Well-being is a Personalized Experience: An Intraindividual Approach to Dynamic Well-Being Networks in Young Adults' Daily Lives

Saida Heshmati[1], Jaymes Paolo Rombaoa[1], Sean H. Merritt[1], and Alexander P. Christensen[2]

[1]School of Social Science, Policy, & Evaluation, Claremont Graduate University

[2]Department of Psychology and Human Development, Vanderbilt University

Author Note

Saida Heshmati: https://orcid.org/0000-0003-4002-128X

Jaymes Paolo Rombaoa: https://orcid.org/0000-0003-0228-8944

Alexander P. Christensen: https://orcid.org/0000-0002-9798-7037

Correspondence concerning this article should be addressed to Saida Heshmati, Claremont Graduate University, 175 E. 12th Street, Claremont, CA 91784. Email: saida.heshmati@cgu.edu.

Abstract

Well-being has been the focus of investigation in psychological sciences in recent years, yet cross-sectional and group-level methods fall short of capturing the dynamics of person-level well-being experiences in daily life. This investigation is particularly important for young adults who are in a developmental phase in which they experience unique fluctuations in their daily life. In the present study we used ecological momentary assessments of well-being from two samples of first-year college students (Sample 1, $N =$ 103, assessments = 2,535; Sample 2, $N = 76$, assessments = 1,796) and dynamic exploratory graph analysis to address the following research questions: (1) How do elements of well-being in young adults' daily life form a dynamic network? (2) Does the well-being dynamic network structure hold across all young adults, or is there heterogeneity in those structures? (3) Is there synchrony among well-being elements, and do they drive a person's well-being network? Findings from this study suggest that while group-level dynamic well-being networks align with theoretical models, young adults' individual experiences vary significantly, with each person demonstrating unique well-being network structures and synchronous elements. These findings underscore the importance of considering individual variability in well-being networks, highlighting the necessity for personalized approaches in understanding and promoting well-being among young adults.

Keywords: well-being, young adulthood, dynamic exploratory graph analysis, network modeling, ecological momentary assessment, PERMA, *m*PERMA

Public Significance Statement

This paper explores the notion that well-being in young adults' daily life is a highly individualized experience, varying significantly from one person to another. By examining first-year college students, we found that well-being elements are interconnected and form a dynamic system, where changes in one aspect of well-being are linked to changes in others. However, the structure and synchronization of these well-being networks vary greatly among individuals. These findings underscore the need for personalized interventions for young adults, especially those transitioning to college. Tailoring support to each person's unique needs and adapting it over time can lead to more effective and sustained well-being, moving beyond one-size-fits-all solutions to more customized and responsive approaches.

General Disclosures

Conflicts of Interest: All authors declare no conflict of interest. Funding: This research received funding from an internal institutional award. Artificial Intelligence: artificial intelligence assisted technologies were only used for grammatical checks and sentence structure editing purposes. Ethics: This research received approval from the Claremont Graduate University ethics board (ID: 3661).

Study One Disclosures

Preregistration: No aspects of the study were preregistered. Materials: All study materials are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116). Data: All primary data are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116). Analysis scripts: All analysis scripts are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116).

Study Two Disclosures

Preregistration: No aspects of the study were preregistered. Materials: All study materials are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116). Data: All primary data are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116). Analysis scripts: All analysis scripts are publicly available (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116).

Well-being is a Personalized Experience: An Intraindividual Approach to Dynamic Well-Being Networks in Young Adults' Daily Lives

The concept of well-being has deep philosophical and scientific roots, with significant growth and development in the psychological sciences in recent decades (Lomas, 2022; Rombaoa & Heshmati, 2023). Despite this growth, the multifaceted and subjective nature of well-being poses challenges for researchers in defining, measuring, and understanding the interplay of its interrelated factors within and between individuals. To address these challenges, there has been a theoretical shift toward understanding well-being as a multidimensional construct. Well-being is thought to comprise various hedonic (i.e., enjoyment and positive feelings; Henderson et al., 2014) and eudaimonic (i.e., fulfillment through contribution, positive relationships, and having meaning and purpose in life; Huppert, 2014) elements that form a "web of well-being" (Merritt et al., 2024). This movement has allowed well-being to be examined as an interrelated network where its elements form a complex system.

This multidimensional approach to well-being is particularly significant for young adults, especially those transitioning to college, a period marked by substantial personal and social change (Roeser, 2012; Schulenberg et al., 2004). The transition to college often involves new academic pressures, social environments, and increased independence, all of which can impact a student's mental health and overall well-being.

Furthermore, young adults in college are more likely to face irregularities and fluctuations in their day-to-day life, participating in risk-taking behaviors, frequent social gatherings, and often irregular work schedules (Finlay et al., 2012). For instance, prioritizing social events and leisure over activities like volunteering or spiritual practices can lead to behaviors such as excessive drinking and disruptive conduct, which negatively affect sleep patterns and overall daily structure (Carney et al., 2006). Given these dynamic experiences, adopting a multidimensional approach to well-being that captures these daily variations can provide a deeper understanding of this critical transition phase into adulthood.

PERMA, a multidimensional framework of well-being introduced by Seligman (2011), explains well-being through five hedonic and eudaimonic elements: Positive emotions, Engagement, Relationships, Meaning, and Accomplishment. It has been argued that while these elements are not an exhaustive list of factors that make up a person's experience of well-being in life, they (1) "can be defined and measured independently of other elements while being interconnected (connectivity)," and (2) "people pursue each element for its own sake and not just to serve another element (exclusivity)" (Seligman, 2018, p. 2). By adopting a network approach, previous research (Heshmati et al., 2022; Merritt et al., 2024) has validated the assumptions of 'exclusivity' and 'connectivity' in young adults' PERMA well-being network **(**Seligman, 2018**)**.

In parallel, the science of well-being is shifting toward a dynamical systems perspective, moving beyond theoretical frameworks that view well-being as a fixed trait (Heshmati, et al., 2024a). This shift challenges the concept of an “ideal,” and unchanging state of well-being and mental health as a stable endpoint (Busseri & Sadava, 2013; Biswas-Diener et al., 2011). A dynamical systems approach emphasizes the fluid and evolving nature of well-being, highlighting its process-oriented characteristic that cultivates stable traits over time. Further, it enables an examination of how well-being changes over short and long time-scales, the variability among individuals, and their impact on a person’s overall journey toward well-being (Heshmati, et al., 2024a).

