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Positive and Negative Emotion Persistence as Transdiagnostic Measures of Psychological Well-Being

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Positive and Negative Emotion Persistence as Transdiagnostic Measures of Psychological Well-Being

A dissertation submitted in partial satisfaction of

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in Psychology

by

Olivia Marie Losiewicz

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ABSTRACT OF THE DISSERTATION

Positive and Negative Emotion Persistence as Transdiagnostic Measures of Psychological Well-Being

by

Olivia Marie Losiewicz

Doctor of Philosophy in Psychology

University of California, Los Angeles, 2026

Professor Michelle Craske, Chair

Understanding emotion dynamics is important in order to ascertain transdiagnostic mechanisms underlying anxiety and mood disorders. Emotional inertia, the stability of emotion over time, and emotion network density, a measure of the interconnectedness of emotions, both represent the *persistence* of emotions over time. Previous literature suggests that emotional persistence, particularly of negative emotions, is related to depression, anxiety, and difficulty with emotion regulation. However, this research is limited in that studies examining idiographic network density, longitudinal relationships, and transdiagnostic, continuous, or objective outcome measures are scarce. Additionally, existing studies present mixed findings on the implications of positive emotional persistence. This dissertation contains three studies designed to address these shortcomings and examine relationships among emotional persistence and transdiagnostic psychological well-being in adults with moderate-to-severe depression, with the

ultimate goal of illuminating mechanisms underlying anxiety and depressive disorders such that current treatments may be improved.

Study 1 examined both cross-sectional and longitudinal relationships among emotional inertia, emotion network density, and self-reported well-being. Inertia and density were both calculated using self-reported affect ratings from ecological momentary assessment (EMA) surveys administered five times per day in two eight-day epochs. Inertia and density were calculated separately for negative and positive affect. Positive contemporaneous network density was positively associated with well-being six weeks later. Positive emotional inertia was inversely associated with well-being six weeks later. Neither negative inertia nor negative network density was associated with subsequent well-being, and emotional persistence was not related to concurrent reports of well-being.

Study 2 examined cross-sectional associations between emotional persistence and heart-rate variability. Inertia and density were again calculated using EMA surveys, this time from three eight-day epochs. Heart-rate variability was measured via Apple Watch both during the day and at bedrest throughout all three epochs. Negative contemporaneous network density was inversely associated with both median daytime and median bedrest heart-rate variability. That is, participants with more densely connected negative emotions demonstrated lower heart-rate variability. Positive emotional persistence was not related to heart-rate variability.

Study 3 examined relationships between emotional persistence and linguistic indicators of well-being. Measures of emotional persistence were the same as in Study 2. Natural linguistic processing was used to analyze transcripts of a ten-minute structured interview where participants answered questions about their previous week. Probability of both positive and negative sentiment was obtained using natural linguistic processing, and tendency towards positive sentiment was operationalized as the participants' average difference between probability of positive and negative sentiment. Tendency towards positive sentiment was examined in relation to positive and negative emotional persistence. No metric of emotional persistence was associated with linguistic sentiment. However, participants who reported higher levels of average positive affect via EMA demonstrated higher tendency towards positive sentiment during the interview.

Taken together, these findings provide insight into the implications of positive and negative emotional persistence. Emotional inertia and emotion network density seem to represent different, and at times opposing, presentations of emotional persistence. Broadly, this dissertation supports the literature suggesting that denser negative emotion networks are maladaptive and denser positive emotions reflect better psychological well-being. Contrasting results for negative and positive emotional persistence suggest that persistence of differently valenced emotions may relate to different components of psychological and physiological well-being. This study also highlights the methodological challenges of using objective measures of emotional functioning such as natural linguistic processing. Future research should continue to address these methodological limitations and investigate the mechanisms underlying the relationship between emotional persistence and psychological well-being to inform clinical interventions.

The dissertation of Olivia Marie Losiewicz is approved.

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2026

Table of Contents

List of Tables and Figures

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PEER REVIEWED MANUSCRIPTS

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SELECTED PRESENTATIONS

Losiewicz, O.M., Adam, E., Zinbarg, R., Mineka, S., Hammen, C., & Craske, M.G (2024, April). *Dynamics of Positive and Negative Affect Predict Chronic Interpersonal Stress in Adolescents.* Poster presented at the 2024 annual convention of the Anxiety and Depression Association of America, Boston, MA.

Losiewicz, O., & Davis, B. (2023, April). Augmenting Exposure with Retrieval-Induced Forgetting. UCLA Symposium on Learning and Memory Research, Los Angeles, CA.

Losiewicz, O.M., LeBeau, R.T., Jester, J., Himle, J.A., & Craske, M.G. (2022, November). *The relationship between social anxiety, depression, and employment in a sample of diverse job seekers.* Poster presented at the 56th annual convention of the Association for Cognitive and Behavioral Therapies, New York, NY.

Losiewicz, O.M. & Craske, M.G. (2022, March) *Irritability Predicts Lower Perceived Social Support*. Poster presented at the 2022 annual convention of the Anxiety and Depression Association of America, Denver, CO.

Losiewicz, O.M., Brown, M.L, Toner, E. R., Baker, A. W., Marques, L., & Robinaugh, D. J. (2019, November). *Predicting the Unpredictable: Critical Slowing Down as a Warning Signal for Panic Attacks.* Poster to be presented at the 53rd annual convention of the Association for Cognitive and Behavioral Therapies, Atlanta, GA.

General Introduction

Depressive and anxiety disorders are among the most commonly experienced mental disorders, with one in three individuals experiencing an anxiety disorder in their lifetime and one in five experiencing a mood disorder (Kessler et al., 2012). Imperatively, these disorders come at significant cost to life and functioning (Aderka et al., 2012; McKnight & Kashdan, 2009; Olatunji et al., 2007). In fact, anxiety and depression are leading causes of disability worldwide (Baxter et al., 2014; Smith, 2014). While traditional categorical systems distinguish depression and anxiety, comorbidity between the two is common (Ruscio et al., 2017; ter Meulen et al., 2021), and newer classification systems trend towards a transdiagnostic approach (Cuthbert, 2022; Roefs et al., 2022). Greater understanding of transdiagnostic mechanisms underlying internalizing disorders is crucial to developing new effective interventions and improving existing ones.

The following section outlines the extant literature on two transdiagnostic markers of psychopathology that stem from the emotion dynamics literature: emotional inertia and emotion network density. Both metrics are thought to represent the transdiagnostic mechanism of emotional persistence. The research on the relationships between each of these constructs and psychopathology is outlined, and limitations are identified. Finally, the goals of the current studies, which seek to address these limitations, are introduced.

Emotional Inertia

Emotional inertia, or the stability of emotion, has been identified as a transdiagnostic marker of psychopathology. Mathematically, inertia is operationalized as an autoregressive coefficient of a particular emotion over time- that is, the extent to which one's previous emotions influence current emotions. Higher emotional inertia indicates that one's emotions are determined by previous emotions, as opposed to being influenced by external events (e.g., learning good news) or internal regulatory strategies (e.g., reappraisal). This may also be conceptualized as a blunted response to emotional inductions, for example, resistance to being calmed or cheered up by a friend. Emotional inertia is considered to be the opposite of emotional flexibility, which is associated with well-being (Sheldon et al., 2010).

Emotional Inertia and Psychopathology

Previous research has demonstrated that inertia of negative emotions is related to psychopathology. Among other characteristics, low psychological well-being in general is associated with inert emotions (Houben et al., 2015). Some individuals may experience a "cascade" of negative emotions, which may activate or serve as a warning sign for depressive episodes (Van De Leemput et al., 2014; Wichers et al., 2016). Indeed, individuals with major depressive disorder show blunted response to both negative and positive emotion inductions (Bylsma et al., 2008). That is, once the individual begins experiencing an emotion, that emotion persists and they may be less responsive to attempts to change these emotions. Inertia of negative emotions has specifically been shown to be related to markers of poor psychological well-being including depression, rumination, and neuroticism (Koval et al., 2016). While there is generally strong evidence for a relationship between negative emotional inertia and various markers of psychopathology and well-being, there was one study that found that negative emotional inertia was not associated with internalizing disorders (though they did find a significant association between negative emotional variability and internalizing disorders) (Scott et al., 2020).

Positive Emotional Inertia and Psychopathology

Studies on inertia of positive emotions show more mixed results. For example, while a set of three studies found that persistence of positive emotions was associated with less severe current and subsequent depression symptoms (Höhn et al., 2013), another study found no differences in positive emotional inertia between participants with depression and healthy controls (Thompson et al., 2012). In contrast, other studies have found a positive relationship between inertia of positive emotions and depression, rumination, and neuroticism (Koval et al., 2016; Kuppens et al., 2010, 2012). However, these studies do note that positive emotional inertia appears to be a weaker predictor than negative emotional inertia.

The variation in this research highlights competing conceptual frameworks through which to view the relationship between inertia of positive emotions and mental health. On the one hand, positive emotional inertia could suggest a blunted response to external mood inductions in general and demonstrate a difficulty with emotion regulation. For example, if an individual's happiness is specifically dependent on previous happiness, it may indicate that they struggle to select situations or use strategies to create positive emotional experiences when they feel down. On the other hand, positive emotional inertia could represent an ability to savor positive emotions, which would be an adaptive regulatory strategy. That is, perhaps individuals with high positive emotional inertia intentionally savor positive emotional experiences to prolong them. If both mechanisms are at play in different individuals, we might be more likely to encounter mixed results.

However, the mixed nature of this literature is likely due to methodological differences as well. The set of three studies that identified positive emotional inertia to be associated with better mental health outcomes used positive affect factor scores calculated from ecological momentary assessment (EMA) measures of affect to assess positive emotional inertia (Höhn et al., 2013). Many of the studies that found inertia of positive emotions to be *positively* related to depression measured emotional inertia by qualitatively coding participants' behavior during laboratory tasks

(Koval et al., 2016; Kuppens et al., 2010, 2012). Studies using EMA data may have more external validity and more aptly capture participants' daily experiences.

Within EMA studies, additional methodological differences in operationalization of variables may account for conflicting results. One study that found a positive relationship between positive emotional inertia and depression measured inertia of individual positive emotions whereas other studies created an aggregate or factor score (Kuppens et al., 2010). However, this does not account for all differences among EMA studies because one study used EMA with aggregate scores and found no differences between diagnostic groups in positive emotional inertia (Thompson et al., 2012). The differences between these results and those found in the three studies conducted by Hohn (2013) may instead be related to operationalization of the mental health outcome variable. Of the studies discussed here, only one study, the first in Hohn's (2013) set, used a continuous representation of mental health as opposed to binary categories. A continuous outcome, such as symptom severity (instead of diagnostic status), may provide increased precision and thus more power to detect significant effects. Notably, the two of Hohn's studies that did use categorical outcomes compared treatment responders to non-responders and to healthy controls, adding the nuance and additional power of a third category that may account for differences in results.

State of the Field: The current literature on emotional inertia provides a cutting-edge lens that allows us to consider internalizing symptoms in a new light. Often, emotional inertia research uses experience sampling data such as that from EMA, where participants are asked multiple times per day to report their emotions in "real-time". This research relies less on recall of past symptoms or aggregation of symptoms over a longer period of time. Thus, EMA research is more robust to recall bias, which is a common drawback of retrospective survey research, and it may also have more external validity than data collected through laboratory-administered surveys (Walz et al., 2014). Moreover, inertia research considers the ways in which symptoms influence each other, in line with the network theory of psychopathology (Borsboom, 2008; Borsboom & Cramer, 2013), in recognition of the impact of symptom dynamics on mental health experiences.

Limitations to be Addressed

However, a number of limitations of the research on emotional inertia merit future research considerations. First, more research is needed on the relationship between positive emotional inertia and markers of mental illness and wellbeing to disentangle the current mixed literature. Additionally, studies of emotional inertia still often rely on either aggregation (i.e., summing various negative or positive affect variables into one sum score) or isolation (i.e., looking at inertia of a single affective variable). These methods may obscure relationships between different affective variables and how they impact each other. The network approach to psychopathology retains many of the benefits of emotional inertia research while also addressing these drawbacks with more advanced methods.

Network Analysis

The network approach to psychopathology is a theoretical perspective that has emerged over the past decade as an influential area of psychiatric research. This conceptualization posits that mental disorders exist as systems, not entities, and that symptoms of psychopathology influence each other (Borsboom & Cramer, 2013). That is, the symptoms *are* the disorder, as opposed to simply being indicative of a disorder (Borsboom & Cramer, 2013; McNally, 2016). For example, insomnia, fatigue, and difficulty concentrating are all considered symptoms of depression. These symptoms are not necessarily independent of each other even after controlling for the presence of depression. In a given individual, difficulty sleeping may result in fatigue, which may result in concentration difficulty. The network approach contrasts from the typical "latent disorder" model underlying frameworks such as the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) or the Research Domain Criteria (RDoC), which are the current gold-standard nosology systems for mental health.

While the network approach is relatively recent, the theoretical implications align well with existing theories including the cognitive behavioral model (Hoffart & Johnson, 2017). In the same way that cognitive behavioral theory recognizes that cognitions, schemas, and affective styles influence behavior and physiology, the network approach posits that symptoms are not just representative of disorders but constitute them. This approach has been identified as more clinically relevant than diagnostic systems that rely on the latent disorder framework of conceptualizing disorders like the DSM-5 and RDOC (Hofmann, 2014).

A network is a visual representation of the relationships between symptoms comprised of "nodes" and "edges". Nodes usually represent symptoms in clinical psychology research. They are connected by edges, which are typically indicative of partial correlations and may represent positive or negative relationships between symptoms. Networks may represent contemporaneous relationships or temporal relationships, the former of which indicate which symptoms are likely to occur within a small time window and the latter indicate which symptoms are likely to predict later occurrence of a given symptom. Temporal networks may also contain autoregressive edges, feedback loops in which a given symptom feeds into itself. Additionally, networks may be calculated at the group-level, incorporating data from many individuals, or the individual level, incorporating many data-points from a single individual. As with emotional inertia research, individual networks are often built using EMA data.

Network analysis has emerged as a useful tool in understanding psychopathology because of the various metrics that can be derived from the networks that provide insight into an individual or group's experience. For example, node centrality metrics identify nodes or symptoms in a network that are most strongly connected to other symptoms (this may be determined by various metrics including the number or weight of edges connected to this node) (McNally, 2016), which is thought to be important for treatment personalization. Treatments that target nodes of high centrality may be more effective in that there may be a trickle-down effect to many other symptoms. Additionally, identification of bridge symptoms, or symptoms commonly on the "pathway" between two other symptoms, often has implications for treating comorbid conditions (Jones et al., 2021).

