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Assessing psychological well-being in early adulthood: Empirical evidence for the structure of daily well-being via network analysis

Saeideh Heshmati[a], Zita Oravecz[b], Timothy R. Brick[b], and Robert W. Roeser[b]

[a]Claremont Graduate University; [b]Pennsylvania State University

ABSTRACT

The transitional years of early adulthood, with key tasks of identity and intimacy development, engender both opportunities and risks for well-being. We propose that the conceptualization and measurement of early adults' well-being can be improved through (a) an integration of ideas from developmental and psychological science on well-being, (b) the use of short, daily momentary assessments of well-being, and (c) a developmentally-informed examination of the structure of well-being within (and not just across) time. We developed a daily assessment of well-being based on the PERMA model (Seligman, 2011) and used network analysis to gain understanding from this data. Using Ecological Momentary Assessments, we assessed the five PERMA elements in college students' daily life and their network properties. Consistent with the PERMA model, network analysis showed items clustered around theorized elements and formed a unitary network of well-being. Consistent with developmental theory, we found that having positive relationships and positive emotion were most central to early adults' daily well-being.

In this paper, we aim to contribute to research at the intersection of human development and psychological well-being during early adulthood. Numerous theories of thriving and positive development in the second decade of life have been offered in developmental science (Benson, 2003; Damon, 2004; Lerner et al., 2009). These theories build upon and extend classic lifespan theories developed by Erikson (1963, 1968) and others (e.g., Franz & White, 1985). They hypothesize that favorable resolutions of developmental tasks involving competence and identity on the one hand (e.g., work and purpose), and social integration and intimacy on the other (e.g., positive relationships and enjoyment) form the foundation of well-being in early adulthood. Central constructs in contemporary work on thriving and positive development during early adulthood echo and extend this previous work by focusing on, for example, issues of competence (see Lerner et al., 2009), purpose (see Damon, 2008), and positive relationships with others (e.g., Benson, 2003) as central to well-being and thriving during these years. The empirical structure of these elements of well-being, with attention to which elements are central to well-being in daily life for particular groups in particular settings across development, remain open questions (Benson & Scales, 2009; Bumbarger & Greenberg, 2002; Lerner et al., 2010).

In psychological science, the study of well-being and human flourishing (in early and later adulthood) has also become an increasingly vibrant area of study (see Ryff & Keyes, 1995; Seligman, 2011). The elements of well-being in these largely adult-oriented psychological models parallel those in developmental science linked with thriving during the second decade of life. These elements include but are not limited to mastery and growth, trusting and caring relationships, meaning and purpose, and social contribution as playing central theoretical roles in the description of the structure of well-being (e.g., Keyes, 2007).

Psychological well-being research distinguishes between two principal forms of well-being: enjoyment and positive feelings (i.e., hedonic view of well-being); and fulfillment through autonomy, mastery, growth, connection, meaning and purpose, and social contribution (i.e., eudaimonic view of well-being; Huppert, 2014). Although the elements of hedonic well-being are often studied separately from those that compose eudaimonic well-being, theorists like Seligman (2011) see them as inter-related. In fact, considering these elements simultaneously as a network structure may

CONTACT Saeideh Heshmati saida.heshmati@cgu.edu 175 E. 12th Street, Claremont, CA 91711.
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allow for both a general understanding of the interrelations between elements and also identification of the elements that are more or less central to individuals' daily well-being (Forgeard et al., 2011; Frey & Stutzer, 2010; Keyes, 2007; Kern et al., 2014; Lerner et al., 2009; Ryff & Keyes, 1995).

In order to understand the interrelation of various elements that comprise the general structure of daily well-being among a sample of early adults (ages 18-22 years), we adopted the PERMA theoretical perspective on well-being (Seligman, 2011). The PERMA model (Seligman, 2011) integrates hedonic and eudaimonic aspects of well-being through five elements: *P*ositive emotions, *E*ngagement, *R*elationships, *M*eaning in life, and *A*ccomplishment. Positive emotions captures feelings of happiness like joy and contentment. Engagement represents being in a state of flow or immersion into intrinsically engaging tasks or activities. Meaning captures having a greater purpose in life and feeling that one's life is valuable. Relationships refer to positive social connections that make a person feel supported and cared for. Accomplishment includes feeling a sense of achievement by having goals and ambition in life. Seligman (2011) argues that these five elements have true value in and of themselves, (e.g., people pursue them each for their own sake), that each element can be measured independently (exclusivity), and that all of the elements contribute to individuals' overall well-being (connectivity). In the study described below we collected data on well-being in early adulthood and used network analysis to study the two informative properties of the structure of well-being (i.e., exclusivity and connectivity)

Assessment of well-being in daily life during early adulthood

Research on well-being has mostly focused on general aspects of well-being as a trait, without considering the momentary aspects of this phenomenon in daily life (Kim et al., 2018) in an ecologically valid way. However, early adulthood is a period in which fluctuations in social rhythms (i.e., daily activities within one's ecological environment) are evident due to the exploratory nature of this stage in life (Roeser, 2012; Schulenberg et al., 2004). Early adults, especially those attending college, are more prone to engage in risk-taking activities, attend frequent socializing events, and may lack a stable work schedule. For instance, on a daily basis, early adults in college on average spend more hours of the day on leisurely activities and socializing as compared to adolescents in high school who spend more time on educational activities (U.S. Bureau-of-Labor-Statistics, 2015). When examining the different types of activities that comprise 'leisure' in early adults' daily lives, on a typical day, these individuals spend most of that time on socializing (~3.5 hours) and media use (~2.5 hours). Conversely, they typically spend the least amount of time on activities such as volunteering (~6 minutes) and spiritual activities (~13 minutes; Finlay et al., 2012). On weekends, the amount of time spent on socializing and attending events for most early adults increases even further (Finlay et al., 2012).

These irregularities and fluctuations in early adults' day-to-day activities in turn have important implications for their health and psychological well-being. For example, by spending more time on leisure activities such as socializing and attending events and less time on volunteering and spirituality, early adults are prone to engage in heavy drinking and disruptive behavior and less likely to build on their sense of meaning and purpose in life. These behaviors could then lead to poor sleep habits and disruptions in regularities of social rhythm (Carney et al., 2006). Additionally, engaging in frequent dating experiences and fleeting relationships that lead to fluctuations in feelings of love and/or heartbreak could lead to changes in early adults' state of relationships as another element of well-being. This is contrary to the more stable lifestyles of older adults who tend to have steady work hours, are either married or in long-term romantic relationships, and may spend less time on leisure involving heavy alcohol consumption, avoiding irregularities in social rhythm and adopting good sleep habits.

Due to the fluctuating nature of early adults' experiences and its potential impact on various elements of well-being, capturing a multidimensional perspective of well-being (e.g., PERMA) in an ecologically valid manner in daily life would give us a better grasp of this transition phase into adulthood. To advance empirical research on the PERMA model, Butler and Kern (2016) developed a measurement scale – the *PERMA-Profiler* – which quantifies the five elements of PERMA as dimensional scales. The PERMA-Profiler captures the five PERMA elements as trait-level factors by asking participants to answer questions about their well-being, such as "In general, how often do you feel joyful?". However, this measure is limited in the sense that as a trait measure, it requires participants to aggregate their well-being experiences over unknown time scales and contexts.

We used Ecological Momentary Assessment (EMA; Stone & Shiffman, 1994) to learn about momentary levels of well-being in early adults' daily life settings to gain rich data in an ecologically valid manner. EMA can be seen as a variation of the Experience Sampling Method (ESM; Bolger et al., 2003; Csikszentmihalyi & Larson, 2014) that aims to assess people's ongoing everyday experiences in real time and naturalistic contexts. "Ecological" refers to the fact that the specific assessments of well-being are collected during the daily contexts of early adults' lives. We consider the EMA method a more reliable and valid way to measure well-being than traditional survey measures collected across longer timescales (see Kahneman & Krueger, 2006, Developments in the Measurement of Subjective Well-being for argument and evidence). This method is reliable in terms of internal consistency as responses are aggregated across many assessments; it does not rely on recall, and has high ecological validity as it captures experiences in natural settings. Our first empirical aim is to document the structure of the PERMA elements of well-being based on momentarily assessments in the context of early adults' daily lives.