There is an emerging consensus on the necessity of idiographic, person-centered approaches in psychological science (Molenaar, 2004). The prevailing use of nomothetic approaches in psychological research, which seek to establish general laws and commonalities across individuals, are insufficient to explain individual-level experiences. These methods presuppose that psychological traits and dynamics, such as those associated with well-being, are consistent across people (i.e., ergodicity; Nesselroade & Molenaar, 1999; Fisher et al., 2018) with a growing body of research highlighting the limitations of this assumption (Hayes & Hofmann, 2021). For instance, although group-level analyses might identify common dimensions of personality across a population, individual-level analysis reveals a much broader spectrum of personal characteristics that vary not only in number but also in kind (Beck & Jackson, 2020; Borkenau & Ostendorf, 1998). This distinction is crucial in the study of well-being in young adults, where heterogeneity in personal significance and the subjective nature of well-being processes play pivotal roles (Heshmati, et al., 2023). Idiographic approaches allow researchers to delve into the unique configurations of well-being elements for each individual, acknowledging that the interrelations among these elements can differ dramatically from person to person.

Dynamic network models are one method that can investigate how the components and the whole of well-being relate across time. In a network, each component (e.g., item) of well-being is represented as a ‘node’ (circle) with ‘edges’ (lines) that connect each component. The edges represent how two components change together across time given all other components. Components that consistently change together can form strong interconnections known as ‘communities’, which are consistent with dimensions of a construct (Golino et al., 2020).

This representation is afforded by Dynamic Exploratory Graph Analysis (DynEGA; Golino, et al., 2022). DynEGA estimates the first-order derivatives of each variable’s time series for each person using the Generalized Local Linear Approximation method (Deboeck et al., 2009) to capture their rate of change (i.e., how quickly a variable increases and decreases) across a time window of consecutive measurement points (e.g., five). Afterwards, networks and communities are estimated from these derivatives for each person and the sample.

Similarities and differences between the individual-level and sample-level as well as pairwise individual-level structures can be examined at various degrees. At the broadest structure, networks can be compared to examine how similar individuals are to each other and the sample. At the intermediate structure, communities can be compared to determine whether dimensions are similar (even if the networks appear different). At the lowest structure, centrality measures can be compared to determine how similar nodes are connected within the networks. Taken together, these comparisons provide evidence for whether the dynamics of well-being are homogeneous across the sample.

The Present Research

In the present investigation, we aimed to explore well-being in first-year college students as a dynamic network, characterized by temporal momentary changes and individual variability through an ecological momentary assessment (EMA; Stone & Shiffman, 2002) research design. This period of young adulthood, especially the transition to college, is marked by significant fluctuations in daily routines and social activities, making it a critical phase for examining well-being. We posit that applying dynamic network analysis to well-being in young adults will enhance our understanding of its underlying structures and driving elements. This approach aligns with the shift in psychological sciences toward more nuanced and process-oriented understandings of mental health and well-being (Hayes & Hoffman, 2021; Heshmati, et al., 2024b), recognizing that static and nomothetic models do not adequately capture the complexity of human experiences (Renner et al., 2020).

In prior well-being research, investigations have often concentrated on general trends and commonalities across people, potentially overlooking the intricacies of individual experiences of well-being in daily life. Our study aims to address this gap by testing whether (a) components that make up young adults' well-being experiences across time form the same theoretical dimensions of well-being as proposed by the PERMA framework, (b) well-being network, dimension, and centrality structures are similar at the sample- and individual-level, and (c) some well-being elements are more synchronous (change together more consistently) across time and that these patterns are consistent across individuals. By focusing on first-year college students, we aim to capture the unique and dynamic nature of well-being during this critical transition period for young adults.

Method

Participants and Procedures

The first sample comprised 103 first-year college students enrolled at one of five undergraduate Claremont Colleges aged 18 to 20 years old (M = 18.41, SD = 0.57). Participants in this sample were from a larger multi-week intervention study across multiple semester cohorts (e.g., Fall 2021, Spring 2021), but the data presented here is based on the pre-intervention period (before any intervention was applied). Participants completed EMAs at semi-random time points within four blocks (9:00–11:00 a.m., 2:00–2:00 p.m., 3:00–5:00 p.m., 6:00–9:00 p.m.) and no two surveys were administered within one hour of each other. The EMAs were signaled four times each day for 1 week. Out of a total of 2,884 possible EMAs (103 people 7 days 4 signals), this sample had 2,535 available EMAs to analyze (sample compliance rate = 88%), with participants completing an average of 24 (*SD* = 3) out of the 28 signaled surveys (individual compliance rate = 86%). The compliance rate for this sample was acceptable (above 80%), according to EMA guidelines by Stone and Shiffman (2002).

The second sample comprised 76 first-year Claremont College students (age: *M* = 18.41 years, *SD* = 0.61) during the weeks following the first state-mandated university lockdowns in California due to the COVID-19 pandemic in Spring 2020. These students had measures identical to Study 1 but were not involved in a larger intervention study with multiple weeks of data collection. We used the one week of EMA data available from Study 2 to replicate Study 1. Out of a total possible 2,128 EMAs (76 people 7 4), the second sample had 1,796 EMAs to analyze (sample compliance rate = 84 %), with participants completing an average of 23 (*SD* = 3) out of 28 signaled surveys (individual compliance rate = 82%). Lastly, components of the data in Study 2 have been used elsewhere (Rombaoa et al., 2023) but have not been analyzed using the current methods. Participants completed a battery of trait and EMA measures. Participants were paid proportional to their survey response rates, with a maximum payment of $30 for trait measures and one week of EMAs. Demographic information for both samples is provided in Table 1.

Table 1

Demographic Characteristics of Two Samples of First-Year Students

Demographics	Sample 1 (*N* = 103)	Sample 2 (*N* = 76)
Gender		
% Female	85	71
% Male	11	24
% Non-Binary	3	4
% Prefer not to say	1	1
Race/Ethnicity		
% Asian or Pacific Islander	44	36
% Black, African American	8	13
% Hispanic, Latino	14	14
% Native American, Eskimo, Aleut	1	1
% Other	2	13
% White, Caucasian	46	46

Note. The total number of ecological momentary assessments was 2,535 for Sample 1 and 1,796 for Sample 2. Participants could “check all that apply” for Race/Ethnicity.

Measure

*m*PERMA

Momentary well-being was assessed using Momentary PERMA (*m*PERMA; Heshmati, Uysal, et al., 2023), the adapted version of the PERMA-Profiler (Butler & Kern, 2016) that is validated for intensive longitudinal designs and measuring elements of well-being in daily life. Like the PERMA-Profiler, *m*PERMA measures various components of well-being (Seligman, 2011, 2018). To emphasize that participants were answering questions about their momentary well-being, participants were prompted with the phrase “in this current moment,” and phrases such as “in general” were removed (see Heshmati et al., 2023). There were three items based on each block of PERMA for a total of 15 items: Positive emotions (e.g., “I am feeling joyful”), Engagement (e.g., “When I noticed this survey, I was absorbed in what I was doing”), Relationships (e.g., “I feel helped and supported by others”), Meaning (e.g., “I have a sense of direction in my life”), and Accomplishment (e.g., “I am making progress towards accomplishing my goals''). Each item was presented in a randomized order on participants’ smartphones to reduce biased responses due to order effects. For each item, participants used a slider scale that ranged from 0 (*not at all*) to 100 (*completely*).