Network Density

The metric of network density closely relates to emotional inertia. Network density measures how closely symptoms in a network relate to and how strongly they influence each other. When causal relations among symptoms in a network are strong, the activation or onset of one symptom can lead to an increase in other symptoms, suggesting that a more inter-connected symptom network is more vulnerable to a "contagion effect" (Borsboom, 2008; Robinaugh, Hoekstra, et al., 2020). Network density, or global network strength, thus extends the idea of emotional inertia, which looks at the persistence of a single symptom, by incorporating relationships *between* symptoms instead of only focusing on one symptom or one aggregated sum. That is, negative emotional inertia is the autocorrelation of a sum of negative emotion variables (or the autocorrelation of an individual emotion variable), and network density considers relationships *among* different negative emotion variables such as sadness, anger, and anxiety. Accordingly, both emotional inertia and emotion network density are measures of emotional flexibility, but network density is more dynamic. Of note, network density is thought to be a stable construct, although research is still somewhat limited, but a recent study did report stability of network connectivity over time (Curtiss et al., 2018).

Network density is typically operationalized based on the edge weights in the network. Edge weights represent strength of relationship, such as partial correlations (Borsboom & Cramer, 2013). Network density is a measure of the strength of those edges, and may be conceptualized as the average edge weight (e.g., as measured in Shin et al., 2022). Global network strength is a similar concept, representing the sum of the absolute values of the edge weights in a network. Either way, these metrics represent the strength of relationships among the network nodes.

Network Density and Psychopathology. Extant research supports the idea that network density is related to psychopathology. Networks with lower connectivity are thought to be more resilient to external stress, while those with higher connectivity are consequently more vulnerable to external stress, rendering those individuals to be more susceptible to experiencing more psychopathology symptoms (Cramer, 2013). Networks comprised of nomothetic data have yielded the finding that stronger connections between symptoms relate to higher severity of disorder. For example, pregnant women with perinatal depression had more connected networks than those without perinatal depression (Santos et al., 2017), adults with major depressive disorder had more dense negative affect networks than healthy controls (Pe et al., 2015), individuals with greater genetic vulnerability for general psychopathology have more connected networks than those without the genetic vulnerability (Hasmi et al., 2017), and networks comprised of data from participants with high levels of neuroticism are denser than those from participants with low levels of neuroticism (Bringmann et al., 2016).

Furthermore, research on idiographic networks has further supported this relationship. Adults with higher network density for negative affect networks are more likely to have a concurrent diagnosis of major depressive disorder or generalized anxiety disorder, even after controlling for average levels of negative affect (Shin et al., 2022). In adolescents, network density for negative affect is also associated with less happiness, more negative emotions, and more depression symptoms (Lydon-Staley et al., 2019). This study also found that network density was associated with non-acceptance of emotions, although not overall use of adaptive emotion regulation skills. In terms of treatment research, adolescent treatment non-responders were found to have denser networks than treatment responders, though this effect was not significant (Serdarevic et al., 2018).

Less research has focused on network density of networks containing positive emotions, though a recent study suggests that it may be indicative of mental health as well. Shin and colleagues (Shin et al., 2022) found that positive emotion network density negatively related to diagnoses of major depressive disorder and generalized anxiety disorder, such that individuals with greater density of positive emotion networks were less likely to have either of these diagnoses, even after controlling for average levels of positive emotions. However, another study found that there was no difference in density for positive emotion networks in depressed participants compared to healthy controls (Pe et al., 2015).

Despite the research in support of the connection between network density and psychopathology, other studies have provided contrasting results. For example, one study found a difference in the number, but not the strength, of network connections among participants with psychosis, relatives of these participants, and healthy controls (Klippel et al., 2018). However, this study encompassed a broader range of symptoms including cognitions and psychotic experiences that were not included in the other network studies described above. Another study found no difference in global network strength for patients with eating disorders compared to healthy controls (Levinson et al., 2018). Two studies have notably found the opposite relationship between network density and psychopathology, including one study of network connectivity in participants with borderline personality disorder (Southward & Cheavens, 2018). The other study looked at connectivity before and after treatment for depression and anxiety, and found that while symptom severity scores decreased following treatment, network connectivity increased (Ding et al., 2023).

There are several possible explanations for the mixed nature of this research. One notable difference in the studies previously discussed (i.e., Levinson et al., 2018; Southward & Cheavens, 2018) is the difference in the populations and disorders of interest. While most of the studies that have found evidence for a positive relationship between density and psychopathology focus on internalizing disorders, studies that have found the opposite effect typically involve participants with personality and eating disorders. Perhaps network density is a transdiagnostic indicator for internalizing disorders that does not extend to other populations. To avoid these potential confounding factors, the studies in this dissertation focus on symptoms pertaining to affect and internalizing disorders. Additionally, methodological differences between studies may be important. Studies of network connectivity vary in their use of nomothetic compared to idiographic networks. We cannot assume that the findings of group-level analyses are interchangeable with individual-level analyses (Bringmann et al., 2013). Studies of individual networks may have more useful implications for personalized interventions. Notably, the studies examining individual networks of negative affect all reported significant findings in the expected direction. Finally, methodological choices such as data preprocessing, the choice to use a multilevel approach, and the definition of density all may contribute to the varied results, as there is not yet one set of standard procedures (De Vos et al., 2017).

Limitations to be Addressed

The literature on the relationship between network density and psychopathology contains several key limitations that we address in this dissertation. One limitation is the variety of different methods used, particularly that most networks use group-level data. This is notably a limitation in that individuals often vary in their symptom presentation, even when they have the same diagnosis (Robinaugh, Brown, et al., 2020). Additionally, there is much to be investigated regarding the usefulness of looking at network density of positive symptoms such as positive affect, which will be important given the role of positive affect in internalizing disorders and treatment (Craske, Treanor, et al., 2019).

Finally, further diversification of outcome variables and correlates is needed. There is a dearth of research regarding the relationship between network analysis in general and constructs outside of the network (McNally, 2021). To our knowledge, no study has examined the relationship between network density and objective indicators such as physiological biomarkers or behavior. Identifying additional biological and linguistic substrates of network density will further elucidate the relationship between network density and well-being. Additionally, much of the network research has been somewhat reifying: for example, the dynamics between self-reported symptoms of depression or anxiety are associated with levels of depression and anxiety. Examination of network density in relation to more transdiagnostic concepts may address this issue of reification and also allow individuals who do not fall neatly into diagnostic categories to benefit from subsequent interventions. That is, this research may inform interventions based on concepts such as negative or positive emotionality, which could be applied across a varied population instead of only targeting individuals who meet criteria for, for example, major depressive disorder. This transdiagnostic research is especially important as diagnostic criteria were normed on individuals from white, western cultures.

Overview of Studies

The aim of this dissertation was to build off the research on both emotional inertia and emotion network density as potential indicators of psychological well-being. These studies focused on the use of idiographic networks to understand person-specific indicators of psychological well-being. This dissertation takes the literature on inertia and density one step further by examining the associative value of inertia and density as they relate to more general, continuous measures of well-being, as opposed to symptom measures that capture similar concepts to those represented in the network or inertia data. Specifically, the three studies use self-report, physiological (heart rate variability), and linguistic (sentiment estimates from natural linguistic processing) indicators of well-being. The studies also aimed to clarify the role of positive emotion dynamics in psychological well-being.

Study 1 examined whether inertia and density of both positive and negative emotions were associated with self-report measures of general psychological well-being cross-sectionally and longitudinally. The goal of Study 1 was to clarify differences in how persistence of positive and negative emotions relate to continuous, transdiagnostic measures of psychological well-being. Additionally, Study 1 was designed to ascertain whether emotional persistence may be viewed as a trait-like feature that may indicate risk for later psychopathology. Study 2 examined potential biological substrates of these metrics, specifically investigating heart rate variability's association with emotional persistence. The goal of Study 2 was to identify possible biological mechanisms for emotional persistence, which has implications for personalized intervention.

Finally, Study 3 investigated linguistic substrates of emotional persistence. Study 3 looked at whether tendency towards positive over negative sentiment, gleaned from natural linguistic processing, was associated with emotional persistence. Like Study 2, this was designed to examine potential mechanisms underlying emotional persistence, which would have implications for interventions for internalizing symptoms.

Study 1: Emotional Inertia and Network Density as Detectors of Self-Reported Well-Being

Abstract

Emotional inertia, or the persistence of affect over time, and emotion network density, a measurement of the interconnected or relatedness of one's emotions, both capture dynamics of emotional experiences. Previous research has found that higher levels of negative emotional inertia and network density may be associated with anxiety and depression. However, there is a dearth of research examining inertia and density of *positive* emotions or associations among inertia, density, and continuous or longitudinal outcome variables. This study sought to address these limitations by examining associations between both positive and negative emotional inertia and network density and continuous, transdiagnostic measures of psychological well-being both cross-sectionally and longitudinally.

Adults with moderate-to-severe depression (N=333) completed two 8-day epochs of ecological momentary assessment (EMA) five times daily. Emotional inertia and idiographic networks were calculated separately for EMA measures of negative and positive affect and associations with self-reported psychological well-being were examined using nested comparison tests and Bayesian multilevel models. In partial support of hypotheses, positive contemporaneous network density was positively associated with self-reported well-being six weeks later. Conversely, positive emotional inertia was inversely associated with well-being six weeks later. Neither negative emotional inertia nor network density was associated with subsequent well-being. Emotional persistence was not related to concurrent reports of well-being. These results suggest that positive emotional inertia and emotion network density may indicate susceptibility to experience changes in well-being in the future. Future research should investigate the underlying mechanisms, discern differences between emotional inertia and emotion network density, and explore potential clinical interventions.

Introduction

Internalizing symptoms and disorders such as anxiety and depression are increasingly prevalent with significant costs to life and functioning (Aderka et al., 2012; Kessler et al., 2012). Emotional inertia, or the stability of emotions, and emotion network density, a measurement of the interconnectedness or relatedness of symptoms, both capture the dynamics of emotional symptoms and are generally considered to be associated with higher levels of internalizing symptoms. Emotional inertia and emotion network density are both measures of emotional flexibility, with emotion network density as the more dynamic measure of the two, since it captures dynamics among different emotions. Inertia of negative emotions has been shown to be related to depression, rumination, and neuroticism (Koval et al., 2016). Likewise, higher individual network density of negative emotions and lower individual network density of positive emotions is associated with greater likelihood of a diagnosis of major depressive disorder or generalized anxiety disorder (Shin et al., 2022).

However, some limitations to the research on emotional inertia and network density render the relationship between these emotion dynamics and mental health unclear. Research on the role of inertia and density of positive affect remains limited, with existing studies showing mixed results. Additionally, research on the relationship between network density and mental health is limited to outcomes representing psychological disorders, such as diagnostic status or symptom severity on diagnostic scales. This is limiting for two reasons: first, research affirming the relationship between *connectivity* of self-reported symptoms and *severity* of self-reported symptoms is somewhat reifying, suggesting that self-reported emotional symptoms are associated with self-reported emotional symptoms. Second, the existing literature has only minimally explored the relationship between network density and positive indicators of mental health (as opposed to indicators of mental illness). Positive emotions and general psychological well-being have implications for daily functioning (Moskowitz et al., 2012). Identifying a connection between network density and general psychological well-being, including a measure of functioning, would suggest that network density may be viewed as a transdiagnostic marker. This transdiagnostic marker may apply to non-clinical populations or individuals who do not meet diagnostic criteria but still experience suffering.

Furthermore, most research on the relationship between inertia or density and mental health uses dichotomous outcome variables, such as the presence or absence of a mental disorder (e.g., Kuppens et al., 2012; Shin et al., 2022). More research using continuous variables, including ratings of symptom severity, is needed to confirm this relationship. This is important because of the heterogeneity present in symptom presentations (Nandi et al., 2009), such that using a diagnostic category as an outcome variable could underestimate an individual's experience with mental health. Using a continuous measure of psychological well-being would also more aptly capture the experience of sub-clinical "edge cases". Further, these continuous measures would have implications for transdiagnostic treatments.

Finally, while cross-sectional research shows that network density is indicative of internalizing symptoms, no research study to date has investigated whether network density longitudinally is associated with later emotional functioning or change in emotional functioning. There is reason to believe that this might be the case, given that inertia, a related construct, is related to subsequent measures of well-being two years later (Kuppens et al., 2012). Additionally, network structure is thought to be relatively stable (Curtiss et al., 2018), suggesting that individual networks may be indicative of future individual symptom networks, and therefore future individual emotional functioning.

Study Aims and Hypotheses: This study aimed to investigate emotional inertia and network density of positive and negative affect as associated with both current measures of socioemotional well-being and future socioemotional well-being. Given the prior literature on inertia and density of negative affective variables and internalizing symptoms, we expected a negative relationship between these variables and well-being. We also predicted a positive relationship between both inertia and density of positive affect variables and well-being. This would be consistent with prior evidence of an inverse relationship between positive affect density and internalizing disorders (Shin et al., 2022) and evidence of positive affect inertia from EMA inversely predicting depression (Höhn et al., 2013). Specifically, we tested four two-part hypotheses:

Hypotheses 1 and 2: Emotional Inertia

Hypothesis 1a: Inertia of negative affect will be negatively associated with well-being, such that individuals with higher negative emotional inertia will report lower well-being scores during the same time period.

Hypothesis 1b: Inertia of positive affect will be positively associated with well-being, such that individuals with higher positive emotional inertia will report higher levels of well-being during the same time period.

Hypothesis 2a: Inertia of negative affect will be negatively associated with future well-being, such that individuals with higher negative emotional inertia will report lower levels of well-being six weeks later, controlling for baseline levels of well-being.

Hypothesis 2b: Inertia of positive affect will be positively associated with future well-being, such that individuals with higher positive emotional inertia will report higher levels of well-being six weeks later, controlling for baseline levels of well-being.

Hypotheses 3 and 4: Emotion Network Density

Hypothesis 3a: Density of individual networks of negative emotion variables will be negatively associated with well-being, such that individuals with higher negative emotion network density will report lower levels of well-being during the same time period.

Hypothesis 3b: Density of individual networks of positive emotion variables will be positively associated with well-being, such that individuals with higher positive emotion network density will report higher levels of well-being during the same time period.

Hypothesis 4a: Density of individual networks of negative emotion variables will be negatively associated with future well-being, such that individuals with higher negative emotion network density will report lower levels of well-being six weeks later, controlling for baseline levels of well-being.

Hypothesis 4b: Density of individual networks of positive emotion variables will be positively associated with future well-being, such that individuals with higher positive emotion network density will report higher levels of well-being six weeks later, controlling for baseline levels of well-being.

Methods

Participants

Participants (*N*= 333) were recruited as part of a larger study, Operationalizing Digital Phenotyping in the Measurement of Anhedonia (OPTIMA), which aimed to objectively measure and track behavioral features of anhedonia. This study was funded by the Wellcome Leap Foundation award 20222084:1 as part of the Multi-Channel Psych Consortium. The study recruited individuals between the ages of 18 and 65 who were fluent in English and owned an iOS smartphone. Because part of the umbrella study incorporated functional magnetic resonance imaging (fMRI), participants were also required to be right-handed, have normal or corrected-to-normal vision, and not have any other contraindications for fMRI. Additional exclusion criteria included being a current smoker of tobacco or nicotine, alcohol or substance use or dependence, recent changes in psychiatric medication, diagnosis of a major neurological condition or psychosis, chronic mobility impairment, refusal to pause benzodiazepine use before scans, history of brain tumor or surgery, and history of stroke. To obtain the desired distribution of depression and anhedonia symptoms, enrollment was only offered to participants whose target groups for symptom severity level was not otherwise filled. See Rotstein et al. (Rotstein et al., 2025) for more details on the methods[1].