The EMA design is particularly relevant for assessing early adults' experiences of well-being due to life changes associated with autonomy and responsibility, social and romantic relationships, increased academic expectations if pursuing post-secondary education, and fluctuations in daily emotional experiences that come with increased life responsibilities (Schulenberg & Zarrett, 2006). Although EMA designs are often married with the study of intra-individual change over time as a means of understanding development, in this study we pursue a different aim. We use momentary data to explore the network structure of well-being in early adults. Our investigation includes an analysis of those elements of well-being that are more closely related to each other, and an analysis of which elements are more central "nodes" in overall well-being.

Conceptualizing momentary well-being as a correlational network

In an effort to look at well-being experiences as they occur on a more momentary and dynamic basis in daily life, Brick, Heshmati, and Oravecz (in prep) adapted the PERMA-Profiler for the EMA paradigm. Specifically, to capture everyday life experiences and changes in well-being, Brick et al. (in prep) developed the *momentary PERMA* (mPERMA) scale that can be applied to measure experiences of each of the PERMA elements as they occur in situ. Specifically, items in the mPERMA scale prompt people to report on their momentary well-being experiences several times a day for an extended period of time (e.g., several weeks). These state measures of well-being show ecological validity and are able to capture changes in well-being over time.

In this EMA study, we used the mPERMA scale to collect in-the-moment evaluations of well-being in early adults while they lived their everyday lives, and analyzed this data via network analysis (Borsboom & Cramer, 2013; Boschloo et al., 2015). Network analysis models manifest indicators of a construct as a network of interconnected nodes, and have been used to explain various psychological phenomena. For example, network analysis has been used in clinical psychology to look at mental disorders as causal systems of interacting symptoms (McNally et al., 2015); in psychiatry to explore how various traumatic experiences relate to specific symptoms of psychotic disorders (Isvoranu et al., 2017); in social psychology to conceptualize attitudes as networks of evaluative reactions interacting together (Dalege et al., 2016); and in personality research to investigate personality as a system of connected affective, cognitive, and behavioral elements (Cramer et al., 2012). However, to the best of our knowledge, network analysis has not been applied to developmental well-being research and more specifically to the PERMA conceptualization of well-being and its structural pattern of elements in early adulthood. By applying this novel approach in combination with EMA data, we aim to study how different elements of the PERMA model relate to each other in the context of early adults' daily experiences to form a network of well-being, and to test whether the items in the mPERMA scale hold together in a manner that is consistent with theory (e.g., the structural elements are differentiated and interrelated).

Advantages of network analysis

The advantage of network analysis over more traditional approaches like factor analysis is that this method provides opportunities to recognize patterns in the data by a unique visualization technique. This visualization represents relationships between variables as weighted edges (i.e., strength of correlation), allowing the researcher to detect significant structures in the data that might be difficult to extract otherwise. In other words, network analysis represents complex statistical patterns using straightforward visualizations without the need of data reduction (Epskamp et al., 2012). Another advantage of network analysis is that

it allows the researcher to identify nodes (e.g., variables, persons, etc.) within the network that are important in determining the network's structure based on the pattern of connections in which a particular node is involved. Researchers can then use this information to understand the degree of tolerance of the network (whether a network will remain connected) upon the removal of that particular node, which in turn can be used to inform applied research or network interventions (Valente, 2012).

The network approach can be seen complementary to traditional latent construct perspectives (such as factor analysis). Importantly, latent construct methods such as factor analysis formalize the relationships among the measures in terms of the relationships among latent constructs, each defined by the correlations among a set of observed variables. In contrast, network analysis models these relationships by treating each observed variable as its own node. Tightly correlated groups in the data appear as clusters of strongly interlinked nodes (called *communities* in network parlance). Whereas many latent variable models only permit interrelationships among the latent constructs, each node in a network model is capable of having a unique pattern of relationships with nodes in other communities. This property provides a succinct representation of the underlying similarity structure without losing the ability to see relationships among the individual variables. In network analysis we do not focus on the manifestation of an underlying theoretical attribute, but instead examine the overall set of individual pairwise relationships between the nodes. For example, Engagement is the label we apply to cases in which a person is absorbed in an activity, excited about or interested in what they are doing, sometimes to the point of losing track of time. In a simple common factor model, any pairwise relationship between excitement and other indicators (e.g., positive affect) beyond the relationship between the latent constructs of Engagement and Positivity would be considered to be "noise"—a failure of simple structure in measurement part of the model. Network analysis resists this idea, arguing that not only may the specific indicators have relationships outside their individual communities, but that these relationships may be meaningful for understanding the underlying phenomena. Network modeling also provides a framework for examining the roles that each node has in the network within the context of its containing construct. One approach is to calculate measures of node *centrality* to capture the amount, type, and shape of influence that each measure has on the global structure, which may have specific applications for intervention.

Network features

To illustrate these relationships, we can visualize our data as an undirected network graph made up of *nodes* representing the measures of interest – in our case items capturing the five core PERMA elements. Nodes are connected by lines called *edges*. Each edge has a strength (indicated by weight of the lines and pattern of line). Edges can be excitatory (indicated by a solid line and a positive weight on the line), displaying a positive correlation, or inhibitory (indicated by a dashed line with a negative weight on it), displaying a negative correlation. Figure 1 shows an example of a simple network with four nodes and six edges. In this figure, the nodes are drawn as circles, and the number on each line represents the weight of the corresponding edge. The thicker an edge, the stronger the association between the nodes that it connects. For example, nodes 'A' and 'C' display a strong positive association ($r = 0.97$) which is displayed with a positive weight and a thicker (strong) solid edge. The association between nodes 'C' and 'B' is also positive but is weak ($r = 0.30$) indicated by a thinner solid edge. On the other hand, the association between 'C' and 'D' is shown with a thick dashed line which displays a fairly strong negative association ($r = -0.58$). This network representation helps us understand how the overall network functions, in terms of how nodes relate to each other.

Typically, in psychological studies, nodes represent observed variables and edges represent statistical relationships between the nodes. For example, if we consider a network using the mPERMA items, each of the measured items would be a node in the network,

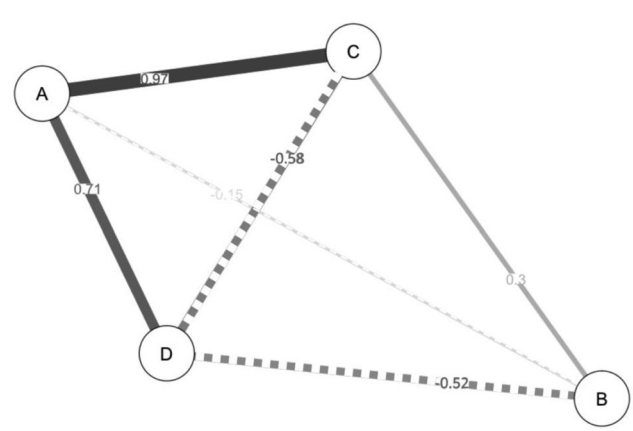

Figure 1. Hypothetical example of a network with four nodes and six edges.

with the unique significant correlations between each pair of items as the edges.

An important feature of network analysis is the ability to quantify the importance of nodes within the network; *centrality* measures provide one approach to doing so. For example, let us look at the hypothetical network in Figure 1. In this example network, node 'D' can be argued to be very important; it is highly predictive of all three other nodes because it has strong connections to them. If these links are causal, changes to 'D' would have a strong influence across the network. We describe this as node "D" showing high *node strength* centrality. By contrast, 'A' is less central in terms of pure strength because the average strength of its connections is lower, but it plays an important role in connecting nodes 'D' and 'C' via a positive link—it is *between* those two nodes, and so has high *betweenness centrality*. Again, assuming an appropriate causal structure, if 'A', 'C', and 'D' are all positive attributes, it would be much more helpful to intervene at node 'A' (i.e., alter the level of 'A' based on the desired impact on the whole network), since 'A' has the smallest negative influence on other surrounding nodes. Even in an intervention that is focused directly on node 'C', the influence of node 'A' is important to track, since it sits cleanly *between* C and D. Finally, considering the displayed network showing only significant correlations among all nodes after controlling for all other nodes in the network, all four nodes of the example network share a common number of links, indicating that they are all quite close to one another.