Data Analysis Plan

Network and Dimension Estimation

Using DynEGA, exploratory graph analysis (Golino al., 2020) was applied to each individual’s first-order derivatives (individual-level networks) and across all individuals' derivatives (sample-level network). To estimate a network, the graphical least absolute shrinkage and selection operator (GLASSO; Friedman et al., 2008) with extended Bayesian information criterion (EBIC; Epskamp & Fried, 2018) was used. To estimate the number and content of dimensions, the lower-order Louvain algorithm (Blondel et al., 2008) was applied.

Network, Dimension, and Node Similarity

To evaluate the similarity of sample-to-individual level and pairwise individual-level networks, we used an information-theoretic metric called Jensen-Shannon Distance (JSD; De Dominico et al., 2015). JSD is a metric used to quantify how different two networks are based on their topology. The more similar the two networks are, the smaller the distance, ranging from 0 (identical) to 1 (completely different; Williams et al., 2020). This metric was converted to a similarity by computing 1 – JSD (Jensen-Shannon Similarity; JSS).

Dimension similarity was computed using the Adjusted Rand Index (ARI; Hubert & Arabie, 1985). The ARI quantifies the similarity between two community solutions by counting the matching pairs and accounting for the expected number of matching pairs by chance. Values can range from -1 (completely different) to 1 (exactly the same) with zero representing similarity expected by random chance. ARI was computed between the sample- and individual-level dimensions to determine the representativeness of the sample-level dimensions. A permutation test was performed to determine whether the ARI value was significantly different from zero (Qannari et al., 2014).

Centrality similarity used node strength (absolute sum of a node's connections to other nodes), which was compared between sample-to-individual level and pairwise individual-level networks. Node strength is commonly used in network psychometrics and is often referenced as "centralness" in terms of rank order (Bringmann et al., 2019). Consistent with this usage, comparisons used Spearman's correlation to determine the similarity of centrality.

Pairwise Node Synchrony

Definitions of synchronicity vary. We define synchrony as "significant overlap" in the rate at which two (or more) variables change together across time (Moulder et al., 2018). To quantify significant overlap, Unique Variable Analysis (Christensen et al., 2023) was used. Values are considered statistically redundant as to be capturing "synchronous" information. Synchronous variable pairs were counted across people representing the frequency of individuals with those synchronous pairs.

For a more thorough treatment of each analytic method applied in this study, full descriptions are provided on the Open Science Framework: https://osf.io/95qvr?view_only=f64237b42caf48f39288b8bb83072116.

Software and Scripts

All analyses were conducted using R (version 4.4.4). DynEGA was applied using the *EGAnet* package (version 2.0.7) and associated results were visualized using the *ggpubr* (version 0.6.0), *GGally* (version 2.2.1), and *ggplot2* (version 3.5.1) packages in R. Data used for this study, analysis scripts, and results are available on OSF (https://osf.io/qvws2/?view_only=f64237b42caf48f39288b8bb83072116).

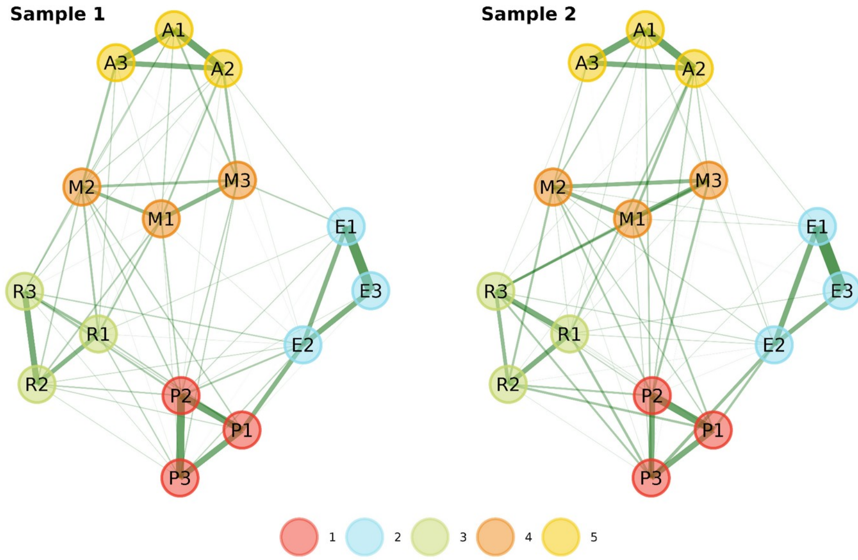
Results

Dynamic PERMA Dimensions

For Sample 1 and 2, the five theoretical PERMA dimensions were identified in the sample-level networks (Figure 1). At the individual-level, the median number of dimensions was five for both samples (Table 2). On the one hand, the individual-level dimensions appear to be relatively consistent with the sample-level dimensions given the median number of dimensions was 5 across individuals and the majority (more than 50%) of individuals had 5 dimensions in both samples (but not necessarily the same content). On the other hand, there was still a good proportion (at least 40%) of the sample that did not have the same number of dimensions as the sample-level. The indication of whether these results reflect homogeneity or heterogeneity is explored next.

Figure 1

Sample-Level Dimensions for Sample 1 and Sample 2



Note. Nodes (circles) represent *m*PERMA variables, green edges (lines) represent positive regularized partial correlations with the thickness indicating magnitude, and the color of the nodes denotes the community (dimension) they belong to.

Table 2

Frequency and Proportions of Dimensions in the Individual-level Networks

Number of Dimensions	**Sample 1 *n* (%)**	**Sample 2 *n* (%)**
One	0 (0.0%)	4 (5.3%)
Two	0 (0.0%)	0 (0.0%)
Three	1 (1.0 %)	1 (1.3%)
Four	20 (19.4%)	15 (19.7%)
Five	59 (57.3%)	41 (53.9%)
Six	20 (19.4%)	14 (18.4%)
Seven	3 (2.9%)	1 (1.3%)

