21900.42					
BIC	2569.30			22246.06					

Note. Estimates (B) are standardized coefficients.

[a]Psychological distress was analyzed in a separate negative binomial model. The two well-being variables were analyzed in one multivariate multilevel linear model.