Goal of the current study

In this study, we explored the five elements of the PERMA model as an interconnected network in early adults' daily lives. The goal was to gain a better understanding of early adults' experiences of daily well-being through the interplay of the five PERMA elements and identify the importance of each of those elements within the well-being network. Drawing on both developmental and psychological models of well-being, we hypothesize that competence and identity-related (e.g., accomplishment) elements of well-being, as well as intimacy-related (e.g., positive relationships, positive emotion) dimensions will be most central to the structure of daily well-being in this sample of college-attending early adults. We test these hypotheses using network analysis and draw out implications for assessing and improving well-being during this developmental period in this social context. A secondary goal was to provide empirical evidence for two properties of the PERMA model. These properties are: (1) each element is defined and measured independently of the other elements (exclusivity) and (2) all elements are intercorrelated to form a network of well-being (connectivity; e.g., Seligman, 2011, p. 16). Butler and Kern's (2016) PERMA Profiler already showed internal consistency without crossloadings (exclusivity) and intercorrelation (connectivity) of the elements. Based on the dense experience sampling data from our study, we demonstrate similar properties by illustrating the dense internal community and sparse external connections of each mPERMA element (exclusivity) this way providing a validity check for the items, and then highlight the connectivity of the overall manifold (connectivity). We then interpret the connectivity and centrality structure of the resulting PERMA network, taking advantage of the network analysis framework to draw new guidance for further studies on early adults' well-being and interventions for momentary well-being in youth.

Methods

Procedures

The data used for this study came from a larger 56-day intervention study that employed EMA methods. A convenience sampling method was used to recruit participants into the study through the university's research website. We use EMA data from the first 14 days of the larger study – this is the period before participants were randomized into intervention and control groups. Participants first came into the lab for an introductory session where they were informed about the study and consented to participation. They filled out a 20-minute survey in which they answered questions about their demographic characteristics and personality. During this session, participants also provided cellular phone information and an approximation of their typical daily sleep schedule. Beginning the next morning and for each of the next 14 days, participants received six daily text messages, each containing a link to a survey which asked them to complete mPERMA items. The timing of the survey prompt was chosen by considering the participants' waking hours, dividing these into six equal intervals and then scheduling a survey randomly into each interval. The text messages were sent such that measurement occasions were not spaced closer than 30 minutes apart. After the 14-day period concluded, participants returned to the lab to be debriefed about this first part of the study and to provide feedback on

their experience. Participants were compensated for their time contingent on the number of surveys they completed.

Importantly, mPERMA answers for each timepoint for each individual were entered simultaneously into the analysis without summarization. The resulting network therefore captures the structure of experiences of well-being elements without regard for person, timing, or context. As a result, we capture here only the static relationships that may exist contemporaneously at a given timepoint, and not the causal or relational processes that may be at play. Although we consider these questions to be important, we present this work as an initial step toward a more complete model of the processes at work. We discuss the implications of this decision in the section on limitations, below.

mPERMA items

Momentary levels of well-being based on the PERMA model were measured by the mPERMA items described in Appendix A. In mPERMA, the five PERMA elements were assessed by three items each, the content of which is based on the matching items of the PERMA Profiler. To reduce participant burden, we implemented planned missingness (Silvia et al., 2014) into our EMA design: we randomly sampled two items out of the three items per element, meaning that for each measurement occasion, participants only had to respond to 10 (2 times 5) mPERMA items instead of 15 (3 times 5). This way, we reduce the items per signal without reducing the number of items in total. As compared to unintended types of missing data where they might not be completely at random, planned missing data are missing completely at random (MCAR). Maximum likelihood methods for missing data have shown that although standard errors might be higher with the planned missingness design, the coefficients themselves estimate the population values in an unbiased way (Davey & Savla, 2010; Enders, 2010; McKnight et al., 2007).

As mentioned, participants provided responses to these items 6 times daily for two weeks. Compliance was high: on average, participants responded to 75 (SD = 6) out of the 84 survey prompts.

Participants

Participants were 160 (106 women) undergraduate students at a major public university in the northeast. Participants ranged from 18 to 22 years old and were recruited. The participants were 74% White/Caucasian, 6% Black/African-American, 9% Asian or Pacific Islander, 4% Hispanic/Latino, and 1% identified themselves as other races. The [blinded] Human Subjects Protection Program approved the research reported in this paper with the project title "Temporal Changes in the Dynamics of Well-being – A Longitudinal Study" and IRB protocol number: STUDY00006362; all participants provided informed consent before enrolling in this study.

Data analysis

Network estimation

We estimated the structure of the mPERMA network using the R package *qgraph* (Epskamp et al., 2012). To construct the mPERMA network we estimated a network of partial correlation coefficients (Borsboom & Cramer, 2013; Epskamp & Fried, 2016; McNally et al., 2015) among the 15 mPERMA indicators (3 items per 5 major elements) using LASSO regularization (Tibshirani, 1996) with EBIC-based model selection (Chen & Chen, 2008). Partial correlation coefficient networks of this type (sometimes termed Gaussian graphical models; Lauritzen, 1996) are frequently used for psychological data that is assumed to be multivariate normally distributed. Technical details on the network estimation are provided in Appendix B. For a tutorial on the analytical steps taken for this analysis, please refer to Epskamp and Fried (2018) and Epskamp and Fried (2018).

Measures of centrality

Network centrality indices are a set of measures imported from graph theory that quantify the importance of a node in the network. The higher the values, the more important the nodes are in the network. Because these characteristics are intended to be measures of the overall influence of a node or pathway on the model, the absolute value of edge weights is used in each case. For example, whether calmness is thought of as reducing stress or increasing relaxation, its effect in each case may be equally strong. In this analysis, we used three commonly-used centrality indices: node strength centrality, closeness, and betweenness (Newman, 2010; Opsahl et al., 2010 Rajendran et al., 2019). Node strength centrality indicates how strongly one node is directly connected to adjacent nodes by taking the sum of absolute values of edge weights directly connected to that node. Closeness and betweenness centrality are related to the shortest paths to travel along edges from one node to another node in the network where the "length" of each path is computed by summing the absolute values of the inverse of the edge weights along that path. Edges

between highly correlated (either positively or negatively) nodes are therefore "short" while paths between nearly uncorrelated nodes are "long". Closeness sums the shortest paths from the node of interest to every other node to summarize how easy it is to get from that node to any other node in the network. Betweenness centrality is calculated by computing the shortest path between each pair of nodes other than the node in question. Betweenness centrality is the change in the sum of shortest paths in the network when the node in question is removed. It therefore quantifies how helpful a given node is in connecting other nodes.

Limitations

The network approach that we chose makes a strong assumption about the commonality of the PERMA structure across individuals. Our data are collected intensively from a variety of different individuals, leading to a multilevel structure where timepoints are clustered by individual. However, our approach does not replicate or model this multilevel structure. Our analyses therefore rely on the idea that the network layout and topology (the nodes and the connections between them) does not differ between individuals—that is, that our data would reveal the same network structure if we intensively measured only a single individual for a much longer timespan, or if we sampled one single momentary occasion each from a much larger number of individuals. This means, for example, that if we find a positive link between Positive emotions and Accomplishment, this applies on the between-person level (i.e., people with more positive relationships are likely to also show higher positive affect), as well as on the within-person level (i.e., if a person has better relationship interactions at a specific timepoint, they would also have more positive affect at that time). We suggest that this is not an unreasonable assumption for this initial work, and suggest that future work, especially work across more heterogeneous populations or across the lifespan, may provide a clearer indication of whether, how, and where this assumption is violated. We elaborate more on this limitation and possible future directions in the Discussion section.