The mean age of the sample was 33.42 (SD=12.10). 62.80% of the sample identified as women, 32.21% identified as men, 2.76% identified as transgender, and 2.15% identified as neither men nor women. The racial distribution was: 57.60% White, 4.39% Black, 1.75% Native American, 4.09% Asian, 9.06% Chinese, 2.92% Filipino, 2.05% Japanese, 4.09% Korean, 2.34% Vietnamese, 2.92% Other Asian, and 9.36% Other Race. Additionally, 33% of the sample identified as Hispanic or Latine.

Procedure

The study lasted about three and a half months and consisted of 12 weeks of weekly surveys assessing various symptoms. Participants attended one in-person visit for a fMRI scan. This visit occurred around week 12 or 13, depending on scheduling. Post-questionnaires were completed the week before this visit (referred to as "pre-scan"). Additionally, participants underwent three eight-day epochs of collection of ecological momentary assessment (EMA) data during baseline (epoch 1), week 6 (epoch 2), and pre-scan (~week 12, epoch 3). Timing of post-assessment EMA questionnaires were arranged such that the last survey was sent the day before

[1] Note that Rotstein et al., 2025 describes the protocol for the ILIAD study, a study paired with OPTIMA that had largely overlapping methodology. See their supplement for further details.

the scan date, and thus it varied as to whether questionnaires were sent on week 12 or 13, depending on the participant.

Measures

EMA Measures. EMA questionnaires were sent five times per day between 10am and 7pm for eight consecutive days during each eight-day epoch. Thus, 40 total EMA surveys were sent during each epoch for each participant. Participants rated each item on a scale from 1 ("not at all") to 5 ("extremely"). EMA items assessing negative and positive affect are described below. Other EMA items were not analyzed in this study.

Negative Affect. The negative affect subscale of the EMA questions contained five items: sad, stressed, anxious, annoyed/irritated, and lonely. Participants rated items from 1 to 5 to reflect the extent to which they felt these items in a given moment.

Positive Affect. The positive affect subscale of the EMA questions contained four items: energetic, happy, motivated, and engaged. Participants rated items from 1 to 5 to reflect the extent to which they felt these items in a given moment.

Well-Being Measures

Hedonic Well-Being. Psychological well-being was measured using the World Health Organization Well-Being Index (1998 Version) (Staehr, 1998). This five-question questionnaire asks participants about their well-being in the past two weeks. Example questions include "I have felt cheerful and in good spirits" and "My daily life has been filled with things that interest me". Participants rated their answers from 0 ("At no time") to 5 ("All the time"), and responses were totaled, with higher response indicating higher levels of well-being. This scale has previously demonstrated high clinimetric validity (Topp et al., 2015). Participants completed this measure at baseline, week 6, and pre-scan (sent at the start of each EMA epoch and completed at some point during that week).

***Eudaimonic Well-Being*.** Eudaimonic well-being was measured using the Eudaimonic Well-Being Questionnaire (Sandman, 2023). This five-question questionnaire was adapted from two previously validated surveys, the Mental Health Continuum Short Form (Lamers et al., 2011) and the Daily Meaning Scale (Steger et al., 2008). Previous research has found both the Mental Health Continuum-Short Form and the Daily Meaning Scale to have good reliability (α= .89 and .98, respectively). The new scale asked participants about the extent to which they have felt a sense of purpose and connection in their life over the past week. Example questions include "How much do you feel your life has a sense of meaning?" and "How much do you feel connected to your values?". Participants rated their answers from 0 ("Not at all") to 4 ("Extremely"). Participants also completed this measure at baseline, week 6, and pre-scan (sent at the start of each EMA epoch and completed at some point during that week).

These measures each represent a different, important facet of well-being (Ryan & Deci, 2003). Nonetheless, there was considerable overlap between the hedonic and eudaimonic scales (rs 0.54-0.61, ps < .001) and thus they were combined into one composite score. To calculate the composite score, both scales were standardized, and we summed the standardized scores for each participant.

Data Analysis

All analyses were preregistered on Open Science Framework (registration DOI: https://doi.org/10.17605/OSF.IO/TK4P2).

Emotional Inertia

Scores for each of the five negative affect variables were summed at each timepoint for a "total negative affect" score at each timepoint for each participant. Likewise, scores for each of the four positive affect variables were summed at each timepoint for a "total positive affect" score at each timepoint for each participant. To account for unequal spacing between the last survey of the day and the first survey the next morning, five rows of missing data were added per day for each participant to approximate the time lag. This strategy, the phantom variable method, has been previously used to account for temporal spacing of measurements in intensive longitudinal data when intervals between surveys is considered equal (Oud & Voelkle, 2014). As inertia and density were conceptualized as trait-like in these studies, we did not add additional spacing to account for the gap between day 8 of one epoch and day 1 of the following epoch. Inertia of total negative or total positive affect was calculated using Bayesian dynamic structural equation models, as described below. All main analyses pertaining to emotional inertia were conducted in MPLUS Version 8.10 (Muthen & Muthen, 2017). The main analysis used only data from EMA epochs 1 and 2 such that cross-sectional and longitudinal hypotheses could both be tested using the same inertia calculations. This process was then repeated for sensitivity analysis using data from epochs 2 and 3, and then from epochs 1-3.

Emotion Network Density

All analyses pertaining to network density were conducted in R Studio version 4.3.2. Separate negative and positive affect networks were calculated for each participant. Networks for the main analyses used data from the first two EMA epochs (i.e., baseline and week 6) so that cross-sectional and longitudinal hypotheses were tested using the same data. Participants without missing data had 80 total EMA points included in each network. This process was repeated for the sensitivity analyses, calculating networks with data from epochs 2 and 3 and then data from all three epochs.

Within individual participants, variables that had a variance of 0 across all included timepoints were removed so that the networks would converge. Thus, some individual participants had fewer nodes in their networks. For negative emotion networks, ten participants had one variable with zero variance (thus with only four nodes in their network) and three had two variables with zero variance (and final networks with three nodes); all other participants had networks with all five variables. For positive emotion networks, one participant had one variable with zero variance, three participants had two variables with zero variance, and one participant had three variables with zero variance (for this participant, a network could not be calculated). Within participants, we then detrended any remaining variables with linear trends to account for any possible changes in values related to time (Fisher et al., 2017). Both contemporaneous (i.e., networks that represent concurrent relationships) and temporal networks (i.e., networks that represent relationships over time) were calculated using the graphicalVAR package in R. These two networks represent related, but different concepts in that contemporaneous networks represent relationships among symptoms within the same window of measurement and temporal networks represent relationships among symptoms in different windows of measurement (Epskamp, van Borkulo, et al., 2018). As symptoms may shift or affect each other in different time windows, both are important to incorporate in analyses. The graphicalVAR package within-person standardizes the data before calculating individual networks. Network density was calculated as a sum of the absolute edge weights divided by the total number of edge weights in the network, thus representing the average absolute edge weight in the network. Participants had four separate network density scores for each combination of positive or negative affect and contemporaneous or temporal networks (e.g., positive contemporaneous density, negative contemporaneous density, etc.).

Hypothesis 1: Cross-Sectional Relationships between Emotional Inertia and Self-Reported Well-Being

Bayesian dynamic structural equation models with noninformative prior distributions for all parameters in the model were used to examine the association between emotional inertia from EMA epochs 1 and 2 (baseline and Week 6) and self-reported well-being from Week 6. Affect was regressed onto lag-1 affect to model emotional inertia, and this parameter was allowed to vary across participants. We regressed well-being at Week 6 onto this parameter and included random intercepts of negative affect and positive affect.

Bayesian analysis produces posterior distributions for its parameters. In the analyses below pertaining to Bayesian analysis (i.e., all inertia analyses), we report the mean for the posterior distribution as the estimate, as well as the 95% credible interval (CI), which refers to the range of values that the parameter has a 95% probability of being given the data.

Hypothesis 2: Longitudinal Relationships between Emotional Inertia and Subsequent Self-Reported Well-Being

Bayesian dynamic structural equation models with noninformative prior distributions for all parameters in the model were used to examine the association between emotional inertia from EMA epochs 1 and 2 (baseline and Week 6) and self-reported well-being from Week 12. Affect was regressed onto lag-1 affect to model emotional inertia, and this parameter was allowed to vary across participants. We regressed well-being at Week 12 onto this parameter and included random intercepts of negative affect, positive affect, and baseline well-being.

Hypothesis 3: Cross-Sectional Relationships between Network Density and Self-Reported Well-Being

A nested multiple linear regression model was used to examine the association between network density from EMA epochs 1 and 2 (baseline and Week 6) and self-reported well-being from Week 6. Network density was entered as the predictor and average levels of affect were entered as covariates. Well-being at Week 6 was entered as the outcome. The null model consisted of only average levels of affect and the well-being score. A log-likelihood ratio test was used to compare the model containing network density to the simpler null model to test whether network density is associated with well-being above and beyond mean levels of affect.

Hypothesis 4: Longitudinal Relationships between Network Density and Subsequent Self-Reported Well-Being

A nested multiple linear regression model was used to examine the association between network density from EMA epochs 1 and 2 (baseline and Week 6) and well-being score at Week 12. Network density was entered as the predictor. Average levels of affect and well-being score at baseline were entered as covariates. Well-being at Week 12 was entered as the outcome. The null model consisted of only average levels of affect and baseline and Week 12 well-being scores. A log-likelihood ratio test was used to compare the model containing network density to the simpler null model to test whether network density is associated with well-being above and beyond mean levels of affect.

Results

Descriptives for Emotional Inertia

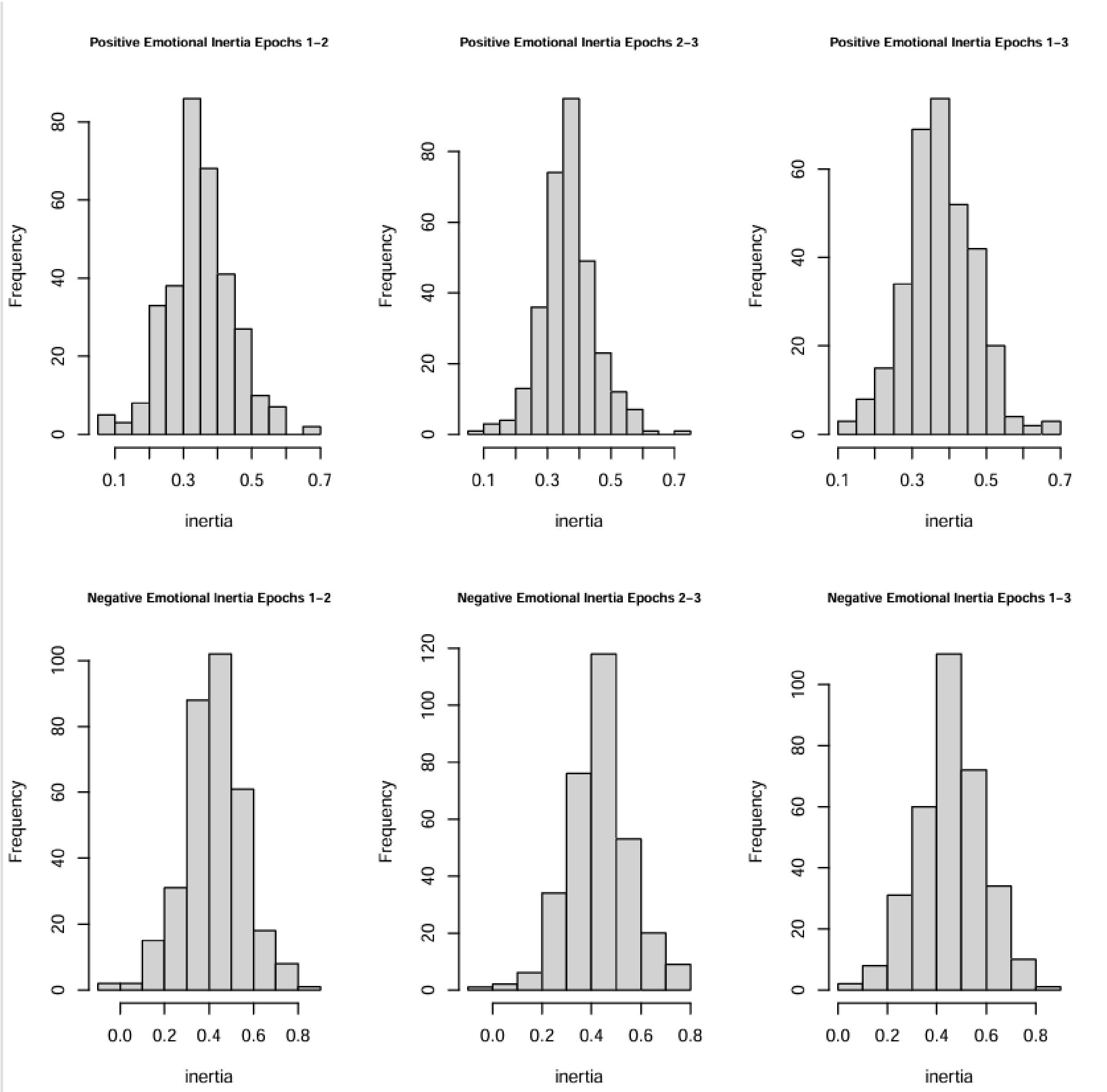
Histograms displaying the spread of values for inertia calculated each for positive and negative affect, across three different timespans (epochs 1 and 2, epochs 2 and 3, and all three epochs) are displayed in Figure 1. Inertia values were relatively normally distributed. Inertia values for the same valence (e.g., positive or negative) and different epochs were highly correlated, as would be expected given the overlap in the data used to calculate these values. Descriptive statistics are displayed in Table 1. Correlations for inertia values can be found in Supplementary Table S1.

Table 1.

Descriptive Statistics for Inertia and Network Density

Variable	Value	SD	Range
Negative Emotional Inertia	0.43	0.14	-0.06-0.85
Positive Emotional Inertia	0.35	0.1	0.06-0.66
Negative Temporal Network Density	0.03	0.04	0-0.28
Positive Temporal Network Density	0.03	0.05	0-0.31
Negative Contemporaneous Network Density	0.03	0.02	0-0.16
Positive Contemporaneous Network Density	0.04	0.03	0-0.24

Figure 1: Histograms of Inertia Plots for Main and Sensitivity Analyses



Descriptives for Emotion Network Density

Histograms displaying the spread of values for network density calculated for each positive and negative affect, across the three different overlapping timespans (epochs 1 and 2, epochs 2 and 3, and all three epochs) are displayed in Figure 2 for temporal network density and Figure 3 for contemporaneous network density. Notably, the spread of values is right-skewed, as a high number of participants had density values of "0", indicating the absence of relationships among symptoms in their network. Network density values for the same valence and different timespans were moderately correlated. Correlations for network density values can be found in Supplementary Table S2. Descriptives for EMA and final sample size for networks in each epoch are displayed in Table 2.