Similarities and Differences

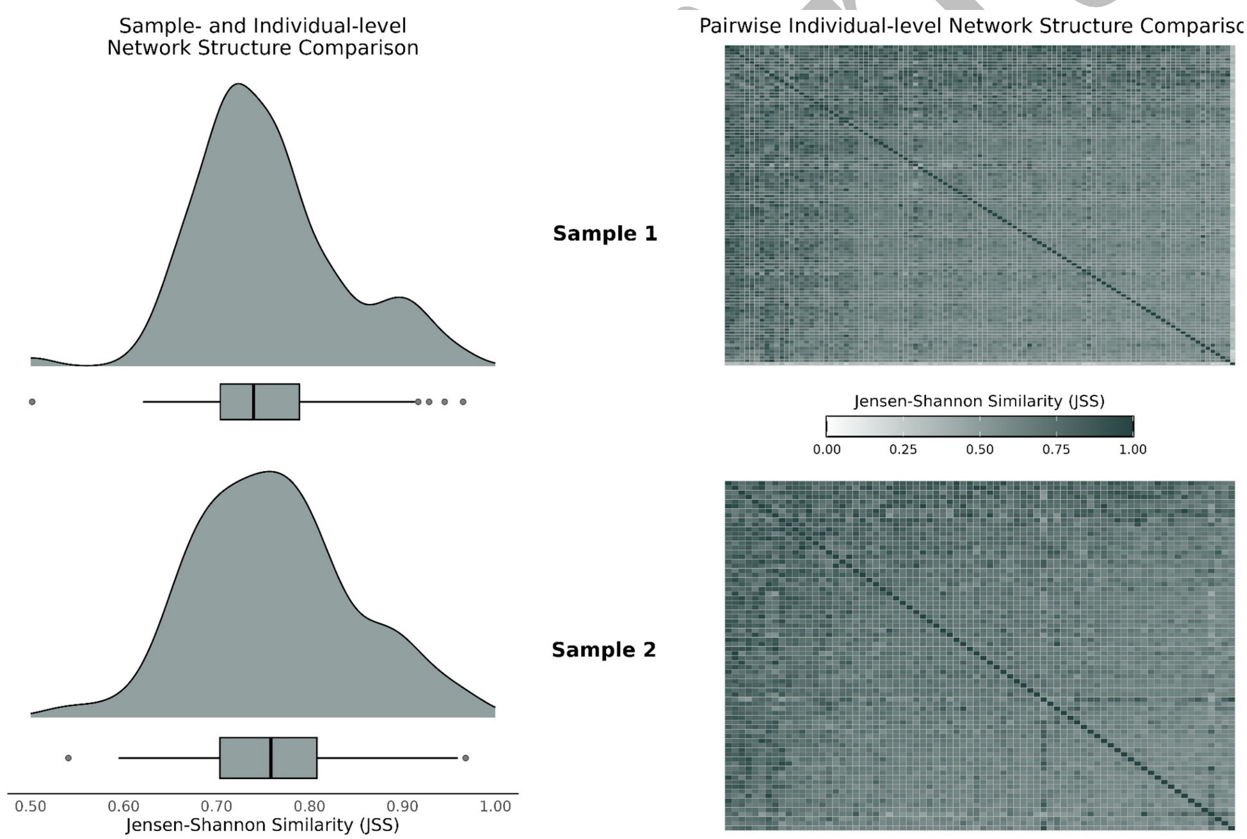
Network Similarity

As a point of reference, the two sample-level networks were highly similar with a JSS of 0.914 (Figure 1). The sample-to-individual level comparison (left in Figure 2) demonstrated lower similarity, on average, and substantial variability (Sample 1: $M = 0.751$, $SD = 0.089$, $range =$ 0.338–0.965; Sample 2: $M = 0.762$, $SD = 0.085$, $range = 0.541–0.968$). Although these similarities were heterogeneous, the heterogeneity was consistent across the two samples, $t(177) = -0.857$, $p = 0.392$, $d = 0.130$.

For the pairwise comparison of the individual-level networks, there was similar heterogeneity (Sample 1: $M = 0.693$, $SD = 0.107$, $range =$ 0.181–0.987; Sample 2: $M = 0.701$, $SD = 0.091$, 0.424–0.997), which was marginally negligible different, $t(6697) = -3.872$, $p < 0.001$, $d = 0.086$. On average, the individual-level networks were more different from one another than their respective sample-level networks. These results suggest that the individual-level networks are heterogeneous when compared to each other and their respective sample-level networks but that this heterogeneity is consistent across samples.

Figure 2

JSS Distributions of the Sample-Level and Individual-Level Networks



Note. Displayed are the Jensen-Shannon Similarity distributions of the sample-level compared to individual-level networks (left); and the pairwise JSS across the individual-level networks (right), where darker boxes represent greater similarity. Sample 1 is the top row; Sample 2 is the bottom row.