Results

The network analysis resulted in an interrelated network of mPERMA items forming tightly interconnected groups (communities) of nodes that represent the five PERMA elements, similar to the five-factor structure of the PERMA-Profiler (Butler & Kern, 2016). This network is consistent with the two properties hypothesized for the PERMA model of well-being, namely exclusivity of PERMA elements (Property 1), and all elements' intercorrelation to form a network of well-being (Property 2). Figure 2 presents this network with the nodes (i.e., items) portrayed as circles that are labeled with the first letter of the PERMA element they are measuring and the edges (i.e., partial correlations between items) with lines connecting the nodes. The direction of the edges are indicated by solid and dashed lines – solid lines indicating positive partial correlations and dashed lines indicating

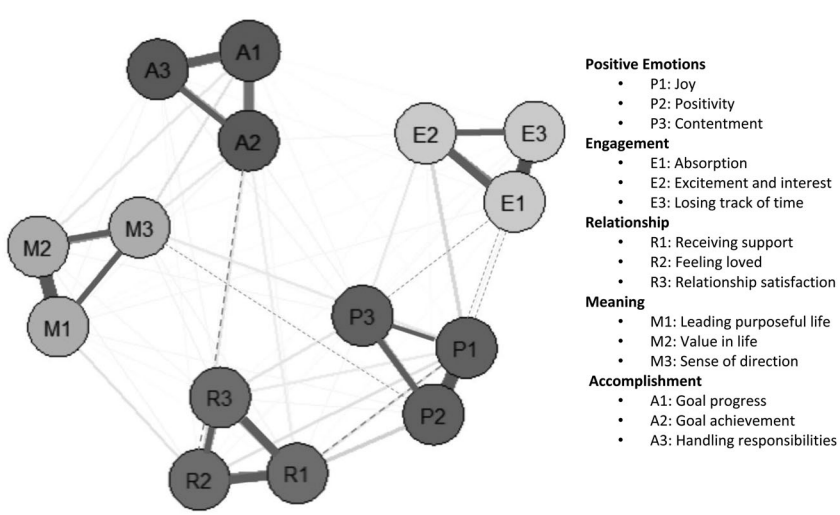

Figure 2. mPERMA Network Visualization: Graph of 15 mPERMA items with three items measuring each PERMA element grouped by shade of gray. Circles indicate network nodes (i.e., items) and lines connecting the circles indicate edges (i.e., relationship between items). Solid lines represent positive association and dashed lines indicate negative association. Thickness of lines indicate the strength of associations.

negative partial correlations. The degree of correlation strength is indicated by the width of the lines (Epskamp et al., 2012). It should be noted that if no line directly connects two nodes, this is an indication that we found no significant correlation between the two nodes after controlling for all other variables in the network and applying the LASSO correction. Detailed information on the LASSO correction as well as the accuracy of the estimation are discussed in Appendix B. Bootstrapped confidence intervals (Appendix B) indicate that all three centrality estimates were stable in their rank order across resampling, with node strength centrality and closeness showing the most stability and betweenness showing a little less stability but still holding up very strongly. We also tested the accuracy of the network and based on the 95% Confidence Interval bootstrapping, found that this network was accurately estimated.

Exclusivity property

The exclusivity property is portrayed in the PERMA network by how items (i.e., nodes) that measure each element are highly correlated and form a dense interconnected group. In other words, items (i.e., nodes) that measure the same element demonstrate higher positive correlations among each other whereas they show weaker correlations with other items in the network. For example, Goal Progress (Accomplishment Item 1) displayed a moderately strong positive connection to Goal Achievement (Accomplishment Item 2; $r = 0.42$), Goal Achievement (A2) showed a moderate positive connection to Handling Responsibilities (Accomplishment Item 3; $r = 0.31$), and Handling Responsibilities (A3) was respectively strongly connected to Goal Progress (A1, $r = 0.41$). The moderately strong interconnection between these three items demonstrate that they measure a similar construct: the Accomplishment element of PERMA. Similar groups are evident for each of the other four PERMA elements (Figure 2; items of the same element are grouped together) which provides evidence for the exclusivity of these elements.

Connectivity property

In addition, while items (nodes) that measure the same PERMA element are strongly correlated, these items also show some (albeit weaker) correlation with other items forming a positively correlated network. This interconnected network demonstrates evidence for the second property of the PERMA model: intercorrelation of all elements to form a network of well-being. In other words, although not as strongly correlated, items measuring different elements are still correlated which indicates that changes in one element of PERMA is related to changes in other elements of PERMA and suggests some consistency across the network of well-being.

In sum, most mPERMA items were positively correlated within the network. The strongest connections were found between pairs of items that measure a common PERMA element, forming five groups that are each strongly connected internally, but sparsely connected to each other. This finding provides the same information as the final five-factor structure of the PERMA-Profiler and mPERMA models. However, the network graph goes beyond this depiction to portray more complexity among the five communities. For instance, when we examine the relationship between the Positive emotion (P) and Relationships (R) communities in Figure 2, we see that the 'Receiving Support' item (R1) within the Relationships community is positively related to the 'Positivity' item (P2; $r = 0.14$) within the Positive emotion community, whereas the other correlations among items between these two communities are very small and negligible. Additionally, looking within each community in the network, although the three items measuring each of the five PERMA elements correlated strongly together, the strength of connections varied. As visualized in Figure 2, items measuring 'Joy' (P1) and 'Positivity' (P2) show a strong association ($r = 0.54$) but the association is lower between 'Contentment' (P3) and both 'Joy' (P1; $r = 0.15$) and 'Positivity' (P2; $r = 0.31$). Looking back at item P3, the item states "I feel contented." Although this item seems very straightforward, based on the post experiment feedback that we received from participants, some participants did not necessarily know what "feeling contented" means. Perhaps if we change the wording of the 'Contentment' item (P3), its connection with the other two items that measure Positive emotions might increase. This hypothesis could be tested by either defining the word "contentment" to participants prior to the survey or by rewording the item so that it conveys the definition in a clearer way. Similarly, the item E1 (Absorption) shows strong correlations with E3 (Losing track of time; $r = 0.58$) but E2 (Excitement and interest) shows weaker correlations with E1 ($r = 0.34$) and E3 ($r = 0.22$). Interestingly, item E2 also shows a moderate positive correlation with P1 (Joy; $r = 0.12$) and a weak association with P3 (Contentment; $r = 0.08$). The item E2 states "When I

noticed the text message, I felt excited and interested in the things around me." One possible problem is that this item includes the feeling of "excitement" and "interest" in the same statement and since both "excitement" and "interest" can be viewed as positive emotions this could explain why this item is showing weaker relationships with the other Engagement items and showing some relationship with the Positive emotion items. In future iterations of this scale, this item could be improved by rephrasing it as "I felt engaged in the things around me" rather than using words that have a positive emotion connotation.

Network centrality

Figure 3 shows a visualization of the standardized centrality estimates of betweenness, closeness, and node strength centrality. This figure helps us compare the centrality measures side by side and in a more convenient way. We examine the centrality of the nodes in order to see how important a node is in the network.

We first test how correlated these three indices are with each other. This correlation depicts how much a difference in one centrality index is related to differences in the others. The correlation between these centrality indices showed that they had a medium positive correlation with $r = 0.46$ between node strength centrality and closeness, $r = 0.45$ between node strength centrality and betweenness, and $r = 0.50$ between closeness and betweenness. This indicates that if an item is high on one of the centrality estimates then other centrality indices will likely also show a high estimate. For example, if node Engagement 3 (Losing track of time) displays a negative centrality estimate of betweenness, it will also show a negative centrality estimate of closeness and strength as these three estimates are correlated.