Table 2

Descriptives for EMA Completion and Sample Size for Networks

Metric	**Epochs 1-2**	**Epochs 2-3**	**Epochs 1-3**
EMA Surveys Completed per Person * (Median (SD) (Range))	60.5 (13.91) (25-80)	57.0 (13.86) (25-80)	85.0 (23.62) (25-117)
Final N for Negative Affect Networks	270	239	276
Final N for Positive Affect Networks	293	256	295

**Excludes participants with less than 25 surveys total, as they were not included in the analysis*

Figure 2: Histograms of Temporal Network Density for Main and Sensitivity Analyses

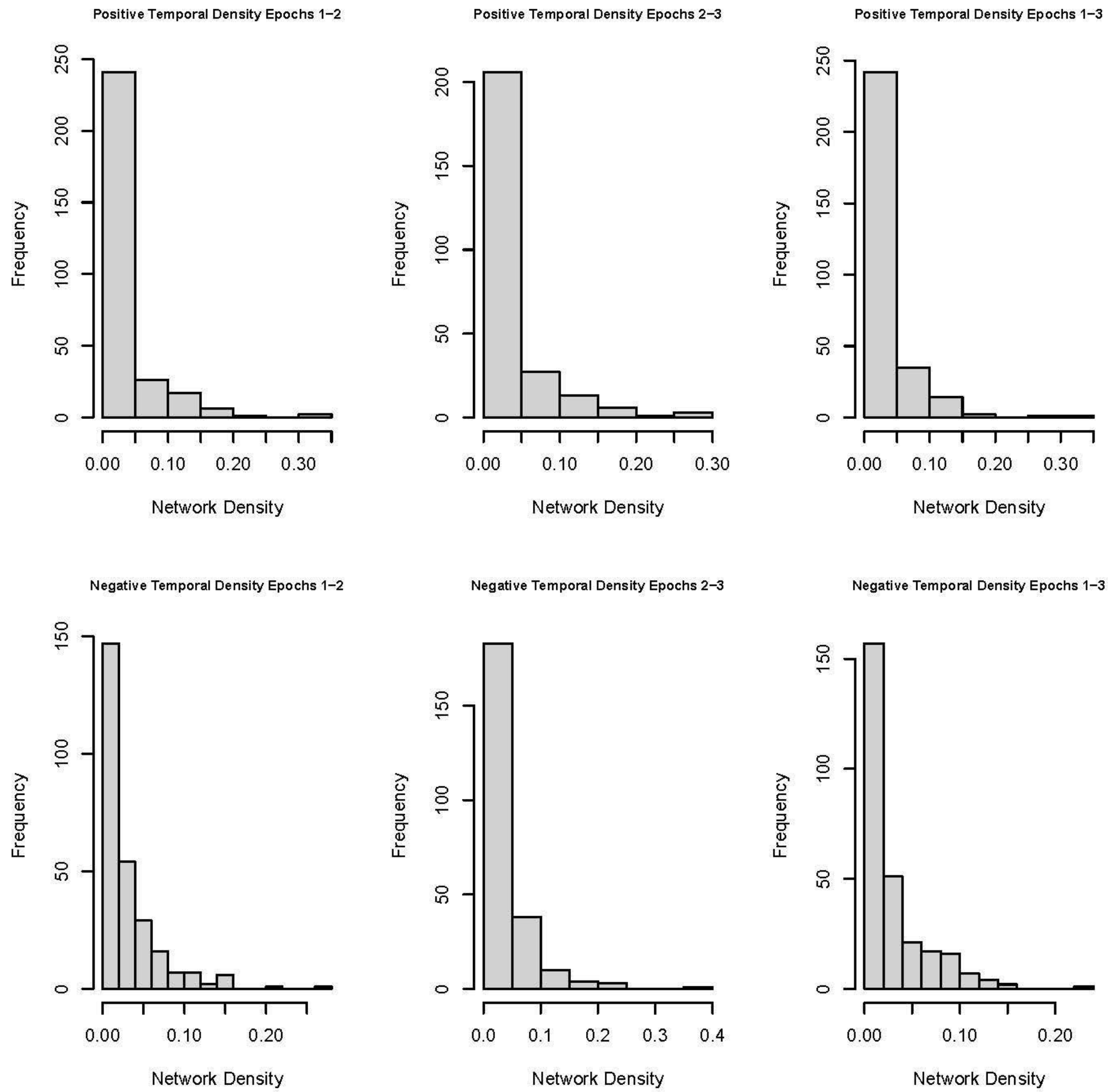
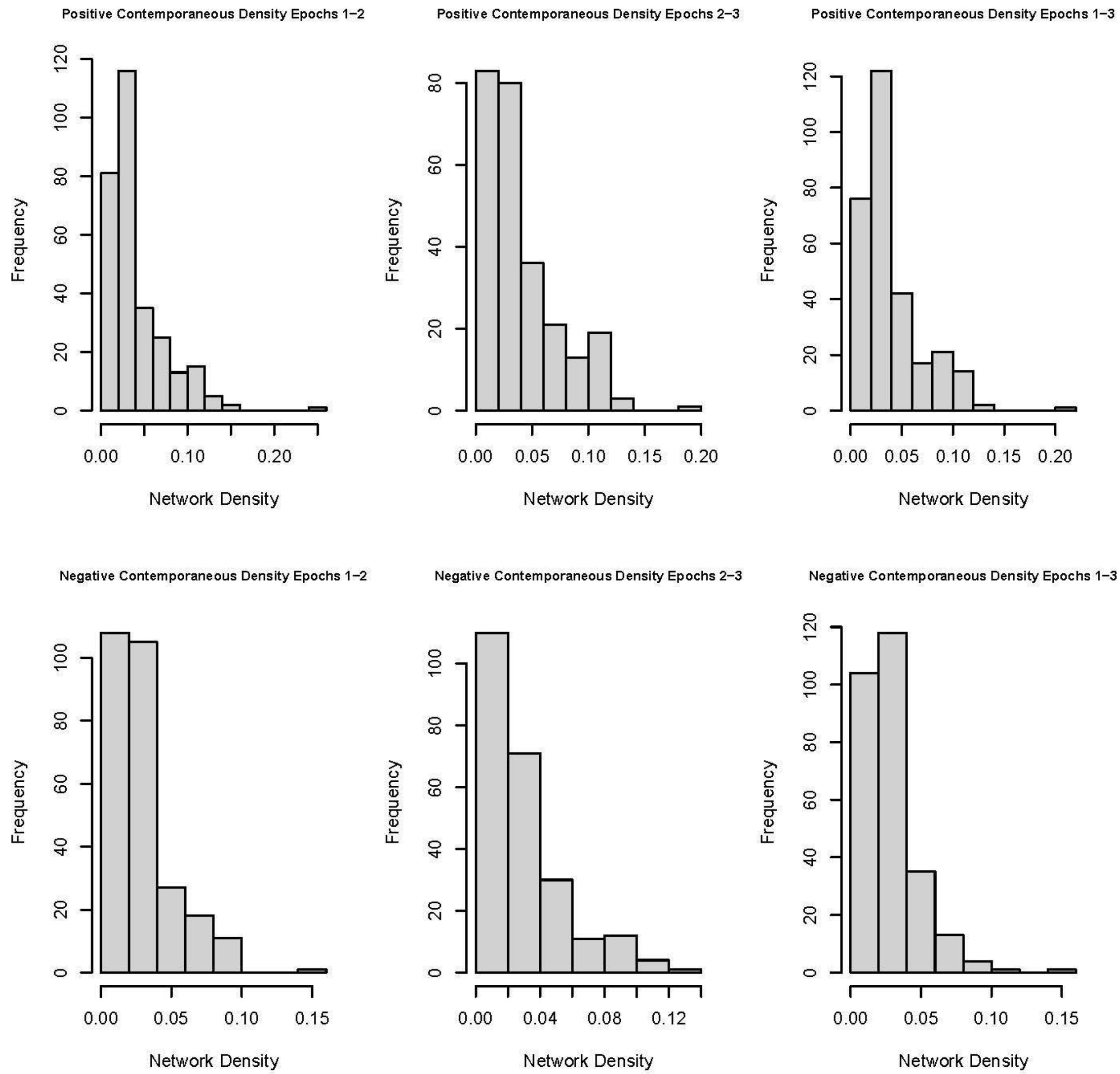


Figure 3: Histograms of Contemporaneous Network Density for Main and Sensitivity Analyses



Changing Network Threshold

Visual inspection of the idiographic networks revealed that about one third of temporal networks were "empty", or consisting of no significant edges between nodes. Additionally, about 10-15% of networks consisted of at least one negative edge. In both cases, this may be representative of true relationships among symptoms. However, this may also be indicative of overfitting due to low power (Bulteel et al., 2018) or low sensitivity to detect true edges, which is more likely in networks with a small number of measurements (Mansueto et al., 2022).

There are no clear guidelines for power in multilevel VAR networks such as those used in this study. Participants with less than 25 surveys were excluded from the main analysis to retain power. Previous studies have found sufficient sensitivity and specificity for VAR networks with eight nodes and 50 measurements per person (Epskamp, Waldorp, et al., 2018). We chose to set the threshold at 25 because these networks had fewer nodes (five for negative affect networks and four for positive affect networks), which increases sensitivity (Mansueto et al., 2022) and because our nodes were expected to be highly correlated. With this threshold, the included participants had a median of 60.5 total measurements, which is in line with or above previous studies with more nodes (Epskamp, Waldorp, et al., 2018; Shin et al., 2022).

To examine whether empty networks may have been empty due to lack of power, we tried increasing the threshold to 40 surveys per person, and then to 60 surveys per person. In both cases, the proportion of participants with empty networks or negative edges remained at about one third. Thus, there was not sufficient evidence to believe that the empty networks were a sign of low power. For all analyses reported below, networks that converged for all participants with at least 25 total surveys were included, as initially planned.

Hypothesis 1: Cross-Sectional Relationships between Emotional Inertia and Self-Reported Well-Being

Given the data, we do not have enough confidence to be sure that the relationship between negative emotional inertia and well-being is positive, as the probability that the relationship is negative is 0.09. The mean of the posterior distribution is 0.64 (CI [-0.32, 1.63]). We also do not have enough confidence to be sure that the relationship between positive emotional inertia and well-being is positive, as the probability that the relationship is negative is 0.29. The mean of the posterior distribution is 0.39 (CI [-1.01, 1.81]). The model did provide strong evidence that there is a negative association between average negative affect and well-being (Mean= -0.11, 95% CI [-0.16, -0.06]) and that there is a positive association between average positive affect and well-being (Mean=0.49, 95% CI [0.41, 0.56]). See Table 3 for full model results.

Table 3.
Model Results for Hypothesis 1

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Well-Being	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	7.13	0.08	0.00	6.98	7.29
Positive Affect	5.55	0.06	0.00	5.43	5.67
Between- Level					
Well-Being on Negative Emotional Inertia	0.64	0.48	0.09	-0.32	1.63
Well-Being on Positive Emotional Inertia	0.39	0.74	0.29	-1.01	1.81
Well-Being on Negative Affect	-0.11	0.03	0.00	-0.16	-0.06
Well-Being on Positive Affect	0.49	0.04	0.00	0.41	0.56
Means					
Negative Affect	11.04	0.18	0.00	10.70	11.38
Positive Affect	9.11	0.12	0.00	8.87	9.34
Negative Emotional Inertia	0.41	0.01	0.00	0.39	0.44
Positive Emotional Inertia	0.35	0.01	0.00	0.33	0.37
Intercepts					
Well-Being	-3.59	0.54	0.00	-4.66	-2.57
Variances					
Negative Affect	9.99	0.81	0.00	8.64	11.87
Positive Affect	4.23	0.33	0.00	3.66	4.98

Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.004	0.00	0.02	0.03
Residual Variances					
Well-Being	1.59	0.13	0.00	1.35	1.88

Hypothesis 2: Longitudinal Relationships between Emotional Inertia and Subsequent Self-Reported Well-Being

Given the data, we do not have enough confidence to be sure that the relationship between negative emotional inertia and subsequent well-being is positive, as the probability that the relationship is negative is 0.09. The mean of the posterior distribution is 0.61 (95% CI [-0.24, 1.65]). The data provided strong evidence that there is a negative relationship between positive emotional inertia and subsequent well-being (Mean=-1.85, 95% CI[-3.28, -0.54]). The data also provided strong evidence that there is a negative association between average negative affect and well-being (Mean= -0.07, 95% CI [-0.11, -0.02]) and that there is a positive relationship between average positive affect and well-being (Mean= 0.27, 95% CI [0.19, 0.35]). See Table 4 for full model results.

Table 4
Model Results for Hypothesis 2

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Baseline Well-Being	0.00	0.00	0.00	0.00	0.00
Week 12 Well-Being	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	7.12	0.08	0.00	6.98	7.27
Positive Affect	5.54	0.06	0.00	5.42	5.66
Between- Level					
Week 12 Well-Being on Negative Emotional Inertia	0.61	0.47	0.09	-0.24	1.65

Week 12 Well-Being on Positive Emotional Inertia	-1.85	0.69	0.00	-3.28	-0.54
Week 12 Well-Being on Negative Affect	-0.07	0.02	0.00	-0.11	-0.02
Week 12 Well-Being on Positive Affect	0.27	0.04	0.00	0.19	0.35
Week 12 Well-Being on Baseline Well-Being	0.43	0.05	0.00	0.34	0.52
Means					
Negative Affect	11.04	0.18	0.00	10.68	11.37
Positive Affect	9.11	0.11	0.00	8.90	9.34
Baseline Well-Being	0.01	0.09	0.47	-0.18	0.18
Negative Emotional Inertia	0.42	0.01	0.00	0.39	0.45
Positive Emotional Inertia	0.35	0.01	0.00	0.33	0.37
Intercepts					
Week 12 Well-Being	-1.36	0.53	0.01	-2.38	-0.33
Variances					
Negative Affect	9.98	0.82	0.00	8.49	11.77
Positive Affect	4.21	0.35	0.00	3.63	4.95
Baseline Well-Being	3.08	0.24	0.00	2.66	3.60
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Week 12 Well-Being	1.31	0.11	0.00	1.09	1.53

Hypothesis 3: Cross-Sectional Relationships between Network Density and Self-Reported Well-Being

All model results are displayed in Table 5.

Temporal Network Density

We failed to reject the hypothesis that the data were equally likely under both models, according to the log likelihood test (χ^2 (2) = 1.37, *p*=.50). Neither temporal negative emotion network density (β=0.02, *p*=.77) nor temporal positive emotion network density (β=0.05, *p*=.28) was significantly associated with well-being. In both models, average negative affect was significantly, inversely associated with well-being (β=-0.18, *p*<.001) and average positive affect was significantly, positively associated with well-being (β=0.63, *p*<.001).

Contemporaneous Network Density

We failed to reject the hypothesis that the data were equally likely under both models according to the log likelihood test (χ^2 (2) = 0.85, p=.65). Neither contemporaneous negative emotion network density (β= 0.04, p=.47) nor contemporaneous positive emotion network density (β= 0.02, p=.59) was significantly associated with well-being. In both models, average negative affect was significantly, inversely associated with well-being (β=-0.18, p<.001) and average positive affect was significantly, positively associated with well-being (β= 0.63, p <.001).