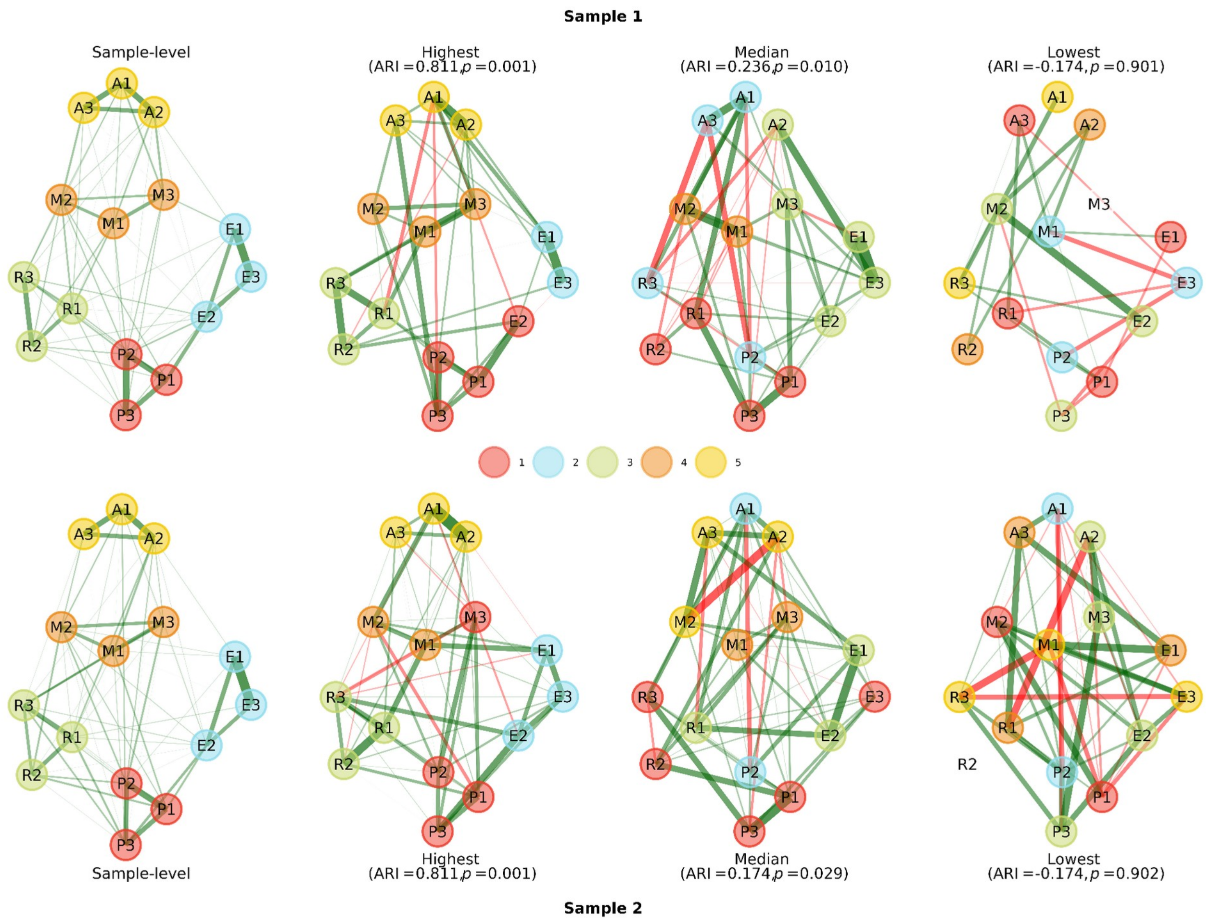
Dimension Similarity

Dimension similarity focused exclusively on sample-to-individual level community comparisons. The individuals whose communities had the highest, median, and lowest values of ARI with their respective sample-level communities are displayed in Figure 3. In Sample 1, the highest (ARI = 0.811) and median (ARI = 0.236) similarities were significantly different ($p < 0.001$ and $p = 0.010$, respectively) than would be expected from random (ARI = 0). The lowest (ARI = -0.174) similarity did not significantly differ ($p = 0.901$) from random. Similarly, in Sample 2, the highest (ARI = 0.811) and median (ARI = 0.174) similarities were significantly different ($p < 0.001$ and $p = 0.029$, respectively) than would be expected from random and the lowest (ARI = -0.174) similarity did not significantly differ ($p = 0.902$) from random.

Across individuals in Sample 1, thirty-seven (35.9% of the sample) had similarities with their respective sample-level communities that were not significantly different from random. Across individuals in Sample 2, thirty (39.5% of the sample) had similarities with their respective sample-level communities that were not significantly different from random. Taken together, these results suggest that although the majority (> 60%) of the individuals had community structures that were more similar than random, there was a substantial proportion of individuals who were not. These results suggest that the sample-level dimensions are not wholly representative of all individuals in their respective samples.

Figure 3

Sample-Level Community Comparisons With Individual-Level Communities

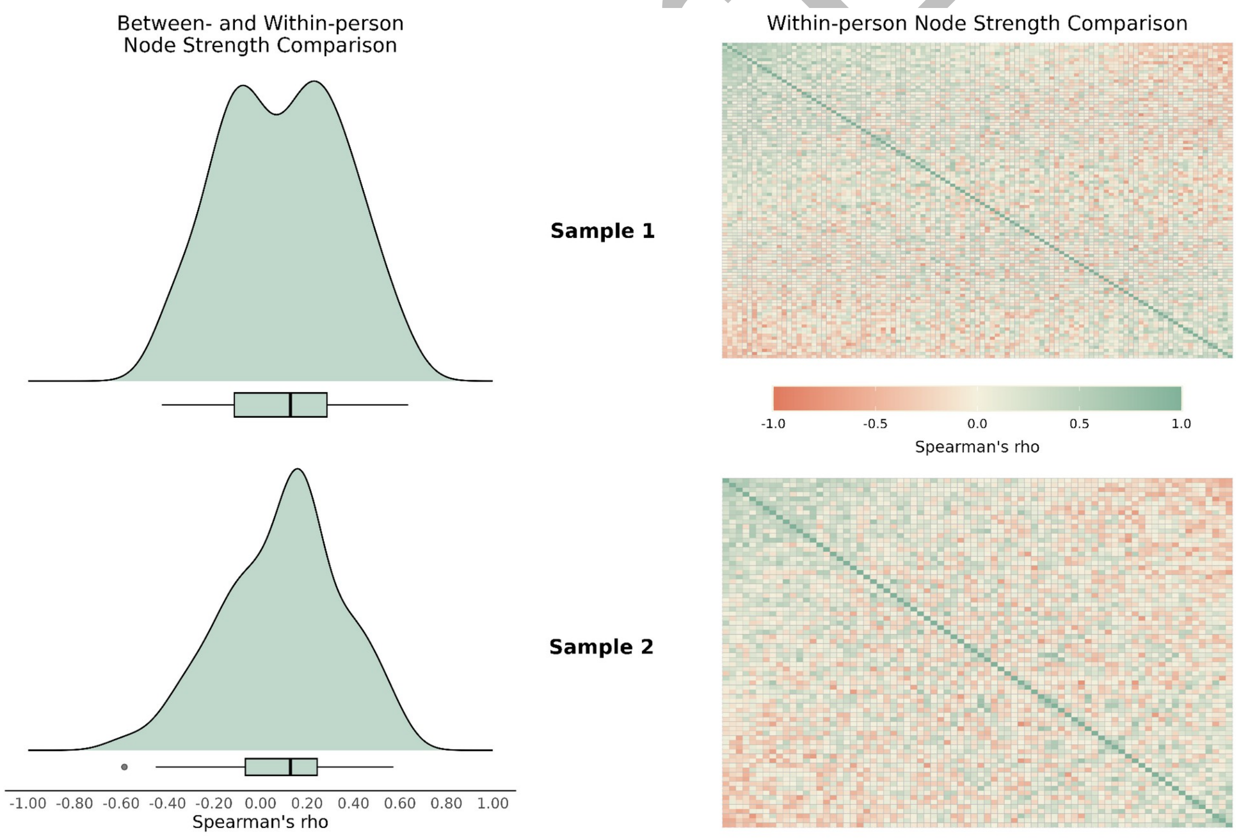


Note. Sample 1 (top) and Sample 2 (bottom) community comparisons with the sample-level communities (leftmost) compared against the highest (second from the left), median (second from the right), and lowest (rightmost) similarities of the individual communities.

Centrality Similarity

At the node-level, despite the strong similarity between centrality for the sample-level networks ($r = 0.793$, $p < 0.001$), there was substantial heterogeneity for the rank-order relationships between the sample-level and individual-level node strengths for Sample 1 (r's between -0.425 and 0.636) and Sample 2 (r's between -0.586 and 0.571; left in Figure 4). When comparing the each sample's distributions (Sample 1: $M = 0.096$, $SD = 0.260$; Sample 2: $M = 0.094$, $SD = 0.252$), there was no significant difference, $t(177) = -0.048$, $p = 0.962$, $d = 0.007$.

Figure 4



Note. Displayed are the Spearman's rho distributions of the sample-level and individual-level centralities (left); and the pairwise Spearman's rho across the individual-level networks (right), where darker boxes represent greater magnitudes and the colors green and red represent positive and negative relationships, respectively. Sample 1 is the top row; Sample 2 is the bottom row.