The 'Strength' panel on the right side of Figure 3 shows the node strength centrality estimate of each of the nodes (i.e., items) of the mPERMA network. The node strength centrality estimate portrays the degree to which that node is directly associated with other nodes in the network. The more a node is directly connected with other nodes in the network, the higher the node strength centrality would be. Based on the 'Strength' panel, the nodes that display more strength are further

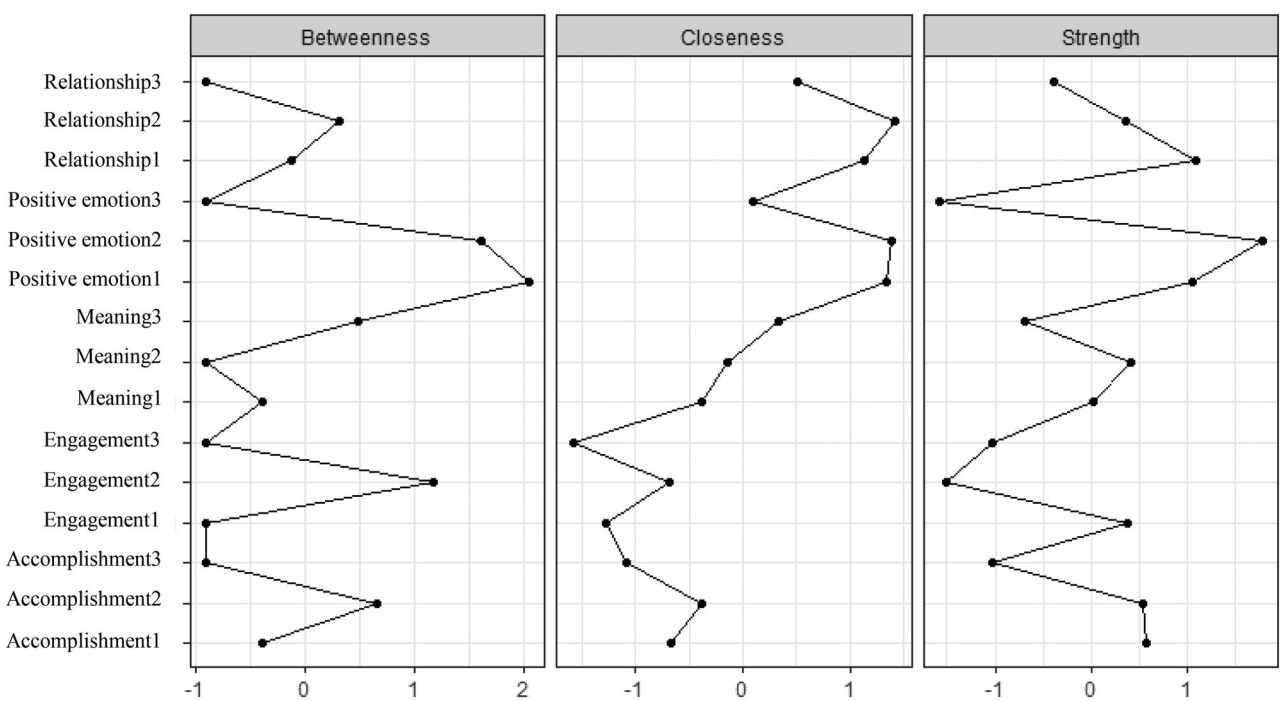

Figure 3. Betweenness centrality, closeness, and node strength centrality indices for the 15 mPERMA item PERMA network. Items corresponding to each node are as follows. Accomplishment1: "I am making progress towards accomplishing my goal", Accomplishment2: "I am achieving the important goals I have set for myself", Accomplishment3: "I am handling my responsibilities", Engagement1: "When I noticed the text message, I was absorbed in what I was doing", Engagement2: "When I noticed the text message, I felt excited and interested in the things around me", Engagegement 3: "When I noticed the text message, I had lost track of time because of what I was doing?", Meaning1: "I lead a purposeful and meaningful life", Meaning2: "What I do in my life is valuable and worthwhile", Meaning3: "I have a sense of direction in my life", Positive emotion1: "I am feeling joyful", Positive emotion2: "I am feeling positive", Positive emotion3: "I am feeling contented", Relationship1: "I feel helped and supported by others", Relationship2: "I feel loved", Relationship3: "I feel satisfied with my personal relationships".

to the right compared to the strength indices for other nodes. These nodes were Relationship1 (Receiving Support), Positive emotion 1 (Joy), and Positive emotion 2 (Positivity). This means that these nodes are the nodes that are most strongly connected to adjacent nodes and therefore are the nodes with the highest strength centrality estimates among all the nodes in the network.

Moving on to the middle panel in Figure 3 ("Closeness"), we can see that Positive emotion 1 (Joy), Positive emotion 2 (Positivity), and Relationship 1 (Receiving Support) show high estimates of closeness in addition to Relationship 2 (Feeling Loved) that also shows high closeness in the network. These results are indicated by their closeness centrality estimates being further to the right and showing higher values compared to other nodes in the "Closeness" panel of Figure 3. The findings imply that the nodes P1, P2, R1, and R2 have the shortest paths from them to every other node and display how easy it is to get from that node to anywhere in the network. This is another indicator of the importance of these nodes in this network.

Finally, zooming in on the betweenness centrality panel on the left side of Figure 3, we can see that P1 (Joy) and P2 (Positivity) are also the two nodes that show the highest betweenness estimates, visible on the plot by placement as the nodes furthest to the right. This finding indicates that the two P1 and P2 nodes are situated on a large number of shortest paths between other nodes, which may suggest that they play an important role in connecting other nodes together. In other words, Positive emotion1 (Joy) and Positive emotion 2 (Positivity) are important nodes in the shortest path between two other nodes. While the causal structure is not entirely clear, it is possible that they act as mediators of the influences among other nodes in the network.

'Joy'(P1) and 'Positivity'(P2) – the two nodes of the Positive emotions element of PERMA – show the highest estimates of node strength centrality, closeness, and betweenness in the network. In addition, 'Receiving Support' (R1) – a node measuring the Relationship element of PERMA – showed high estimates of node strength centrality and closeness but not betweenness in the network. Also, 'Feeling Loved'(R2) – another node measuring the Relationship element of PERMA – only showed high estimates of closeness in the network. This indicates that for the most part, nodes (i.e., items) measuring the Positive emotions and the Relationship elements of PERMA (i.e., 'Joy', 'Positivity', 'Receiving Support', and 'Feeling Loved') play a crucial role in the mPERMA network. If either of these nodes are removed from the network, the whole network might not remain interrelated among the other nodes, or nodes may be less connected together. In other words, if these are causal links, changes in Positive emotions and Relationship aspects of early adults' lives will highly impact their overall well-being, making them viable targets for intervention and prevention.

Discussion

The purpose of this study was to investigate the relationship between the five elements of the PERMA model of well-being in early adults' daily experiences by using repeated measurement data from the ecology of daily life. We focused on two properties of the PERMA network proposed by Seligman (2011). These properties include the notion that (1) each element is defined and measured independently of the other elements (exclusivity) and (2) all elements' intercorrelation to form a network of well-being (connectivity). By working in the EMA paradigm, we were able to capture ecologically valid momentary experiences of the PERMA elements. Using smartphones – an appropriate tool tailored to the technology-laden lives of early adults – we were able to tap directly into the dynamics of early adults' ongoing everyday experiences of well-being. Applying network modeling to this data, we can study the two properties mentioned above. It should be noted that the focus of this network model is at the global level examining intercorrelations among variables and not about individual-specific findings regarding the participants in the sample. To the best of our knowledge, this represents the first study to examine the elements of PERMA as a correlational network using network analysis in early adulthood.

Distinct elements, unitary network

Our analysis provided a validity check that the items (nodes) that measured the same PERMA element in a momentary framework were most strongly correlated with each other (i.e., items of the same PERMA element grouped together in Figure 2). As one example, items assessing the element of Engagement such as absorption in a task and losing track of time and excitement and interest shared moderate to strong correlations (rs .22-.58). This network analysis demonstrated that the items showed the attribute of exclusivity (Property 1).