Table 5
Results for Hypothesis 3

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-3.83	0.56	-6.87	<.001
	Negative Network Density	0.62	2.07	0.30	.77
	Positive Network Density	2.10	1.94	1.08	.28
	Average Negative Affect	-0.10	0.03	-3.77	<.001
	Average Positive Affect	0.54	0.04	13.06	<.001
Contemporaneous Network Density					
	Intercept	-3.86	0.56	-6.87	<.001
	Negative Network Density	2.63	3.60	0.73	.47
	Positive Network Density	1.50	2.78	0.54	.59

	Average Negative Affect	-0.10	0.03	-3.68	<.001
	Average Positive Affect	0.53	0.04	12.87	<.001

Note: Estimates represent unstandardized estimates.

Hypothesis 4: Longitudinal Relationships between Network Density and Subsequent Self-Reported Well-Being

All model results are displayed in Table 6.

Temporal Network Density

We failed to reject the null hypothesis that the data were equally likely under both models according to the log likelihood test (χ^2 (2) = 0.04, *p*=.98). In the initial model, neither temporal network density of negative emotions (β=0.01, *p*=.88) nor temporal network density of positive emotions (β=0.004, *p*=.92) was significantly associated with subsequent well-being. Average level of negative affect (β=-0.13, *p*= .01), average level of positive affect (β=0.35, *p*<.001), and baseline well-being (β=0.44, *p*=<.001) were all significantly associated with subsequent well-being.

Contemporaneous Network Density

The hypothesis that the data were equally likely under the two models was rejected (χ^2 (2) = 9.31, *p*=.01). In the initial model, contemporaneous network density of positive emotions was significantly, positively associated with subsequent well-being (β=0.12, *p*=.003). Contemporaneous network density of negative emotions was not significantly associated with subsequent well-being (β=-0.03, *p*=.46). Average level of positive affect (β=0.34, *p*<.001), average level of negative affect (β=-0.13, *p*=.002), and baseline well-being (β=0.44, *p*<.001) were also all significantly associated with subsequent well-being.

Table 6.
Results for Hypothesis 4

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-1.93	0.53	-3.65	<.001
	Negative Network Density	0.31	2.14	0.15	.88
	Positive Network Density	0.17	1.75	0.10	.92
	Average Negative Affect	-0.07	0.02	-2.81	.01
	Average Positive Affect	0.29	0.04	6.60	<.001
	Baseline Well-Being	0.44	0.05	8.10	<.001
Contemporaneous Network Density					
	Intercept	-1.98	0.52	-3.78	<.001
	Negative Network Density	-2.37	3.16	-0.75	0.46
	Positive Network Density	7.50	2.53	2.96	.003
	Average Negative Affect	-0.07	0.02	-3.01	.003
	Average Positive Affect	0.28	0.04	6.44	<.001
	Baseline Well-Being	0.44	0.05	8.39	<.001

Note: Estimates represent unstandardized estimates.

Sensitivity Analyses

Sensitivity Analysis #1: Using Data from Epochs 2 and 3 for Hypotheses 1 and 3

We repeated the analysis for Hypotheses 1 and 3 in MPLUS and RStudio respectively, this time using EMA data from epochs 2 and 3 (instead of 1 and 2) and self-reported well-being from Week 12. There were no meaningful changes in the results. Results are in Supplementary Tables S3 (Hypothesis 1) and S4 (Hypothesis 3).

Sensitivity Analysis #2: Using Data from Epochs 1-3 for Hypotheses 1 and 3

We repeated the analysis for Hypotheses 1 and 3 in MPLUS and RStudio respectively, this time using EMA data from epochs 1, 2, and 3 (instead of just 1 and 2) and self-reported well-being from Week 12. There were no meaningful changes in the results. Results are displayed in Supplementary Tables S5 and S6.

Sensitivity Analysis #3: Addition of an Interaction Term

We repeated the analysis for all main hypotheses including an interaction term between emotional persistence and average level of affect. Given constraints of the MPLUS software, this analysis was run in RStudio for all hypotheses. Estimates of emotional inertia from each participant were obtained by regressing affect at time t onto affect at time t-1and extracting the regression coefficient estimate for each participant. Then, multiple linear regression models with log likelihood model comparisons were used to examine the association between well-being and the interaction between emotional inertia and average levels of affect. Additional models with log likelihood model comparisons were used to examine the association between well-being and the interaction between network density and average levels of affect. The interaction term was not significant in any model. Results are displayed in Supplementary Tables S7-S10.

Discussion

This study examined associations between self-reported well-being and emotional persistence, which was operationalized in two ways. Emotional inertia measured persistence as stability of emotions over time, while emotion network density measured persistence as the interconnectedness of emotions over time. Hypotheses were partially supported.

Stability: Neither negative nor positive emotional stability was associated with cross-sectional well-being (hypothesis 1). While negative emotional stability was not associated with well-being six weeks later (hypothesis 2a), positive emotional stability was significantly, inversely associated with well-being six weeks later, such that participants with higher stability of positive emotions during weeks 1 and 6 of the study reported *lower* well-being during week 12 (hypothesis 2b).

Interconnectedness: Neither interconnectedness of negative nor positive emotions was associated with concurrent well-being (hypothesis 3), and interconnectedness of negative emotions was not associated with well-being six weeks later (hypothesis 4a). However, in line with our hypothesis, interconnectedness of positive emotions was positively associated with well-being six weeks later. That is, participants with more interconnected positive emotions within a given two-hour time frame reported higher levels of well-being six weeks later, above and beyond average levels of positive and negative affect.

Overall, emotional persistence of positive affect was associated with well-being six weeks later. No measures of emotional persistence (i.e., inertia or density) were associated with concurrent self-reported well-being, and no measure of negative emotional persistence was associated with subsequent well-being. In all models, average positive affect was positively associated with both concurrent and future well-being, and average negative affect was negatively associated with concurrent and future well-being.

Implications

Positive Emotional Inertia and Well-Being

While the inverse relationship between positive emotional inertia and subsequent well-being did not support our hypothesis, it aligns with some previous research. For example, one study found higher positive emotional inertia in adolescents with depression compared to healthy controls (Kuppens et al., 2010) and another found that inertia of positive emotions predicted the onset of depression two years later (Kuppens et al., 2012). These results suggest that emotional inertia may represent overall blunted affect, which previous research has found to be associated with depression (Bylsma et al., 2008). Higher emotional inertia, even of positive emotions, may represent deficits in emotion regulation and reliance on external sources for changes in emotion. Higher inertia of positive affect may also be particularly driven by persistence of *low* positive affect, or anhedonia, and thus be a characteristic of individuals with high anhedonia.

Positive Emotion Network Density

In line with hypotheses, contemporaneous network density, or interconnectedness, of positive emotions was associated with higher subsequent well-being. This finding is in line with previous research finding that higher idiographic network density for positive emotion networks corresponded with lower risk of diagnosis of generalized anxiety disorder or major depressive disorder (Shin et al., 2022). Network density is more nuanced than positive emotional inertia, as it incorporates relationships among individual symptoms (e.g., happiness and motivation) instead of only viewing positive affect in the aggregate. This may render network density as a more apt representation of regulation strategies such as savoring, or other forms of prolonging positive emotions. Indeed, previous research has found that savoring is related to life satisfaction and psychological well-being (Growney et al., 2025; Quoidbach et al., 2010).

To our knowledge, this is the first study to directly compare emotional inertia and idiographic emotion network density in the same dataset. The contrasting results may indicate that the two metrics, while both thought to represent emotional persistence, may characterize different dynamic processes. Alternatively, the contrast may also indicate unreliability or instability in this field of research, and it highlights a need for further research on positive emotion dynamics. The alignment of our positive network density results with theoretical research related to savoring suggests that emotion network density may be a more valid measure of positive emotional persistence than emotional inertia, though more research is needed to confirm this.

Negative Emotional Persistence

The finding that negative emotional persistence was not associated with concurrent or subsequent well-being was surprising in light of previous research that provides strong support for the relationship between negative emotional inertia and depression (Koval et al., 2012; Kuppens et al., 2012). Additionally, these findings contrast with previous research connecting network density of negative emotions or depression symptoms with poor psychological well-being (e.g., Pe et al., 2015; Shin et al., 2022). However, the finding that negative emotional inertia was not associated with well-being was consistent with one study that found that only variability, and not inertia, of negative emotions was associated with internalizing disorders (Scott et al., 2020).

It is possible that the discrepancy between these results and previous research is due to methodological differences. For example, the timing between measurements or the specific emotions measured may have impacted the results. Perhaps the relationship between persistence of negative emotions and well-being exists on a different timescale. For example, perhaps persistent negative emotions become maladaptive only in increments of more than two hours, such as six-hour or day-by-day increments, and these more frequent EMA measures increased noise. Alternatively, the ideal timescale may be smaller, such as the 10 daily surveys used in (Kuppens et al., 2010) in which case more frequent EMA measurements may provide better insight into this relationship. Additionally, there was a high proportion of empty negative affect networks in this dataset. It is difficult to discern whether these networks are empty due to lack of power or because they represent the true relationships (or lack thereof) between symptoms for these participants. True empty networks would suggest that participants' emotions at one time do not relate to their emotions at the next time, indicating very low emotional persistence. For negative affect, this would be somewhat at odds with previous research on negative emotion dynamics (Koval et al., 2016; Van De Leemput et al., 2014). Future research with larger samples of EMA responses will be useful to parse out this relationship.

Despite these limitations, taken at face value, these results suggest that negative emotional persistence may not provide information about well-being above and beyond average levels of negative affect, which were consistently inversely associated with well-being.

Longitudinal vs Cross-Sectional Hypotheses

It is notable that only the longitudinal analyses, and not the cross-sectional analyses, yielded significant results in this study. To our knowledge, this is the first study that examined longitudinal relationships between idiographic networks and psychological well-being, although previous emotional inertia research has found both cross-sectional (Koval et al., 2016) and longitudinal (Kuppens et al., 2012) associations with markers of psychological well-being such as depression. Results in both of these models held above and beyond average levels of positive affect. The results of this study suggest that positive emotional persistence may represent a susceptibility to experience changes in well-being in the future, rather than simply reflecting the current state of well-being. This finding may indicate that regulatory ability for positive emotions, and ability to cultivate a *variety* of positive emotions (as indicated by network density), is adaptive for general psychological well-being. Individuals who can regulate their positive emotions and experience multiple positive emotions within the same timeframe (those with higher network density) may find it easier to engage in more meaningful activities or respond to positive events, which, in the long term, may increase their well-being. This is in line with the broaden-and-build theory of positive emotions, which notes that positive emotions cue the urge to engage in enjoyable activities, savoring of positive moments, and fostering of relationships (Fredrickson, 2004).

For cross-sectional data, affective persistence and interconnectedness may not be informative compared to average levels of affect. Average levels of both positive and negative affect may be sufficient markers of current levels of well-being; these covariates were significant in every cross-sectional model while measures of emotional persistence were not.

Sensitivity Analyses

Changing Data Timeline

When using EMA data from different timepoints to run the analysis (epochs 2-3 or 1-3 instead of epochs 1-2), the results did not change. This suggests the potential stability of network density and the model results when using data from different timepoints or different amounts of data.

Moderation Term for Average Affect Not Significant

Results did not change when examining a potential moderation between emotional persistence and average levels of affect. This suggests that the relationship between emotional inertia and psychological well-being does not depend on average levels of affect. To our knowledge, no other studies have examined this interaction. This result was somewhat surprising, particularly for the emotional inertia hypotheses. The idea that the impact of emotional persistence depends on which *level* of affect persists is intuitive. More nuanced analysis may be needed to accurately pinpoint this mechanism. Notably, this sensitivity analysis was limited by methodological constraints for the emotional inertia hypotheses. The computing abilities of MPLUS prevented us from running this multilevel model in MPLUS, and instead, inertia values for each participant were saved and included in a separate model in R. This model thus did not include residual error values for the inertia estimates.

Limitations

This study is not without limitations. One limitation is the timing of the EMA questions. Persistence may occur on a scale different than the two-hour window between EMA surveys that this study used. A smaller scale, such as 1 hour between surveys, or a larger scale like six hours or even one day, may yield different results. An additional limitation of the EMA surveys is the specific emotions that were measured. Other negative emotions (such as stronger emotions like anger or depression instead of “irritated” and “sad”, or different emotions like guilt or shame) may yield different results. In particular, the addition of emotions such as guilty or ashamed may indicate judgment of negative emotions, which is linked with negative psychological health (Willroth et al., 2023) and may serve as a mechanism for prolonging negative emotions. On the other hand, additional positive emotions, particularly lower intensity positive emotions such as calm, grateful, or hopeful, may provide a different representation of positive emotional persistence.

Additionally, the sample size was still relatively small for idiographic networks. Many participants were removed from the analysis due to their networks not converging or not having enough variation in their answers. Of the participants who were retained in the analysis, many had “empty” networks (networks with no significant connections). These empty networks may represent the true relationship between emotions for these participants (indicating very low emotional persistence), or for some, they may be a result of the network being underpowered. Likewise, some networks unexpectedly had negative edges between symptoms, and parsing out whether this was due to misestimation or a true representation of the participant’s experience is difficult. Future studies that replicated these analyses, ideally with more data per person, would clarify these questions.

Future Directions

In addition to clarifying how methodological changes may impact the results, future research should strive to discern the mechanisms underlying emotional persistence, as represented by emotional inertia and network density. For example, researchers should assess whether certain emotions drive these findings, i.e., whether inertia of a specific emotion predicts future well-being, and whether that emotion differs across individuals. Additionally, future studies should continue to discern the differences between persistence as represented by emotional inertia and network density. Finally, researchers should continue to investigate mechanisms behind the relationship between positive affect network density and well-being to inform intervention work. If specific emotion regulation strategies lead to higher positive emotion network density, intervention studies could use network density as a risk marker signaling that a participant should receive an additional intervention to improve this skill.

Conclusion

This study examined relationships between measures of emotional persistence and self-reported well-being, both cross-sectionally and longitudinally. Emotional persistence was operationalized in two different ways, as both emotional inertia and emotion network density, for both negative and positive emotions. We found that positive emotional inertia was associated with lower subsequent well-being and positive emotion network density was associated with higher subsequent well-being. This may indicate that positive emotion regulatory skills, particularly the cultivation of multiple different positive emotions, allow individuals to more easily seek and enjoy meaningful experiences, thereby improving well-being. Negative emotional persistence was not associated with well-being. This research has potential implications for identifying individuals at risk for decreased psychological well-being. Future studies should continue to research the mechanisms behind these relationships to discern which interventions would be most effective.