For the pairwise individual-level centrality similarities, there was similar heterogeneity in Sample 1 (M = 0.029, SD = 0.267, *range* = -0.796–0.764) and Sample 2 (M = 0.013, SD = 0.264, *range* = -0.782–0.786) such that the difference was negligible, $t(8101) = -2.627$, $p < 0.001$, $d = 0.061$. Taken together, these results suggest that despite consistency in centrality at the sample-level (three most central for Sample 1: P2, P1, E2, and Sample 2: P2, P3, P1), there was consistent and considerable variability at the individual-level in both samples.

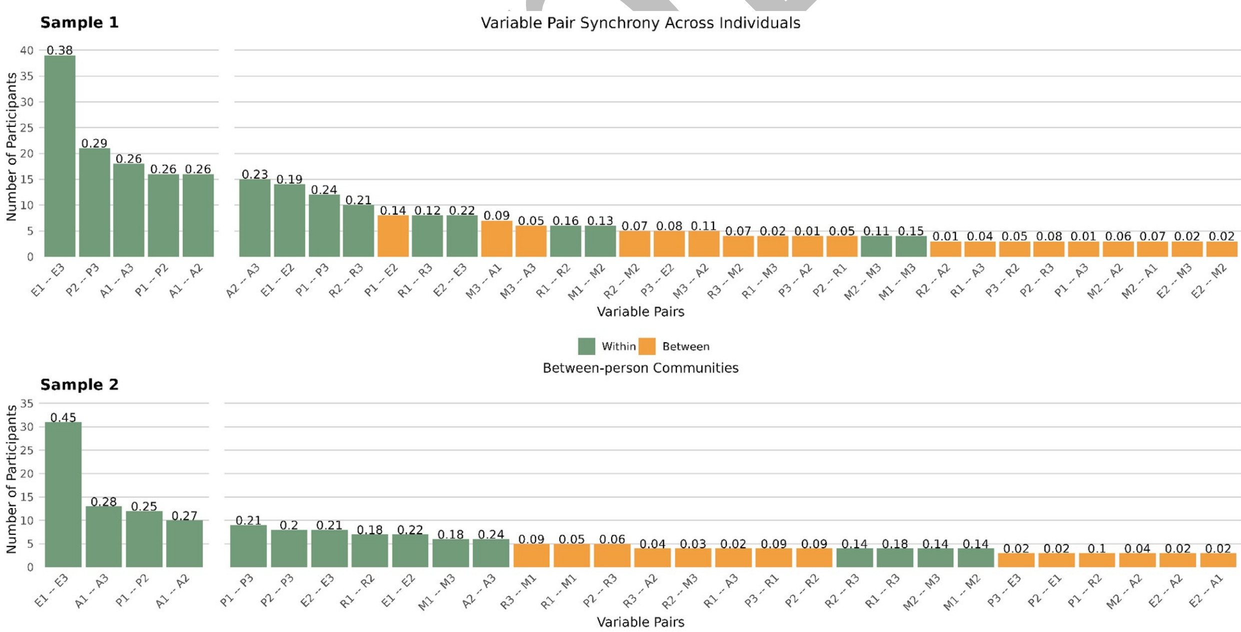
Synchronous Components

Pairwise synchrony was largely consistent across both samples at both the sample- and individual-level (Figure 5). Four out of five possible variable pairs that were identified as synchronous were found in both samples and were similarly some of the most frequently identified variable pairs at the individual-level (E1–E3, A1–A3, P1–P2, A1–A2). The majority of the most frequently identified synchronous variable pairs at the individual level for both samples were variables that belonged to the same theoretical P, E, or A dimension at the sample-level. This result is not surprising as these variables were crafted to represent the same underlying construct.

There were, however, several variable pairs that were not in the same dimension at the sample-level that were synchronous for a few individuals. These different sample-level dimension variable pairs reflect the relative unique processes of each person's well-being and support the different network and dimension structures reported earlier. In sum, there were several synchronous variable pairs across many people but the majority of pairs were identified in 10% or less individuals suggesting heterogeneous processes across individuals.

Figure 5

Frequency Distributions for Individuals With Synchronous Variable Pairs



Note. Frequencies of the number of individuals with variable pairs reaching synchrony (wTO > 0.25) in Sample 1 (top) and Sample 2 (bottom). The bar colors represent whether the variable pairs were in the same (green) or different (yellow) dimension in the respective sample-level network. Values at the top of the bars represent the sample-level wTO values and the gap represents the cut-off between variable pairs that are synchronous at the sample-level.

Summary

Broadly, there is consistency at the sample-level in network structure, dimensionality, and centrality across both samples. At the individual-level, this consistency turns to heterogeneity for the between sample- and individual-level structures as well as pairwise similarities between individuals across network structure, dimensionality, and centrality. The distributions of the similarities of the network structure and centrality, however, did not significantly differ. These individual-level results support the conclusion that there is consistency of heterogeneity.

Discussion

We investigated how elements of well-being, as experienced in daily life by first-year young adult college students, form dynamic networks, examining both sample-level trends and individual-level patterns. Using a multidimensional perspective of well-being, theorized to be made up of various dimensions that form a web of well-being (Merritt et al., 2024; Seligman, 2018), we implemented a dynamic psychometric network approach to examine how well-being changes as a system over time. From this analysis, several key conclusions emerged.

First, the structure of well-being was visualized and analyzed over time at both sample and individual levels, revealing how well-being elements theorized in the PERMA model form dynamic networks. At the sample-level, our analysis focused on identifying common patterns and structures within the well-being networks across the entire sample and replicated in a second sample. We observed that all items (nodes) measuring the same construct were highly correlated with each other and formed the P, E, R, M, A communities, while also remaining connected to other nodes in the network but on a weaker level. We also found similar results when assessing centrality in the sample-level networks. Across the two first-year college student samples, we found that the Positive emotions nodes were most central (highly connected to other nodes) in the sample networks, consistent with previous findings using single time points (Heshmati et al., 2022).

At the individual-level, we examined whether these sample-level findings held true at the individual-level. The individual-level results highlighted the fluid nature of well-being experiences in first-year college students, where the strength and nature of interactions between elements as experienced in daily life, could fluctuate based on personal life circumstances and individual characteristics. In fact, we found that although around 50% of individuals' well-being networks had five communities, at least 40% of the individuals in both samples did not have the same number of communities as the sample-level.

Second, our results demonstrated that while nodes that were theorized to be measuring the same well-being element were highly synchronized across people, there was considerable variability in how well-being elements are synchronized among individuals in both samples. This variability in synchronization reveals that the dynamics between well-being elements are not uniformly experienced across all young adults. One individual, for example, might experience a strong synchronous relationship between Positive emotions and Relationships, indicating that their emotional well-being is closely tied to the quality of their interpersonal connections. Another individual might have more pronounced synchrony between Meaning and Accomplishment, suggesting that their sense of purpose and fulfillment is related to their achievements and productivity. These differences in synchronization not only underscore the personalized nature of well-being in daily life for young adults but also highlight the complex ways in which different dimensions of well-being can be interdependent.