Second, we also were able to validate that the overall set of items also showed positive (albeit weaker)

correlations with other items from all other elements. This finding demonstrates that the items formed a network of well-being as a totality (i.e., all items, regardless of which element they measure, are in some way correlated and connected to other items in the network in Figure 2; Property 2). These attributes of exclusivity and network totality support the proposed model of Seligman (2011), in this case, using momentary items to assess PERMA (e.g., mPERMA).

Centrality of positive emotion and relationship in early adults' daily well-being

Network analysis also allowed us to examine several measures of importance for each individual measure in the mPERMA scale to further understand early adults' momentary experiences of well-being from both hedonic and eudaimonic perspectives. Our third finding was that the most central and important elements of the early adult daily well-being network were items (nodes) indexing two specific dimensions of PERMA: Relationships (e.g., receiving care and experiencing love) and Positive emotion (e.g., joy and positivity); eudaimonic and hedonic elements of well-being, respectively. In other words, we found a strong interlinkage between items measuring Positive emotions and Relationships (i.e., receiving care, love, positivity, joy) and other items from all other PERMA elements (Accomplishment, Engagement, Meaning) in addition to having the shortest paths of connection to those elements. Specifically, Joy, Positivity, and Support nodes (items) also showed high betweenness in the well-being network indicating that they have high ability to connect other nodes to each other.

These findings highlight the fact that the two elements, Positive emotions and Relationships, are highly correlated with all other elements and are deeply tied to the other constructs that make up early adults' well-being. This is consistent with our hypotheses that support, felt love, and relationship satisfaction, as well as experiencing joy and positivity may be of importance to well-being during this period (Oravecz et al., 2020; Heshmati et al., 2019). This is in line with the daily lifestyles of typical college-attending early adults and also the transitional developmental stage that they are in.

In the early adulthood stage, individuals typically continue to work on identity issues concerning work and values/purpose, as well as building new peer and romantic relationships (Dunkel & Harbke, 2017). This focus on creating bonds with others and the ability to share with and commit to others in this stage of development might explain why we found the element of Relationships to be one of the most central elements of PERMA, with the most connections to other nodes of the network. This could imply that since establishing relationships is of focal interest to early adults, all other aspects of well-being are intertwined with levels of positive relationships in this developmental stage. Similarly, we found the Positive emotions element such as joy and positivity as another component of well-being that is central in early adults' network of well-being connecting other aspects of well-being to each other. Specifically, with Positive emotions being tightly connected to the element of Relationships in the well-being network, hedonic pleasure in the context of peer relationships is what seems to be the focal point of well-being for these college-attending early adults. This could be explained by these particular college students' lifestyle, spending the majority of their time on a typical day in leisurely activities with peers and friends leading to instant pleasure and hedonia (Finlay et al., 2012).

We did not confirm our hypothesis that the eudaimonic element of 'Accomplishment' would be a central and important element in the daily well-being of college-attending early adults. We had anticipated that since 18-22 year olds in this sample were involved in an educational setting and attending college, Accomplishment might have been one eudaimonic element that would be central to their well-being. However, developmentally in this stage, this sample of early adults in college seems focused primarily on social relationships (Erikson, 1968). Thus, even though our sample of early adults were attending college, a context rife with clear achievement benchmarks such as grades, our results indicated that Positive emotions and Relationships are the most important elements in the correlational network of well-being.

We also note that Engagement and Meaning items (nodes) were also not as central or important as Relationships and Positive emotions. This finding suggests, perhaps, that the impacts of these elements on our sample early adults' daily well-being may be mediated through the positive relationships and feelings that occur in relation to life activities in which one experiences Accomplishment (e.g., in classroom learning), Engagement (e.g., in arts or sports), or Meaning (e.g., through spiritual gatherings and practice). These conjectures, which really bear on the developmental scientific question of the structure and shape of change in well-being during early adulthood was not a focus of this study, and cannot be

ascertained with this correlational data. Such issues warrant future research.

Finally, it seems plausible that contextual factors matter here. Perhaps the social environment in the USA around college, or the particular university environment from which the participants of this study were recruited, shapes a kind of local cultural concensus about what well-being means during college for students – being socially integrated and having fun may be more salient than finding a sense of vocation and purpose, or becoming socially engaged and giving back. The utility of the approach outlined here is that in different settings, with different populations, we may be able to discern different patterns of what constitutes well-being at this stage, and also infer how this may be affected by different social environments that young people experience.

Implications for science and practice

The question of how to define, assess, and map change in the structure of thriving, flourishing, and well-being across the lifespan is receiving more and more empirical attention. Although the network approach we have taken here is a correlational analysis and no causal inferences can be taken, we believe that it provides information about placements of the nodes within the network as potentials for future causality testing of the PERMA well-being structure. Two methods that might be employed to understand and test the causal structure of well-being in more detail along the lines of this study are implicated: one statistical and one experimental. From a statistical perspective, approaches modeling Granger causality (e.g. Molenaar & Lo, 2016) use the temporal relationships in the data to determine a form of putative cause. Second, our final network model – which in and of itself does not imply causality – provides several points of potential manipulation that might allow for causality tests via experimental or quasi-experimental manipulation of well-being variables. Network intervention approach (Valente, 2012) is one example of how network data can be used to inform future intervention studies for the purpose of generating influence, accelerating change, or achieving desirable outcomes among communities (Valente, 2012). Depending on the goal of the intervention, different centrality measures may be adopted to induce or accelerate change within the network. An intervention focused on increasing social support in early adults' daily lives, for example, would be a good induction strategy to examine (a) whether this improves overall well-being, (b) how other elements in the well-being network change with respect to the change in social support, and (c) whether these changes are true only for early adults compared to older adults. These tests would illuminate whether there is a causal relationship between the different elements of the PERMA network or if they are merely correlational, as the network implies.

Related, the findings of this study have implications for the putative targets in well-being-oriented intervention and prevention efforts in early adulthood. Given that nodes measuring Positive emotions and Relationships elements showed high *strength* in the network, meaning that they are directly and strongly connected to other nodes, network interventions to increase a person's overall well-being may be effective. Using an induction strategy (Valente, 2012) we can aim to increase a person's experience/awareness of feelings of joy, positivity, love, and support that might make a considerable impact on his/her overall well-being – contingent upon a causal relationship being present among these nodes which requires further experimental testing. Intervention and prevention programs for college-aged students that teach mindfulness may increase awareness and experiences of Positive emotion, thereby affecting well-being (see Dvořáková et al., 2017). In addition, programs that teach care and compassion in terms of receiving care, self-care, and extending care to others in a balanced way may also be implicated by such findings and particularly effectively for well-being improvement (see Dvořáková et al., 2019). More generally, this finding implies that interventions intended for this age group might not successfully increase overall well-being if they target eudaimonic elements other than those involving social relationships (i.e., accomplishment, meaning, engagement), although future research is needed to confirm causality among these elements and overall well-being.

Second, these nodes demonstrate high closeness centrality, indicating that there are short paths from them to many other nodes within the network. Therefore, if for instance we aim to increase an individuals' sense of Meaning – which is one of the non-central elements in early adults' well-being – it may be important to monitor his/her Positive emotions and feelings of love and care (Relationships), given that these elements are tightly interrelated with many other metrics of well-being. If causality is established among the elements, this could imply that if an early adult is experiencing emotional pain or lack of support and love, his/her sense of Meaning or purpose in life would most likely be affected and therefore intervening to increase Meaning might not be very

effective, if his/her Positive emotions and Relationships are not intact.

Third, Joy, Positivity, and Support nodes show high betweenness centrality, meaning that they are very impactful in connecting other nodes together because they are positioned between other nodes in the network. Interventions focused on transfer effects (e.g., using engagement interventions to improve a person's sense of Meaning and Accomplishment) may benefit from close tracking of changes in Joy, Positivity, and Support in early adults, since they may act as important bridges in the global well-being network to connect constructs to each other. However, this is only possible if causality is established among these nodes in future studies.