Table S1. Correlation Matrices for Inertia Values Calculated with Different Epochs

Negative Affect, Inertia

Variable	*1*	*2*	*3*
1. Inertia Epochs 1-2	1.00		
2. Inertia Epochs 2-3	0.62	1.00	
3. Inertia Epochs 1-3	0.92	0.78	1.00

Positive Affect, Inertia

Variable	*1*	*2*	*3*
1. Inertia Epochs 1-2	1.00		
2. Inertia Epochs 2-3	0.53	1.00	
3. Inertia Epochs 1-3	0.90	0.71	1.00

Table S2. Correlation Matrices for Network Density Values Calculated with Different Epochs

Negative Affect, Temporal Networks

Variable	*1*	*2*	*3*
1. Density Epochs 1-2	1.00		
2. Density Epochs 2-3	0.34	1.00	
3. Density Epochs 1-3	0.62	0.28	1.00

Negative Affect, Contemporaneous Networks

Variable	*1*	*2*	*3*
1. Density Epochs 1-2	1.00		
2. Density Epochs 2-3	0.13	1.00	
3. Density Epochs 1-3	0.64	0.24	1.00

Positive Affect, Temporal Networks

Variable	*1*	*2*	*3*
1. Density Epochs 1-2	1.00		
2. Density Epochs 2-3	0.33	1.00	
3. Density Epochs 1-3	0.64	0.39	1.00

Positive Affect, Contemporaneous Networks

Variable	*1*	*2*	*3*
1. Density Epochs 1-2	1.00		
2. Density Epochs 2-3	0.22	1.00	
3. Density Epochs 1-3	0.54	0.33	1.00

Table S3: Results for Sensitivity Analysis #1, Hypothesis 1

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5%	Upper 2.5% Credible Interval

				Credible Interval	
Within-Level					
Variances					
Well-Being	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	6.03	0.07	0.00	5.88	6.16
Positive Affect	4.71	0.05	0.00	4.61	4.82
Between- Level					
Well-Being on Negative Emotional Inertia	0.48	0.44	0.14	-0.41	1.34
Well-Being on Positive Emotional Inertia	0.19	0.64	0.38	-1.18	1.33
Well-Being on Negative Affect	-0.09	0.03	0.00	-0.14	-0.04
Well-Being on Positive Affect	0.46	0.04	0.00	0.39	0.53
Means					
Negative Affect	11.09	0.19	0.00	10.70	11.43
Positive Affect	9.00	0.13	0.00	8.75	9.25
Negative Emotional Inertia	0.42	0.02	0.00	0.38	0.45
Positive Emotional Inertia	0.36	0.01	0.00	0.33	0.38
Intercepts					
Well-Being	-3.36	0.54	0.00	-4.43	-2.29
Variances					
Negative Affect	11.18	0.91	0.00	9.64	13.21
Positive Affect	4.90	0.42	0.00	4.20	5.88
Negative Emotional Inertia	0.05	0.01	0.00	0.04	0.06
Positive Emotional Inertia	0.03	0.004	0.00	0.02	0.04
Residual Variances					
Well-Being	1.69	0.14	0.00	1.44	2.00

Table S4: Results for Sensitivity Analysis #1, Hypothesis 3

Model	**Variable**	**Estimate**	**Std Error**	**T value**	**P value**
Temporal Network Density					
	Intercept	-3.27	0.53	-6.13	<.001
	Negative Network Density	1.27	1.86	0.68	.50

	Positive Network Density	-4.13	1.94	-2.13	.03
	Average Negative Affect	-0.10	0.03	-3.77	<.001
	Average Positive Affect	0.48	0.04	11.72	<.001
			Df	**X^2**	**P value**
			2	4.64	.10
Contemporaneous Network					
	Intercept	-3.50	0.55	-6.36	<.001
	Negative Network Density	3.88	3.37	1.15	.25
	Positive Network Density	1.64	2.72	0.60	.55
	Average Negative Affect	-0.09	0.03	-3.63	<.001
	Average Positive Affect	0.48	0.04	11.46	<.001
			Df	**X^2**	**P value**
			2	2.02	.37

Note: Estimates represent unstandardized estimates.

Table S5: Results for Sensitivity Analysis #2, Hypothesis 1

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Well-Being	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	6.76	0.06	0.00	6.63	6.89
Positive Affect	5.28	0.05	0.00	5.19	5.37
Between- Level					
Well-Being on Negative Emotional Inertia	0.53	0.49	0.5	-0.43	1.45
Well-Being on Positive Emotional Inertia	0.15	0.70	0.41	-1.19	1.60

Well-Being on Negative Affect	-0.11	0.03	0.00	-0.16	-0.06
Well-Being on Positive Affect	0.49	0.04	0.00	0.41	0.56
Means					
Negative Affect	11.01	0.17	0.00	10.69	11.35
Positive Affect	9.05	0.11	0.00	8.83	9.28
Negative Emotional Inertia	0.45	0.01	0.00	0.42	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.39
Intercepts					
Well-Being	-3.52	0.54	0.00	-4.58	-2.49
Variances					
Negative Affect	9.66	0.82	0.00	8.22	11.41
Positive Affect	4.29	0.35	0.00	3.71	5.03
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.04
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Well-Being	1.64	0.13	0.00	1.40	1.91

Table S6: Results for Sensitivity Analysis #2, Hypothesis 3

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-3.70	0.55	-6.75	<.001
	Negative Network Density	-0.23	2.35	-0.10	.92
	Positive Network Density	-1.33	2.07	-0.64	.52
	Average Negative Affect	-0.10	0.03	-3.90	<.001
	Average Positive Affect	0.53	0.04	13.02	<.001
			Df	**X^2**	**P value**
			2	0.44	.80
Contemporaneous Network Density					

Intercept	-3.72	0.56	-6.69	<.001
Negative Network Density	-2.56	4.38	-0.58	.56
Positive Network Density	2.02	3.05	0.66	.51
Average Negative Affect	-0.10	0.03	-3.93	<.001
Average Positive Affect	0.53	0.04	12.97	<.001
		Df	**X^2**	**P value**
		2	0.64	.73

Note: Estimates represent unstandardized estimates.

Table S7: Results for Sensitivity Analysis #3, Hypothesis 1

Variable	Estimate	Std Error	T value	P value
Intercept	-6.91	1.85	-3.74	<.001
Negative Emotional Inertia	2.60	2.18	1.19	.23
Positive Emotional Inertia	5.51	4.22	1.30	.19
Average Negative Affect	-0.01	0.09	-0.16	.87
Average Positive Affect	0.73	0.16	4.61	<.001
Negative Emotional Inertia*Average Negative Affect	-0.18	0.19	-0.96	.34
Positive Emotional Inertia*Average Positive Affect	-0.52	0.44	-1.18	0.24
		Df	*X^2*	*p*
		4	4.45	.35

Note: Estimates represent unstandardized estimates.

Table S8: Results for Sensitivity Analysis #3, Hypothesis 2

Variable	Estimate	Std Error	T value	P value
Intercept	-3.87	1.64	-2.37	.02

Negative Emotional Inertia	2.25	1.97	1.14	.25
Positive Emotional Inertia	3.29	3.71	0.89	.38
Average Negative Affect	0.003	0.08	0.04	.97
Average Positive Affect	0.46	0.14	3.26	.001
Baseline Well-Being	0.45	0.05	9.06	<.001
Negative Emotional Inertia*Average Negative Affect	-0.16	0.17	-0.97	.33
Positive Emotional Inertia*Average Positive Affect	-0.53	0.39	-1.37	0.17
		Df	X^2	*p*
		4	8.44	.08

Note: Estimates represent unstandardized estimates.

Table S9: Results for Sensitivity Analysis #3, Hypothesis 3

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-3.70	0.64	-5.81	<.001
	Negative Network Density	-10.02	7.88	-1.27	.20
	Positive Network Density	9.49	6.85	1.39	.17
	Average Negative Affect	-0.13	0.03	-3.80	<.001
	Average Positive Affect	0.56	0.05	12.14	<.001
	Negative Network	1.00	0.70	1.43	.15

	Density * Average Negative Affect				
	Positive Network Density*Average Positive Affect	-0.88	0.78	-1.13	.26
			Df	**X^2**	**P value**
			4	4.62	.33
Contemporaneous Network Density					
	Intercept	-3.33	0.73	-4.56	<.001
	Negative Network Density	16.49	13.62	1.21	.23
	Positive Network Density	-23.83	13.66	-1.74	.08
	Average Negative Affect	-0.07	0.04	-1.67	.10
	Average Positive Affect	0.44	0.06	6.93	<.001
	Negative Network Density * Average Negative Affect	-1.39	1.28	-1.09	.28
	Positive Network Density*Average Positive Affect	2.71	1.44	1.89	.06
			Df	**X^2**	**P value**
			4	5.19	.27

Note: Estimates represent unstandardized estimates.

Table S10: Results for Sensitivity Analysis #3, Hypothesis 4

Model	Variable	Estimate	Std Error	T value	P value

Temporal Network Density					
	Intercept	-1.97	0.60	-3.30	<.001
	Negative Network Density	-2.62	7.46	-0.35	.73
	Positive Network Density	4.19	6.21	0.67	.50
	Average Negative Affect	-0.08	0.03	-2.40	.02
	Average Positive Affect	0.31	0.05	6.35	<.001
	Baseline Well-Being	0.44	0.05	8.09	<.001
	Negative Network Density * Average Negative Affect	0.30	0.69	0.43	.66
	Positive Network Density*Average Positive Affect	-0.48	0.71	-0.68	.50
			Df	**X^2**	**P value**
			4	0.66	.96
Contemporaneous Network Density					
	Intercept	-1.71	0.67	-2.56	.01
	Negative Network Density	5.66	12.24	0.46	.64
	Positive Network Density	-6.62	12.01	-0.55	.58
	Average Negative Affect	-0.05	0.03	-1.56	.12

Average Positive Affect	0.23	0.06	3.91	<.001
Baseline Well-Being	0.44	0.05	8.23	<.001
Negative Network Density * Average Negative Affect	-0.80	1.14	-0.70	.48
Positive Network Density*Average Positive Affect	1.50	1.26	1.20	.23
		Df	**X^2**	**P value**
		4	11.11	.02

Study 2: Heart-rate variability as a biological substrate of emotional inertia and density

Abstract

Emotional flexibility, the ability to adapt to internal and external environmental changes, is associated with psychological well-being. Emotional inertia and emotion network density are two measures of emotion dynamics thought to represent lower emotional flexibility. No study has examined emotional inertia or network density in relation to biological substrates. Heart-rate variability (HRV) is a transdiagnostic biomarker for psychopathology thought to be associated with emotional flexibility and regulation. This study examined whether emotional inertia and network density were associated with HRV. Adults with moderate-to-severe depression completed three 8-day epochs of ecological momentary assessment (EMA) five times daily. Apple Watches measured heart rate throughout the study. Emotional inertia and idiographic networks were calculated separately for EMA measures of negative and positive affect. Bayesian dynamic structural equation models with noninformative prior distributions examined the association between emotional inertia and HRV, and hierarchical linear modeling examined associations between network density and HRV. Both daytime and bedrest HRV were inversely associated with temporal network density of negative emotions. HRV was not associated with inertia, positive network density, or average EMA-reported affect, though it was associated with age, antidepressant medication, and physical exercise. This was the first study to examine HRV in relation to measures of emotional persistence. The results suggest that experiencing a variety of negative emotions within a short period of time may be associated with underlying biological inflexibility. Future studies should examine the directionality and mechanisms behind this effect and explore potential clinical interventions.

Introduction

Emotional flexibility, the ability to adapt to changes in one's internal and external environments, is associated with general psychological well-being (Sheldon et al., 2010). Two measures of emotion dynamics that capture emotion persistence, emotional inertia and emotion network density, are both thought to be inversely related to emotional flexibility. These two measures represent the same construct; network density may be the more precise and dynamic of the two. Emotional inertia, which represents the stability of emotions, is considered to be the opposite of emotional flexibility in that it suggests that emotions are determined by previous emotions rather than regulation strategies or environmental stimuli (Sheldon et al., 2010). Network density, a related and more nuanced version of emotional inertia that incorporates several different emotion variables and the relationships between them, is considered to represent a "contagion effect" or a sort of emotion spiral. Again, an individual with higher levels of emotion network density, at least in the case of negative emotions, may demonstrate lower levels of emotional flexibility.

To our knowledge, no study has examined emotional inertia or network density in relation to potential biological substrates. In fact, the network analysis literature generally lacks studies investigating how constructs outside of symptom networks, such as psychophysiological variables, influence or relate to networks (McNally, 2021). Specifically, heart rate variability (HRV) is a biomarker that may be related to these measures of emotion dynamics. Examining these possible connections has important implications for treatment. That is, if emotion network density is related to HRV, interventions that target HRV may be useful for individuals with more dense networks of emotions. Such interventions include heart rate variability biofeedback, which serves to increase HRV and has been found to be effective in treating depression (Karavidas, 2008).

Heart-Rate Variability

Like inertia and network density, HRV is considered an index of emotion regulatory capacity and ability to adapt to changing environmental stimuli (Appelhans & Luecken, 2006; Heiss et al., 2021; Karpyak et al., 2014; Luecken et al., 2006). HRV is a measure of the variability in intervals between heart beats. A smaller HRV is associated with lower control from the sympathetic nervous system, which is associated with greater difficulty in emotion regulation and increased impulsivity (Heiss et al., 2021). The two leading theories for this connection are the neurovisceral integration model and polyvagal theory.

Neurovisceral integration model. The neurovisceral integration model notes that physical and emotional flexibility are related, and that the disruption of this system may lead to the development of psychopathology (Thayer & Lane, 2000). The most important system for regulating emotion is the central autonomic network, which uses many different pathways including the prefrontal cortex and the vagus nerve (Thayer & Lane, 2000). There is a biological feedback loop in which the vagus nerve detects an increase in physiological activity and lowers arousal by increasing vagal tone (Thayer & Lane, 2000). Disruptions in this negative feedback loop may cause alterations in HRV (Thayer & Lane, 2000).

Polyvagal theory. Polyvagal theory identifies that the vagal brake allows one to respond to their environment (Porges, 2011). This theory notes that in addition to the “fight or flight” response, mammals have an additional pathway, through the vagus nerve, that is used for social engagement (Porges, 2011). This “vagus brake” myelinates through early positive relationships with others, but individuals that have fewer positive interactions and relationships with other people may thus have an unmyelinated vagus nerve, and thus, a malfunctioning vagus brake (Porges, 2011). This malfunctioning vagus brake (signaled by low HRV) makes it such that assessing what is and is not a threat is difficult (Porges, 2011). In this theory, as with the neurovisceral integration model, physical and emotional flexibility influence each other; higher HRV signifies more emotional flexibility and lower HRV signifies less emotional flexibility.

HRV and Psychopathology

HRV is considered a transdiagnostic biomarker for psychopathology. The relationship between lower HRV and psychopathology has been found both in clinical populations (Hamilton & Alloy, 2016) and non-clinical populations (Paniccia et al., 2017). Specifically, lower HRV has been found compared to healthy controls in various psychiatric diagnoses (Beauchaine & Thayer, 2015), including alcohol use disorder (Quintana et al., 2013), borderline personality disorder (Koenig et al., 2016), various anxiety disorders (Chalmers et al., 2016; Cheng et al., 2022), depression (Koch et al., 2019), bipolar disorder (Faurholt-Jepsen et al., 2017), and schizophrenia (Clamor et al., 2014). The one exception to this pattern seems to be eating disorders, which are associated with higher HRV (Mazurak et al., 2011). Further emphasizing its transdiagnostic nature, lower HRV is associated with neuroticism (Di Simplicio et al., 2012), a personality trait typically associated with higher risk for internalizing disorders (Hur et al., 2019; Michelini et al., 2021) and higher levels of emotional inertia (Koval et al., 2016) and network density (Bringmann et al., 2013).