Such differences suggest that each person’s well-being is shaped by a unique combination of factors, which may not be fully represented by general models. For example, a first-year college student may be experiencing periods of academic success, showing strong connections between Accomplishment and Positive emotions in their well-being network, while another student may find meaning through personal relationships, showing stronger connections between Meaning and Relationship dimensions. This divergence in the composition and dynamics of individual well-being networks highlight the inherently person-specific nature of well-being in young adults and that well-being is not a static construct but a continuously evolving interplay of various factors. Each individual's network of well-being elements can change in response to external pressures and internal traits, highlighting the need for dynamic approaches in both research and practical applications.

For young adults, especially those transitioning to college, our findings—replicated in two studies—have significant implications. This developmental period accompanied by a drastic change in environment and lifestyle for those transitioning to college, is marked by substantial changes in daily routines, social interactions, and responsibilities, which can lead to fluctuations in well-being (Rombaoa et al., 2023). First-year college students face unique challenges, including adapting to a new academic environment, establishing new social connections, and often living away from home for the first time. These changes can result in heightened stress, homesickness, and a sense of uncertainty. Additionally, the demands of academic performance, time management, and navigating new social dynamics can create a complex and often overwhelming experience. Recognizing that each student's well-being network is unique allows for the development of targeted strategies that consider individual differences in experiences and needs. For example, some students might benefit from interventions that emphasize positive emotions and engagement in enjoyable activities, while others might need support in building strong relationships or finding purpose in their academic and personal lives. By tailoring interventions to the specific dynamics of each student's well-being network, we can promote better mental health and overall well-being, helping first-year college students navigate this important transition with greater ease and success.

This variability also underscores the importance of developing a deeper understanding of the mechanisms that drive these differences. There is a need for dynamic models that can more accurately reflect the fluid and evolving nature of well-being, which would ideally incorporate methods that capture these fluctuations over time and adapt to individual differences. More recently, theoretical perspectives and methodological approaches centered on capturing individual differences in well-being dynamics (e.g., GoHiAR; Li et al. 2022; Heshmati et al., 2024a) are on the rise, and investigations examining well-being as a process are emerging (Heshmati et al., 2022; Stocker et al., 2023). Such approaches would provide a deeper understanding of how well-being elements interact and change, offering a richer, more nuanced perspective than is possible with traditional static models.

Our findings also highlight the need for integrating intra- and inter-individual approaches in investigations of psychological constructs. While inter-individual research helps identify general trends and common patterns across large groups of people, intra-individual research focuses on the unique experiences of individuals as they live their daily lives (Molenaar, 2004). Combining these approaches could lead to a richer understanding of fluid psychological constructs such as well-being in fluctuating developmental stages such as young adulthood, one that acknowledges and incorporates the variability and personalization evident in our findings.

Our findings prompt rethinking well-being intervention designs and implementations for young adults, especially those transitioning to college, moving beyond one-size-fits-all approaches that overlook the nuances that characterize a person's well-being. Moreover, the dynamic nature of these networks – where the importance and influence of certain elements can shift over time – suggests that well-being interventions should be adaptable and responsive to changes in an individual's life context. The Process-Based Therapy approach (Hayes & Hofmann, 2021; Heshmati et al., 2024b) is one example of such an approach in the clinical sciences (e.g., Westhoff et al., 2024).

Conclusion and Limitations

The current investigation of well-being as a dynamic system challenges the status quo of its static study in the psychological sciences. Although our study offers significant insights into well-being's complexity, it is not without limitations. Reliance on self-reported data may introduce biases; however, the use of EMA reduces recall bias from participants with their in-the-moment responses about their experiences. Moreover, the sample size and convenience sampling, though adequate for initial explorations, may prevent us from drawing generalizable conclusions to more diverse populations. Ultimately, this study marks a critical step toward redefining how well-being is conceptualized and studied in young adults. By embracing the complexity and individuality revealed in our analysis, both researchers and practitioners can better serve the diverse needs of individuals in this stage of life.

References

Beck, E. D., & Jackson, J. J. (2020). Idiographic traits: A return to Allportian approaches to personality. *Current Directions in Psychological Science, 29*(3), 301-308. https://doi.org/10.1177/0963721420915860

Biswas-Diener, R., Kashdan, T. B., & Minhas, G. (2011). A dynamic approach to psychological strength development and intervention. *The Journal of Positive Psychology*, *6*(2), 106–118. https://doi.org/10.1080/17439760.2010.545429

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, *2008*, P10008. https://doi.org/10.1088/1742-5468/2008/10/P10008

Borkenau, P., & Ostendorf, F. (1998). The Big Five as states: How useful is the five-factor model to describe intraindividual variations over time? *Journal of Research in Personality, 32*(2), 202–221. https://doi.org/10.1006/jrpe.1997.2206

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T., & Snippe, E. (2019). What do centrality measures measure in psychological networks? *Journal of Abnormal Psychology*, *128*(8), 892–903. https://doi.org/10.1037/abn0000446

Busseri, M. A., & Sadava, S. W. (2013). Subjective well-being as a dynamic and agentic system: Evidence from a longitudinal study. *Journal of*

Happiness Studies, *14*(4), 1085–1112. https://doi.org/10.1007/s10902-012-9368-9

Butler, J., & Kern, M. L. (2016). The PERMA-Profiler: A brief multidimensional measure of flourishing. *International Journal of Wellbeing*, *6*(3), 1–48. https://doi.org/10.5502/ijw.v6i3.526

Christensen, A. P., Garrido, L. E., & Golino, H. (2023). Unique variable analysis: A network psychometrics method to detect local dependence. *Multivariate Behavioral Research*, *58*(6), 1165–1182. https://doi.org/10.1080/00273171.2023.2194606

De Domenico, M., Nicosia, V., Arenas, A., Latora, V. (2015). Structural reducibility of multilayer networks. *Nature Communications, 6*, Article 6864. https://doi.org/10.1038/ncomms7864

Deboeck, P. R., Montpetit, M. A., Bergeman, C., & Boker, S. M. (2009). Using derivative estimates to describe intraindividual variability at multiple time scales. *Psychological Methods*, *14*(4), 367–386. https://doi.org/http://dx.doi.org/10.1037/a0016622

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*, 617–634. https://doi.org/10.1037/met0000167

Fisher, A. J., Reeves, J. W., Lawyer, G., Medaglia, J. D., & Rubel, J. A. (2017). Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of Abnormal Psychology*, *126*(8), 1044–1056. https://doi.org/10.1037/abn0000311

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*, 432–441. https://doi.org/10.1093/biostatistics/kxm045