In sum, Joy, Positivity, and Support, and to a lesser extent Feelings of Love may act as mediators of influences among other elements of well-being in early adults' daily lives. Hence, it may be important to measure and support these elements in any intervention that attempts to generate overall daily flourishing in early adults. While our results do not directly capture causal influence and further testing is required, these results are consistent with a view that positive changes in these feelings, which constitute both hedonic and eudaimonic elements for this age group, may be strongly related to youths' overall well-being and closely tied to each of the other elements of well-being.

Limitations and future directions

Although we had a large sample size for such an intensive study, our study was limited by the lack of diversity of our participants. Testing the same models in samples more diverse in cultural background and region of the world would be useful. In this study, we focused on understanding the well-being experience of college students within the age range of 18 to 22 years old as a representative sample of the early adulthood stage of life. It would be interesting for future research to explore what the mPERMA network would look like for people in a variety of age ranges and to examine how conceptualizations of human flourishing may differ across periods in the lifespan, and by implication, develop over ontogenetic time. Perhaps the centrality of the PERMA dimensions would change if mPERMA was explored in adulthood or older adulthood compared to early adulthood. Moreover, further examination of discriminate and predictive validity of the scale with multiple samples would be recommended in order to improve the items and theory of well-being (John & Benet-Martínez, 2000).

We emphasize here again that our data analytic approach is limited in the sense that it cannot distuingish within-person and between-person structures. This assumption is related to the assumption of ergodicity: Molenaar (2004) conceptualizes an ergodic process as one for which the within-person (intra-individual) and between-person (inter-individual) structures are the same. In this case, the ergodicity assumption essentially means that the network structure is the same for all individuals, such that timepoints selected from one individual are freely exchangeable with timepoints selected from another. Although Molenaar (2004), likely correctly, argues that the assumption of ergodicity might not be met for many psychological processes, we made this assumption for our analysis in order to provide a simplified starting point for introducing a network approach for understanding psychological well-being.

Future work may question this assumption by attempting to fit a multilevel network model instead of our more simplified common network model. For example, as described in Lazega and Snijders (2015), there are several forms of multilevel network analysis, ranging from Siena-type actor-oriented models to HLM-type models, as well as VAR-based approaches like GIMME (Gates & Molenaar, 2012), each of which focus on different characteristics of the model to answer different hypotheses, and each of which make different assumptions about the processes at work and the data in use. Importantly, in order to relax the ergodicity assumption by using any of these models, we would need to make additional assumptions about the processes involved in well-being across time. For example, a multilevel VAR model (Epskamp et al., 2018) makes assumptions of a homogeneous decay process across time, and might require assuming that, for example, the emotional influence of an event across time decays at the same rate between evening and morning (across a long period of sleep) as between early and late afternoon. These assumptions are nontrivial.

Similarly, the use of a traditional multilevel VAR model implies a single set of processes across all people (allowing for normally-distributed variability); by contrast, a group-iterative approach (e.g. using GIMME; Gates & Molenaar, 2012) relaxes this assumption to allow individuals to each have their own unique network structures. It is not entirely clear from current theory which approach would be an optimal model, nor what the implications are if one of these types of models provides better fit than

another. We therefore present the current work as a first step toward understanding the organization of well-being by making the broadest of assumptions, and hope that it serves as a springboard for expanded work using these more intricate networks.

Finally, our specific network model examines only the bidirectional connections among the components of well-being, which for example does not allow us to distinguish the influence of Joy on Positivity from the influence of Positivity on Joy. We are therefore unable to directly infer causal structure from our model. Future work is needed to overcome this limitation. For instance, intervention studies that target changes in Joy by manipulating Positivity, while controling all other elements, can shed light on the causal relationship of Joy and Positivity and the direction of this causal structure.

Conclusion

In this study, we investigated the complex interrelation between the elements of the PERMA model of well-being in early adults' daily lives using network analysis. In this method, we consider our measurements to be distinct but interrelated individual items instead of indicators of underlying latent quantities. This study presents an approach to examine this intricate network of thoughts and feelings and provides further clarity on how the mPERMA indicators relate to each other in youths' day-to-day life. We believe that these unique features of our study complement the newly built body of literature on the PERMA well-being framework and provide insight into the complex relationship between these elements in early adults' daily experiences of well-being in addition to informing future daily well-being interventions for this age group.

We have described the practical considerations of identifying elements of well-being as a group of highly connected variables that explains the importance of each element in relation to the network of well-being as a whole. We believe our findings on specific constructs within the network having greater importance in driving early adults' well-being (e.g., Positive emotions or Relationships) and being highly connected to other constructs within the well-being network, can inform future interventions. We hope that these results will also provide developmental researchers with new tools and measures for use in experience sampling studies and intervention studies aimed at documenting and improving early adults' well-being in everyday life.

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ORCID

Saeideh Heshmati http://orcid.org/0000-0003-4002-128X
Robert W. Roeser http://orcid.org/0000-0003-3326-5921

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Appendix A. mPERMA item descriptions

Item Name	PERMA-Profiler Items	mPERMA Items
Positive emotions1 (P1)	In general, how often do you feel joyful?	I am feeling joyful.
Positive emotions2 (P2)	In general, how often do you feel positive?	I am feeling positive.
Positive emotions3 (P3)	In general, to what extent do you feel contented?	I am feeling contented.
Engagement1 (E1)	How often do you become absorbed in what you are doing?	When I noticed the text message, I was absorbed in what I was doing.
Engagement2 (E2)	In general, to what extent do you feel excited and interested in things?	When I noticed the text message, I felt excited and interested in the things around me
Engagement3 (E3)	How often do you lose track of time while doing something you enjoy?	When I noticed the text message, I had lost track of time because of what I was doing?
Relationship1 (R1)	To what extent do you receive help and support from others when you need it?	I feel helped and supported by others.
Relationship2 (R2)	To what extent do you feel loved?	I feel loved.
Relationship3 (R3)	How satisfied are you with your personal relationships?	I feel satisfied with my personal relationships.
Meaning1 (M1)	In general, to what extent do you lead a purposeful and meaningful life?	I lead a purposeful and meaningful life.
Meaning2 (M2)	In general, to what extent do you feel that what you do in your life is valuable and worthwhile?	What I do in my life is valuable and worthwhile.
Meaning3 (M3)	To what extent do you generally feel you have a sense of direction in your life?	I have a sense of direction in my life.
Accomplishment1 (A1)	How much of the time do you feel you are making progress toward accomplishing your goals?	I am making progress toward accomplishing my goals.
Accomplishment2 (A2)	How often do you achieve the important goals you have set for yourself?	I am achieving the important goals I have set for myself.
Accomplishment3 (A3)	How often are you able to handle your responsibilities?	I am handling my responsibilities.

Appendix B. Technical details on network estimation

Network estimation

In order to avoid false positive connections, we used the Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani, 1996). LASSO regularization technique limits these false positive connections by setting very small edges to zero, resulting in a sparse network with potentially spurious connections removed. Typically, LASSO estimates a range of networks from a fully connected network to a network with no connections. By optimizing the fit of the network to the data the best network is then selected. We used LASSO regularization with EBIC model selection (i.e., removing edges to minimize the Extended Bayesian Information Criterion; Chen & Chen, 2008). This procedure is known to work well in retrieving the true network structure, especially when the generating network does not contain many edges (Epskamp & Fried, 2016; Foygel & Drton, 2010).