HRV is also associated with transdiagnostic symptoms that are often implicated in psychopathology. For example, low HRV seems to be related to several markers of emotion dysregulation, including trait-level worry (Chalmers et al., 2016) and slow recovery from external stressors (Cattaneo et al., 2021). Likewise, emotion regulatory ability is associated with increased resting-state HRV (Butler et al., 2006). Another study found that participants with higher neuroticism showed decreased high frequency HRV during cognitive reappraisal, demonstrating a link between loss of emotional flexibility in parasympathetic cardiovascular tone and emotion regulation (Di Simplicio et al., 2012). Lower HRV is also associated with certain neuropsychological skills including slower psychomotor speed and attention tasks (Huang et al., 2023). Finally, social disengagement, which is often present in internalizing disorders such as depression and social anxiety, has been shown to lower HRV (Shahrestani et al., 2014).

HRV and positive emotions. While HRV has primarily been studied in relation to negative emotionality, previous research has identified a relationship between HRV and positive emotions as well. Overall, HRV seems to be positively related to state and trait positive emotions (Määttänen et al., 2021; Oveis et al., 2009; Sveinsdóttir & Jóhannsdóttir, 2023). However, the relationship may not be linear; Duarte and Pinto-Gouveia found a quadratic relationship between HRV and the specific positive emotions of contentment and safeness, while finding no relationship between HRV and excitement or arousal (Duarte & Pinto-Gouveia, 2017b). There is less research on how the relationship between HRV and positive emotions might reflect emotion regulation. A recent study found that at low levels of positive affect, positive emotion dysregulation was negatively related to HRV (Weiss et al., 2021). That is, when experiencing low levels of positive emotion, individuals who experienced more dysregulation had lower HRV.

While most of the above studies represent the results of laboratory tests of resting-state HRV, additional research has identified a relationship between negative emotionality and HRV assessed via 24-hour ambulatory assessment. For example, one study found that 24-hour HRV was negatively correlated with depression and rumination (Carnevali et al., 2018) and another found that participants who received cognitive behavioral therapy for depression experienced a greater increase in HRV following treatment compared to waitlist controls (Euteneuer et al., 2023). More passive sensing research is needed to confirm the external validity of these studies. Controlled laboratory environments may not provide accurate representations of how individuals' sympathetic nervous systems interact with the environment. Additionally, some studies have found differential effects depending on recording length. A recent meta-analysis and another review article both found greater power in studies that used 24-hour recordings as opposed to shorter (i.e., 2-10 minute) recordings (Heiss et al., 2021; Shaffer & Ginsberg, 2017). This suggests that studies that use passive sensing mechanisms such as having participants wear smartwatches throughout the day, which allows for longer recording time, may produce clearer results.

State of the field. Higher emotional inertia, higher emotion network density, and lower HRV have been demonstrated to be associated with internalizing disorders, emotion regulation, and neuroticism, and all are thought to represent the same overarching construct of emotional flexibility. However, while emotion network density and emotional inertia are related to similar constructs to HRV, neither has been examined in relation to HRV.

Study Aims and Hypotheses

This study aimed to identify whether lower HRV is cross-sectionally related to emotional inertia and emotion network density. Two main hypotheses were tested:

Hypothesis 1: Inertia of negative affect will be inversely related to HRV, after controlling for average levels of negative affect.

Hypothesis 2: Network density of negative affect will be inversely related to HRV, after controlling for average levels of negative affect.

To test the specificity of the effects, we also included inertia and network density of positive affect and HRV and controlled for average levels of positive affect. However, prior research on HRV and positive emotions has only demonstrated associations between trait levels of positive affect and HRV (and not savoring, persistence, or dynamics of positive affect). Additionally, there is a dearth of research identifying a connection between positive emotional inertia and network density and constructs such as neuroticism. Thus, there does not currently exist evidence to suggest that there is a significant relationship between inertia or density of positive emotions and HRV. However, identification of whether the relationship between HRV and inertia or density extends to positive emotions is imperative in order to understand whether HRV is related to persistence of emotions in general or to the persistence of specifically negative emotions.

Methods

Participants

This study used data from the same umbrella study as Study 1. See Study 1 methods for details on participants. A total of N=315 participants had data for daytime HRV and N=241 participants had data for bedrest HRV and were included in the analyses.

Procedure

For the duration of the 12-week study, participants underwent passive sensing data collection through an Apple Watch series 7 given to them by the study. At the start of the study, participants downloaded the Depression Grand Challenge (DGC) Study Application on their smartphone and enabled sharing of sensor data via HealthKit and SensorKit. This study only analyzed data from HealthKit, which continuously collected heartrate data throughout the 12+ weeks. Data collected included heart rate, activity levels, and sleep and wake times.

Emotional Inertia and Emotion Network Density

This study used the same data and methods for calculating inertia and contemporaneous and temporal network density as Study 1. The only discrepancy is that this study used EMA from all three epochs for calculations of emotional inertia and network density. See Study 1 for measures and methods.

HRV

Heart rate variability data was compiled from baseline and weeks 6 and 12 (as to align with the timing of the EMA data). HRV was sampled about 15 times per day, for about a one-minute duration, in intervals as frequent as 15-20 minutes apart. The watch dynamically sampled heart rate such that it was more likely to be sampled in situations where the watch was likely to get the best signal (such as when the participant was not moving). Heart rate variability was measured using the standard deviation of N to N interval (SDNN), a commonly-used time-domain measure of heart rate variability (Koch et al., 2019). HRV was filtered to be within a plausible range (0-300ms) and then resampled to median value per hour to account for the Apple Watch's dynamic sampling rate methods. Both median daytime and median bedrest HRV were examined. Daytime and bedrest times were delineated using annotations for bedrest and sleep times from Apple Health annotations.

Covariates

The following variables were included as covariates in the analysis due to their demonstrated relationship with HRV.

Demographics. Participant age (in years) and sex assigned at birth were covaried due to previous research demonstrating age and sex differences in HRV (Jensen-Urstad et al., 1997; Reardon & Malik, 1996).

Physical activity. Previous research has shown that physical activity can impact heart rate variability (Kiviniemi et al., 2007). Physical activity data, operationalized as average steps per day as extracted from the Apple Watch data, from baseline and weeks 6 and 12 (as to align with the timing of the EMA data) was included as a covariate. This variable was linearly rescaled such that the units represented 1000 steps for more interpretable parameters for the analyses.

Average Bedrest Duration. Average time spent in bed over the 24 days comprising the EMA epochs in baseline and weeks 6 and 12 was included as a covariate in analysis of bedrest HRV. HRV tends to be higher when sampled among large time periods, so this controlled for time differences among participants (Report, 1996).

Medication. Antidepressant medication has been found to impact heart rate variability (O'Regan et al., 2015), and thus was included as a binary (presence/absence) covariate.

Removed Covariates. The following variables were considered for inclusion as covariates in the initial proposal and removed.

Resting Heart Rate. Resting heart rate has been shown to be negatively correlated with HRV (Migliaro et al., 2001). We considered including average resting heart rate during the time period comprising the three EMA epochs as a covariate. However, resting heart rate and HRV were highly correlated (ranging from -0.44 to -0.56), and thus this variable was removed to avoid confounding effects.

Night-Shift Status. Night-shift work has been shown to be associated with lower HRV (Hulsegge et al., 2018). However, there was not a sufficient distribution of night-shift versus day-shift workers among participants, so this variable was not included in final analyses

Cardiac Medication. While cardiac medication has been found to relate to HRV (Thayer et al., 2010) and was included in the study proposal, the umbrella study did not collect data on whether participants took cardiac medication and this covariate was thus not included in the final analyses.

Data Analysis

All analyses were preregistered on Open Science Framework (registration DOI: https://doi.org/10.17605/OSF.IO/TK4P2). Several changes were made to the analytical plan since it was filed. We noted in our pre-registration that we would use structural equation modeling to conduct analyses for Hypothesis 2 (network analysis) to account for the format of the HRV data (three separate median values, one from each epoch). However, analysis using structural equation modeling for these hypotheses demonstrated poor model fit indices, and we decided that hierarchical linear modeling with HRV as a time-varying outcome variable would be more fitting and enable us to 1) account for possible change in HRV over time and 2) reasonably draw inferences from models.

Emotional Inertia

Emotional inertia was calculated as described above in Study 1. All analyses pertaining to emotional inertia were conducted in MPLUS Version 8.10 (Muthen & Muthen, 2017).

Emotion Network Density

Emotion network density was calculated as described above in Study 1. All analyses pertaining to network density were conducted in RStudio version 4.3.2.

Heart Rate Variability

Heart rate variability estimates were aggregated over the 8-day EMA epoch for each participant. Separate estimates were obtained for HRV during the day and HRV at bedrest (delineated by the "bedtime" feature in Apple Health). Each of the three epochs was represented by the median value for the eight days. HRV was rescaled to be reported in milliseconds as to match existing published studies (Chen et al., 2017; Kemp et al., 2012) and log transformed to address skew.

Hypothesis 1: Emotional Inertia and HRV

Bayesian dynamic structural equation models with noninformative prior distributions for all parameters in the model were used to examine the association between HRV and emotional inertia from EMA from all three epochs. Affect was regressed onto lag-1 affect to model emotional inertia, and this parameter was allowed to vary across participants. Time-varying HRV was regressed onto this parameter, and we included random intercepts of negative and positive affect. Additionally, age, sex, antidepressant medication status, and physical activity were added to the between level.

Bayesian analysis produces posterior distributions for its parameters. In the results below pertaining to Bayesian analysis (i.e., all inertia analyses), the mean for the posterior distribution is reported as the estimate, as well as the 95% credible interval (CI), which refers to the range of values that the parameter has a 95% probability of being given the data.

Hypothesis 2: Network Density and HRV

Multilevel models were conducted using hierarchical linear modeling. The model contains time (in epochs) as the Level 1 predictor and median HRV as the outcome. Negative emotion network density was added as the Level 2 predictor. To test the specificity of the relationship, positive emotion network density was also added as a Level 2 predictor. Separate models were run for median daytime HRV and median bedrest HRV, and separate models were run for temporal and contemporaneous network density. Given their demonstrated relationship to HRV, age, sex, antidepressant medication status, and physical activity (operationalized as step count) were added as Level 2 covariates. Average levels of negative and positive affect across all three epochs were also included as Level 2 covariates due to the relationship with network density. For bedrest HRV models, average bedrest duration was added as a Level 2 covariate. Slopes were included such that the models also examined the association between network density on the rate of change of HRV across epochs. Full information maximum likelihood was used. The model was specified as follows:

Level 1

$HRV_{ti} = \pi_{0i} + \pi_{1i}$ x $(epoch_{ti}) + e_{ti}$

Level 2

$\pi_{0i} = \beta_{00} + \beta_{01}$ x (Negative Network $Density_i$) + x β_{02} (Positive Network Density) β_{03} x (age_i) + β_{04} x (sex_i)+ β_{05} x ($medication_i$) + β_{06} x (physical $activity_i$) + β_{06} x (Negative $Affect_i$) + β_{07}(Positive Affect) + r_{0i}

$\pi_{1i} = \beta_{10} + \beta_{11}$ x (Network $Density_i$) + β_{12} x (Network $Density_i$) + r_{1i}

Results

Descriptives

Sample size and descriptive statistics for HRV at each epoch are displayed in Table 1. These values are in line with those from other studies examining SDNN in participants with depression (Chen et al., 2017; Kemp et al., 2012; Schumann et al., 2017). Correlations between median heart rate variability estimate and median heartrate estimates ranged from -0.44 to -0.49 for daytime estimates and -0.40 to -0.56 for bedrest estimates. Due to the moderate correlation between the two variables, we chose not to include heart rate as a covariate in the analysis. Table 2 displays the descriptive statistics for emotional inertia and emotion network density. For analyses pertaining to network density, negative emotion networks successfully converged for N=276 participants and positive emotion networks successfully converged for N=295 participants. See Study 1 for histograms of emotional inertia and network density values.

Table 1
Sample size and descriptive statistics for HRV variables

	Daytime- Median	Bedrest- Median	Daytime- SD	Bedrest-SD
Epoch 1	40 ± 20 (10-110) (313)	50 ± 20 (10-170) (226)	20 ± 10 (10-110) (312)	10 ± 10 (0-90) (216)
Epoch 2	40 ± 20 (10-170) (315)	50 ± 30 (10-240) (241)	20 ± 10 (0-140) (314)	20 ± 10 (0-90) (234)
Epoch 3	40 ± 20 (10-170) (287)	40 ± 30 (10-350) (227)	20 ± 10 (0-140) (287)	20 ± 10 (0-120) (224)

Notes: M ± SD (range) (N). Units are in ms^2.

Table 2
Descriptive statistics for emotional inertia and emotion network density

Variable	Mean	SD	Range
Negative Emotional Inertia	0.46	0.13	0.01-0.86
Positive Emotional Inertia	0.38	0.09	0.11-0.66
Negative Temporal Network Density	0.03	0.04	0-0.23
Positive Temporal Network Density	0.03	0.04	0-0.31
Negative Contemporaneous Network Density	0.03	0.02	0-0.15
Positive Contemporaneous Network Density	0.04	0.03	0-0.22

Emotion Network Density

Changing Network Threshold

Visual inspection of the idiographic networks revealed that about one third of temporal networks were "empty", or consisting of no significant edges between nodes. Additionally, about 10-15% of networks consisted of at least one negative edge. In both cases, this may be representative of true relationships among symptoms. However, this may also be indicative of overfitting due to low power (Bulteel et al., 2018) or low sensitivity to detect true edges, which is more likely in networks with a small number of measurements (Mansueto et al., 2022).

There are no clear guidelines for power in multilevel VAR networks such as those used in this study. Participants with less than 25 surveys were excluded from the main analysis to retain power. Previous studies have found sufficient sensitivity and specificity for VAR networks with eight nodes and 50 measurements per person (Epskamp, Waldorp, et al., 2018). We chose to set the threshold at 25 because these networks had fewer nodes (five for negative emotion networks and four for positive emotion networks), which increases sensitivity (Mansueto et al., 2022) and because our nodes were expected to be highly correlated. With this threshold, included participants had a median of 60.5 total measurements, which is in line or above previous studies with more nodes (Epskamp, Waldorp, et al., 2018; Shin et al., 2022).

To examine whether empty networks may have been due to lack of power, we tried increasing the threshold to 40 surveys per person, and then to 60 surveys per person. In both cases, the proportion of participants with empty networks or negative edges remained at about one third. Thus, there was not sufficient evidence to believe that the empty networks were a sign of low power. For all analyses reported below, networks that converged for all participants with at least 25 total surveys were included, as initially planned.