Golino, H., Christensen, A. P., Moulder, R., Kim, S., & Boker, S. M. (2022). Modeling latent topics in social media using dynamic exploratory graph analysis: The case of the right-wing and left-wing trolls in the 2016 US elections. *Psychometrika*, *87*(1), 156–187. https://doi.org/10.1007/s11336-021-09820-y

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods, 25*(3), 292–320. https://doi.org/10.1037/met0000255

Hayes, S. C., & Hoffman, S. G. (2021). “Third-wave” cognitive and behavioral therapies and the emergence of a process-based approach to intervention in psychiatry. *World Psychiatry, 20*(3), 363–375. https://doi.org/10.1002/wps.20884

Henderson, L. W., Knight, T., & Richardson, B. (2014). The hedonic and eudaimonic validity of the orientations to happiness scale. *Social Indicators Research*, *115*(3), 1087–1099. https://doi.org/10.1007/s11205-013-0264-4

Heshmati, S., Muth, C., Li, Y., Roeser, R. W., Smyth, J. M., Vandekerckhove, J., Chow, S., & Oravecz, Z. (2023). Capturing the heterogenous effects of a mobile-health psychological well-being intervention for early adults: Results from a process-oriented approach. *PsyArXiv.* https://doi.org/10.31234/osf.io/mb79u

Heshmati, S., Muth, C., Roeser, R. W., Smyth, J., Jamalabadi, H., & Oravecz, Z. (2024a). Conceptualizing psychological well-being as a dynamic process: Implications for research on mobile health interventions. *Social and Personality Psychology Compass, 18*(1), e12933. https://doi.org/10.1111/spc3.12933

Heshmati, S., Oravecz, Z., Brick, T. R., & Roeser, R. W. (2022). Assessing psychological well-being in early adulthood: Empirical evidence for the structure of daily well-being via network analysis. *Applied Developmental Science, 26*(2), 207–225. https://doi-org.ccl.idm.oclc.org/10.1080/10888691.2020.1766356

Heshmati, S., Uysal, N. K., Kim, S. H., Oravecz, Z., & Donaldson, S. I. (2023). Momentary PERMA: An adapted measurement tool for studying well-being in daily life. *Journal of Happiness Studies*. https://doi.org/10.1007/s10902-023-00684-w

Heshmati, S., Westhoff, & Hofmann, S. G. (2024b). Novel approaches toward studying change: Implications for understanding and treating psychopathology. *Psychiatric Clinics of North America, 47*(2), 283–300. https://doi.org/10.1016/j.psc.2024.02.001

Hubert, L., & Arabie, P. (1985). Comparing partitions. *Journal of Classification*, *2*, 193–218. https://doi.org/10.1007/BF01908075

Huppert, F. A. (2014). The state of well-being science: concepts, measures, interventions and policies. In F.A. Huppert & C.L. Cooper (Eds.) *Wellbeing: A complete reference guide,* (Vol. 6, pp. 1–49). Wiley. https://doi.org/10.1002/9781118539415.wbwell036

Li, Y., Heshmati, S., Chow, S. M., & Oravecz, Z. (2022). A growth of hierarchical autoregression model for capturing individual differences in changes of dynamic characteristics of psychological processes. *PsyArXiv*. https://osf.io/preprints/psyarxiv/vr3ce

Lomas, T. (2022). Making waves in the great ocean: A historical perspective on the emergence and evolution of wellbeing scholarship. *The Journal of Positive Psychology, 17*(2), 257–270. https://doi.org/10.1080/17439760.2021.2016900

Merritt, S. H., Heshmati, S., Oravecz, Z., & Donaldson, S. I. (2024). Web of well-being: Re-examining PERMA and subjective well-being through networks. *The Journal of Positive Psychology*, *19*(3), 499–509. https://doi.org/10.1080/17439760.2023.2209538

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research and Perspectives, 2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Moulder, R. G., Boker, S. M., Ramseyer, F., & Tschacher, W. (2018). Determining synchrony between behavioral time series: An application of surrogate data generation for establishing falsifiable null-hypotheses. *Psychological Methods, 23*(4), 757–773. https://doi.org/10.1037/met0000172

Nesselroade, J. R., & Molenaar, P. C. M. (1999). Pooling lagged covariance structures based on short, multivariate time-series for dynamic factor analysis. In R. H. Hoyle (Ed.), *Statistical strategies for small sample research* (pp. 224–250). Sage.

Qannari, E. M., Courcoux, P., & Faye, P. (2014). Significance test of the adjusted Rand index. Application to the free sorting task. *Food Quality and Preference*, *32*(A), 93–97. https://doi.org/10.1016/j.foodqual.2013.05.005

Renner, K. H., Klee, S., & von Oertzen, T. (2020). Bringing back the person into behavioural personality science using big data. *European Journal of Personality, 34*(5), 670–686. https://doi.org/10.1002/per.230

Rombaoa, J. P., & Heshmati, S. (2023). *Mapping the history, anatomy, and trajectory of research on well-being: A bibliometric review of the psychological sciences*. PsyArXiv. https://doi.org/10.31234/osf.io/cr4x3

Rombaoa, J. P., Heshmati, S., Rodriguez, M., & Owen, T. (2023). *Prioritizing lifestyle factors for effective emotion regulation: A daily study on first-*

year college students' well-being during COVID-19. PsyArXiv. https://doi.org/10.31234/osf.io/7gxta

Seligman, M. E. P. (2011). *Flourish: A visionary new understanding of happiness and well being*. Free Press.

Seligman, M. (2018). PERMA and the building blocks of well-being. *The Journal of Positive Psychology*, *13*(4), 333–335. https://doi.org/10.1080/17439760.2018.1437466

Stocker, J. E., Koppe, G., Reich, H., Heshmati, S., Kittel-Schneider, S., Hofmann, S. G., Hanh, T., van der Maas, H. L. J., Waldorp, L., & Jamalabadi, H. (2023). Formalizing psychological interventions through network control theory. *Scientific Reports, 13*, Article 13830. https://doi.org/10.1038/s41598-023-40648-x

Stone, A. A., & Shiffman, S. (2002). Capturing momentary, self-report data: A proposal for reporting guidelines. *Annals of Behavioral Medicine*, *24*(3), 236–243. https://doi.org/10.1207/S15324796ABM2403_09

Westhoff, M., Berg, M., Reif, A., Rief, W., & Hofmann, S. G. (2024). Major problems in clinical psychological science and how to address them. Introducing a multimodal dynamical network approach. *Cognitive Therapy and Research*. https://doi.org/10.1007/s10608-024-10487-9

Williams, D. R., Rast, P., Pericchi, L. R., & Mulder, J. (2020). Comparing Gaussian graphical models with the posterior predictive distribution and Bayesian model selection. *Psychological Methods*, *25*(5), 653–672. https://doi.org/10.1037/met0000254