Network accuracy and stability estimation

When taking a network analysis approach for psychological data, the parameters are *estimated* values on connections between nodes rather than actual values. With increases or decreases in sample size, the precision of the parameters changes, either approaching the true value or moving away from them. Hence, when we have limited sample sizes, as is typical in psychological research, parameter estimates might not be estimated precisely and lead to questionable interpretations of the network. For example, referring back to the network displayed in the main text (Figure B1), it is difficult to interpret whether the stronger edge between nodes C and D is meaningfully stronger than the slightly less weighted edge between B and D. Similarly, it is often difficult to select the most important node out of two similarly central nodes in a network. To avoid these problems, we assess the accuracy and stability of the network parameters with a bootstrap analysis using the R package *bootnet* (Epskamp & Fried, 2018). Bootstrapping (Efron, 1979) is a way of estimating model parameters by repeatedly drawing samples from the data with replacement, and then estimating the statistics of interest on each draw. We first bootstrapped the 95% intervals of the edge weights with a 1000-sample nonparametric bootstrap. We then calculated the stability of the network centrality estimates by indicating if the order of centrality indices remains the same when we re-estimate the network with select cases or nodes instead of all of them. This is done by eliminating each measurement occasion from the dataset in sequence and re-estimating the network. If the centrality order of the network that includes all the cases is highly correlated with the centrality order of the network with fewer cases, then the centrality estimates are considered stable (see Epskamp & Fried, 2018). We calculated both the accuracy of the network and the stability of the node strength centrality in the network. Figure B1 demonstrates the accuracy of the 15-item PERMA network. This plot shows bootstrapped confidence intervals (gray area) around each edge weight (red line).

In order to test the stability of our centrality measures, we conducted a subset bootstrapping technique. In this technique we test whether the order of centrality estimates

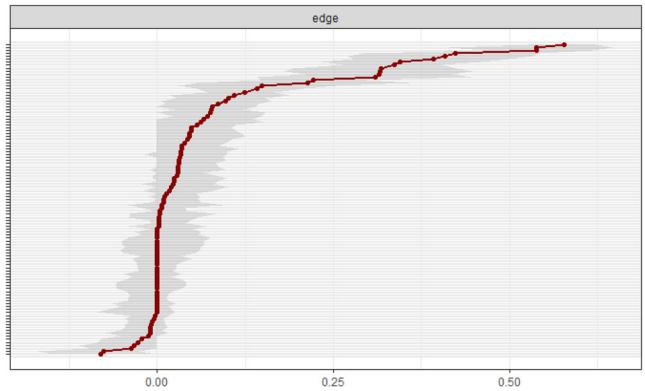

Figure B1. mPERMA Network Accuracy: Graph shows bootstrapped 95% Confidence Intervals of the edge weights in the 15-item mPERMA network. The red line portrays actual edge weight values and the gray area portrays the 95% Confidence Intervals.

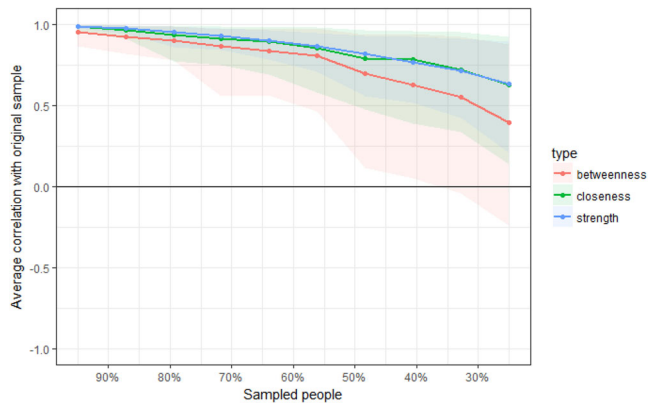

Figure B2. mPERMA Network Stability. This graph shows bootstrap subsetting to estimate the stability of the three centrality estimates for the 15-item PERMA network. This graph shows the average correlations between centrality indices of the original PERMA network based on the full data and the networks estimated based on the subsets of the sample used.

from a mPERMA network in which many participants are excluded is still correlated with the order of the centrality estimates from the original mPERMA network that includes all participants. If we find a high correlation between the two, then we can assume that the centrality estimates are stable. Figure B2 displays the result for this subset bootstrapping technique on the mPERMA network. Results indicate that the order of all three centrality estimates – as discussed under the measures section – are very stable with node strength centrality and closeness showing the most stability and betweenness showing a little less stability but still holding up very strongly. This is consistent with the Correlation Stability coefficient (CS-coefficient) of 0.44 for node strength centrality, 0.36 for closeness, and 0.28 for betweenness. As a general guideline, in order to have a stable order of centrality estimate, the CS-coefficient should not be below 0.25 and preferably above 0.50. The centrality estimate, CS-coefficients for this data fit this criterion. For more explanation on the stability and accuracy methods and metrics please refer to Epskamp et al. (2016 Epskamp et al., 2016).

Appendix C. Descriptive statistics and correlation matrices

Table C1. Descriptive statistics of the 15 items measuring the five PERMA elements.

PERMA items	Mean	SD	P1	P2	P3	E1	E2	E3	R1	R2	R3	M1	M2	M3	A1	A2	A3
P1	67.34	22.31	1.00														
P2	71.91	20.07	0.80	1.00													
P3	71.32	20.36	0.65	0.71	1.00												
E1	63.65	28.30	0.22	0.24	0.19	1.00											
E2	56.96	28.61	0.37	0.35	0.33	0.62	1.00										
E3	58.17	29.41	0.18	0.17	0.18	0.73	0.58	1.00									
R1	74.78	17.95	0.53	0.62	0.54	0.19	0.24	0.13	1.00								
R2	74.74	19.34	0.57	0.59	0.52	0.18	0.25	0.14	0.78	1.00							
R3	74.54	19.37	0.58	0.61	0.55	0.18	0.25	0.12	0.77	0.76	1.00						
M1	76.46	17.64	0.48	0.52	0.46	0.19	0.22	0.12	0.58	0.59	0.57	1.00					
M2	76.04	17.83	0.48	0.51	0.47	0.19	0.21	0.12	0.56	0.58	0.56	0.84	1.00				
M3	74.72	18.94	0.49	0.49	0.43	0.17	0.21	0.11	0.57	0.54	0.55	0.75	0.77	1.00			
A1	73.51	18.61	0.49	0.52	0.46	0.20	0.25	0.15	0.54	0.49	0.52	0.61	0.64	0.64	1.00		
A2	72.86	18.74	0.47	0.52	0.43	0.18	0.25	0.13	0.52	0.44	0.49	0.59	0.60	0.61	0.82	1.00	
A3	71.79	20.17	0.46	0.52	0.43	0.20	0.24	0.14	0.51	0.48	0.50	0.58	0.59	0.58	0.81	0.78	1.00

Table C2. Correlation coefficients of mPERMA items reflected by the network graph.

PERMA items	P1	P2	P3	E1	E2	E3	R1	R2	R3	M1	M2	M3	A1	A2	A3
P1	1.00														
P2	0.54	1.00													
P3	0.15	0.31	1.00												
E1	−0.03	0.04	−0.04	1.00											
E2	0.12	0.01	0.08	0.34	1.00										
E3	0.01	0.02	0.02	0.58	0.22	1.00									
R1	−0.08	0.14	0.03	0.01	0.00	0.00	1.00								
R2	0.10	0.00	0.02	0.00	0.00	0.00	0.40	1.00							
R3	0.07	0.04	0.09	0.00	0.00	−0.01	0.35	0.32	1.00						
M1	0.00	0.03	0.00	0.03	−0.01	−0.01	0.00	0.10	0.02	1.00					
M2	0.00	0.00	0.03	0.00	0.00	0.00	0.03	0.05	0.00	0.54	1.00				
M3	0.07	0.03	0.01	0.00	−0.01	0.00	0.04	0.00	0.05	0.21	0.32	1.00			
A1	0.01	0.00	0.03	0.01	0.00	0.00	0.03	0.00	0.00	0.00	0.79	0.11	1.00		
A2	0.00	0.06	0.00	0.00	0.03	−0.01	0.06	−0.08	0.00	0.05	0.01	0.08	0.42	1.00	
A3	0.00	0.05	0.00	0.01	0.00	0.00	0.00	0.02	0.04	0.03	0.02	0.00	0.41	0.31	1.00

Note. Correlation coefficients in this table are smaller compared to Table 1 due to the LASSO regularization, which applies a shrinkage operation to the matrix.