Hypothesis 1: Emotional Inertia and HRV

Median Daytime HRV

Table 3 displays the model results. Given the data, the probability that the relationship between negative emotional inertia and median daytime HRV is negative is 0.32, which does not give us enough confidence to be sure that the relationship is positive. The mean of the posterior distribution is 0.06 (CI[-0.18, 0.30]). The model did provide evidence for a negative relationship between median daytime HRV and both age (Mean=-0.02, 95% CI [-0.02, -0.01]) and antidepressant medication status (Mean= -0.21, 95% CI[-0.29, -0.13]). Additionally, the model provided strong evidence for a positive relationship between median daytime HRV and physical activity (Mean= 0.03, 95% CI [0.01, 0.04]).

The model suggests that the probability that the relationship between positive emotional inertia and HRV is positive is 0.11, which does not give us enough confidence that the relationship is negative (Mean= -0.23, 95% CI [-0.60, 0.12]). Regarding average levels, the model suggests that the probability that the relationship between average negative affect and median daytime HRV is positive is 0.27, which does not give us enough confidence that the relationship is negative (Mean= -0.004, 95% CI [-0.02, 0.01]). The model also suggests that the relationship between average positive affect and median daytime HRV is negative is 0.35, which does not give us enough confidence that the relationship is positive (Mean= 0.01, 95% CI [-0.02, 0.02]). Additionally, the model suggests that the probability that the relationship between male sex and median daytime HRV was positive was 0.36, which does not give us enough confidence that the relationship is negative (Mean= -0.01, 95% CI [-0.10, 0.07]).

Table 3
Model Results for Hypothesis 1a- Median Daytime HRV

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Daytime HRV	0.01	0.00	0.00	0.01	0.01
Residual Variances					
Negative Affect	6.57	0.07	0.00	6.44	6.71
Positive Affect	5.28	0.05	0.00	5.18	5.38
Between- Level					
HRV on Negative Emotional Inertia	0.06	0.12	0.32	-0.18	0.30

HRV on Positive Emotional Inertia	-0.23	0.18	0.11	-0.60	0.12
HRV on Negative Affect	-0.004	0.01	0.27	-0.02	0.01
HRV on Positive Affect	0.01	0.01	0.35	-0.02	0.02
HRV on Age	-0.02	0.002	0.00	-0.02	-0.01
HRV on Sex	-0.01	0.04	0.36	-0.10	0.07
HRV on Medication	-0.21	0.04	0.00	-0.29	-0.13
HRV on Steps	0.03	0.01	0.00	0.01	0.04
Means					
Negative Affect	10.98	0.20	0.00	10.57	11.35
Positive Affect	9.03	0.13	0.00	8.77	9.28
Negative Emotional Inertia	0.44	0.01	0.00	0.41	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.40
Intercepts					
Median Daytime HRV	4.08	0.16	0.00	3.78	4.42
Variances					
Negative Affect	10.36	0.95	0.00	8.61	12.41
Positive Affect	4.56	0.43	0.00	3.85	5.51
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Median Daytime HRV	0.09	0.01	0.00	0.08	0.11

Median Bedrest HRV

Table 4 displays the model results. Given the data, the probability that the relationship between negative emotional inertia and median bedrest HRV is negative is 0.46, which does not give us enough confidence to be sure that the relationship is positive. The mean of the posterior distribution is 0.03 (CI[-0.43, 0.44]). The model did provide evidence for a negative relationship between median bedrest HRV and both age (Mean=-0.01, 95% CI [-0.02, -0.01]) and antidepressant medication status (Mean= -0.29, 95% CI[-0.43, -0.14]). Additionally, the model provided strong evidence for a positive relationship between median bedrest HRV and both physical activity (Mean= 0.05, 95% CI [0.02, 0.07]) and bedrest duration (Mean=0.03, 95% CI [0.001, 0.07]).

Given the data, the model suggests that the probability that the relationship between positive emotional inertia and median bedrest HRV is positive is 0.19, which does not give us enough confidence that the relationship is negative (Mean= -0.26, 95% CI[-0.87, 0.34]). Regarding average levels, the model suggests that the probability that the relationship between average negative affect and median bedrest HRV was negative was 0.33, which does not give us enough confidence to be sure that the relationship is positive (Mean= 0.01, 95% CI [-0.02, 0.03)]. The model also suggests that the probability that the relationship between average positive affect and median bedrest HRV is negative is 0.14, which does not give us enough confidence that the relationship is positive (Mean= 0.02, 95% CI [-0.02, 0.05]). Similarly, the model suggested that the probability that the relationship between male sex and median bedrest HRV was negative was 0.41, which does not give us enough confidence to be sure that the relationship is positive (Mean=0.02, 95% CI [-0.12, 0.16]).

Table 4

Model Results for Hypothesis 1b- Median Bedrest HRV

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Bedrest HRV	0.03	0.00	0.00	0.03	0.03
Residual Variances					
Negative Affect	6.57	0.07	0.00	6.45	6.71
Positive Affect	5.29	0.05	0.00	5.18	5.39
Between- Level					
HRV on Negative Emotional Inertia	0.03	0.22	0.46	-0.43	0.44
HRV on Positive Emotional Inertia	-0.26	0.30	0.19	-0.87	0.34
HRV on Negative Affect	0.01	0.01	0.33	-0.02	0.03
HRV on Positive Affect	0.02	0.02	0.14	-0.02	0.05
HRV on Age	-0.01	0.003	0.00	-0.02	-0.01
HRV on Sex	0.02	0.07	0.41	-0.12	0.16
HRV on Medication	-0.29	0.07	0.00	-0.43	-0.14

HRV on Steps	0.05	0.01	0.00	0.02	0.07
HRV on Bedrest Duration	0.03	0.02	0.02	0.001	0.07
Means					
Negative Affect	10.97	0.20	0.00	10.57	11.38
Positive Affect	9.03	0.14	0.00	8.76	9.30
Negative Emotional Inertia	0.44	0.01	0.00	0.41	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.40
Intercepts					
Median Bedrest HRV	3.52	0.34	0.00	2.85	4.17
Variances					
Negative Affect	10.51	0.96	0.00	8.82	12.60
Positive Affect	4.55	0.42	0.00	3.81	5.45
Negative Emotional Inertia	0.04	0.01	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Median Daytime HRV	0.28	0.05	0.00	0.20	0.37

Hypothesis 2: Network Density of Negative Affect and HRV

Hypothesis 2a: Temporal Network Density

Median Daytime HRV: Table 5 displays model results. This model showed an overall nonsignificant association between temporal negative emotion network density and the slope of median daytime HRV, *p*= .93. Temporal negative emotion network density was not significantly associated with HRV (p=.20). The model also showed overall nonsignificant associations between positive emotion network density and the slope of median daytime HRV, *p*=.27. Temporal positive emotion network density was also not significantly associated with HRV (*p*=.54). Results showed that age showed a significantly negative association with HRV (*p*<.001), physical activity showed a significantly positive association with HRV (*p*=.02), and use of antidepressant medication showed a significantly negative association with HRV (*p*<.001). All other covariates showed nonsignificant associations with HRV (*p*s >.22).

Median Bedrest HRV: Table 5 displays model results. This model showed an overall nonsignificant positive association between temporal negative emotion network density and the slope of median bedrest HRV, *p*=.99. Temporal negative emotion network density was not significantly associated with median bedrest HRV (p =. 50). The model also showed overall nonsignificant associations between positive emotion network density and the slope of median bedrest HRV, p=.52. Temporal positive emotion density was also not significantly associated with HRV (p=.97). Model results showed that age showed a significantly negative association with HRV (p<.001), physical activity showed a significantly positive association with HRV(p=.003), and use of antidepressant medication showed a significantly negative association with HRV(p<.001). All other covariates showed nonsignificant associations with HRV (ps >.12).

Table 5
Results for Hypothesis 2a- Temporal Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	258.62	4.16	0.15	<.001
Negative network density β_{01}	252.16	0.77	0.60	.20
Positive network density β_{02}	250.52	-0.33	0.55	.54
Epoch β_{03}	244.22	0.002	0.01	.85
Average NA β_{04}	254.33	-0.01	0.01	.22
Average PA β_{05}	253.88	0.001	0.01	.91
Age β_{06}	254.13	-0.02	0.001	<.001
Sex β_{07}	254.09	-0.03	0.04	.42
Step Count β_{08}	254.23	0.02	0.01	.02
Medication β_{09}	254.23	-0.22	0.04	<.001
Negative Network Density x Epoch β_{11}	240.24	0.01	0.16	.93
Positive Network Density x Epoch β_{12}	239.60	-0.16	0.15	.27
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.27		
Epoch var(r_{1i})	0.0003	0.02		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				

Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	213.53	3.98	0.22	<.001
Negative network density β_{01}	195.12	0.57	0.84	.50
Positive network density β_{02}	190.61	0.03	0.78	.97
Epoch β_{03}	185.42	-0.01	0.01	.37
Average NA β_{04}	207.85	-0.001	0.01	.89
Average PA β_{05}	202.84	0.02	0.01	.12
Age β_{06}	204.30	-0.02	0.002	<.001
Sex β_{07}	205.88	-0.04	0.05	.46
Step Count β_{08}	204.89	0.03	0.01	.003
Medication β_{09}	204.53	-0.23	0.05	<.001
Bedrest Duration β_{010}	209.64	0.004	0.01	.75
Negative Network Density x Epoch β_{11}	185.35	0.003	0.28	.99
Positive Network Density x Epoch β_{12}	182.77	-0.17	0.26	.52
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.11	0.33		
Epoch var(r_{1i})	0.004	0.07		
Residual var(e_{ti})	0.03	0.17		

Hypothesis 2b: Contemporaneous Network Density

Median Daytime HRV: Table 6 displays model results. This model showed an overall nonsignificant association between contemporaneous negative emotion network density and the slope of median daytime HRV, *p*=.08. Contemporaneous negative emotion network density was significantly, inversely associated with median daytime HRV, *p*=.01. Additionally, the model showed an overall nonsignificant association between contemporaneous positive emotion network density and the slope of median daytime HRV, *p*=.51. Contemporaneous positive emotion network density was not significantly associated with HRV (*p*=.56).

Results showed that age showed a significantly negative association with HRV ($p<.001$), physical activity showed a significantly positive association with HRV ($p=.01$), and use of antidepressant medication showed a significantly negative association with HRV($p<.001$). All other covariates showed nonsignificant associations with HRV (*p*s >.06).

Median Bedrest HRV: Table 6 displays model results. This model showed an overall nonsignificant positive association between contemporaneous negative emotion network density and the slope of median bedrest HRV, $p=.14$. Contemporaneous negative emotion network density was significantly, inversely associated with median bedrest HRV, $p=.02$. Additionally, the model showed an overall nonsignificant association between contemporaneous positive emotion network density and the slope of median bedrest HRV, $p=.44$. Contemporaneous positive emotion network density was not significantly associated with HRV ($p=.78$).

Model results showed that age showed a significant negative association with HRV ($p<.001$), physical activity showed a significant positive association with HRV($p=.002$), and use of antidepressant medication showed a significant negative association with HRV($p<.001$). The model also indicated that median bedrest HRV decreased overtime (p=.02). All other covariates showed nonsignificant associations with HRV (*p*s >.11).

Table 6
Results for Hypothesis 2b- Contemporaneous Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	263.40	4.25	0.15	<.001
Negative network density β_{01}	253.90	-2.85	1.09	.01
Positive network density β_{02}	253.90	0.46	0.79	.56
Epoch β_{03}	246.70	-0.02	0.12	.06
Average NA β_{04}	254.50	-0.01	0.01	.13

Average PA β_{05}	253.90	0.001	0.01	.94
Age β_{06}	254.30	-0.02	0.002	<.001
Sex β_{07}	254.10	-0.03	0.04	.43
Step Count β_{08}	254.30	0.02	0.01	.01
Medication β_{09}	254.40	-0.21	0.04	<.001
Negative Network Density x Epoch β_{11}	248.10	0.52	0.30	.08
Positive Network Density x Epoch β_{12}	244.50	0.14	0.21	.51
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.07	0.27		
Epoch var(r_{1i})	0.002	0.02		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	215.18	4.12	0.22	<.001
Negative network density β_{01}	185.04	-3.79	1.56	.02
Positive network density β_{02}	187.93	-0.32	1.15	.78
Epoch β_{03}	181.83	-0.05	0.02	.02
Average NA β_{04}	206.67	-0.003	0.01	.69
Average PA β_{05}	202.03	0.02	0.01	.11
Age β_{06}	203.62	-0.02	0.002	<.001
Sex β_{07}	205.43	-0.04	0.05	.45
Step Count β_{08}	204.11	0.03	0.01	.002
Medication β_{09}	203.92	-0.22	0.05	<.001
Bedrest Duration β_{010}	208.34	0.004	0.01	.77
Negative Network Density x Epoch β_{11}	177.13	0.80	0.53	.14
Positive Network Density x Epoch β_{12}	178.72	0.30	0.39	.44
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.10	0.32		
Epoch var(r_{1i})	0.004	0.06		
Residual var(e_{ti})	0.03	0.17		

Notes: Medication is measured as a binary variable where "1" represents use of antidepressant medication. Sex assigned at birth is measured as a binary variable where "1" represents male *sex. Step count is rescaled such that it is operationalized as 1/1000th of the average daily steps taken*

Sensitivity Analysis

Sensitivity Analysis #1: Using Data from Epochs 1 and 2

We re-ran the main analyses, calculating emotional inertia and emotion network density using data only from epochs 1 and 2 to examine the influence of sample size on the effects. The only notable difference in results was that the model containing median daytime HRV and contemporaneous network density no longer contained a significant association between negative network density and median daytime HRV. Contemporaneous negative emotion network density remained significantly associated with median bedrest HRV. All other associations between HRV, measures of emotional persistence, and covariates did not differ meaningfully from the main analyses. Model results are displayed in Supplementary Tables S1-S4.

Sensitivity Analysis #2: Using Data from Epochs 2 and 3

We re-ran the main analyses, calculating emotional inertia and emotion network density using data only from epochs 2 and 3 to examine the influence of sample size on the effects and evaluate whether the effects changed over time. While associations among HRV and all covariates (age, medication, physical activity, and sex) remained the same, the contemporaneous network density models no longer found support for a significant relationship between contemporaneous negative emotion network density and daytime or bedrest HRV. Model results are displayed in Supplementary Tables S5-S8.

Sensitivity Analysis #3: Including Interaction Term

We re-ran the main analyses, including an interaction term between emotional persistence and average levels of affect to test for a moderation effect on the association between emotional persistence and HRV. Estimates of emotional inertia were obtained as described in Study 1 sensitivity analyses. The interaction between emotional persistence and average affect was not significant for any model. Model results are displayed in Supplementary Tables S9-S11.

Exploratory Analysis: Adding Daily Stress as a Covariate

Given the relationship between HRV and daily stress, we conducted additional exploratory analysis in which the average level of stress reported in the EMA surveys (on a scale of 1-5) was added as a covariate. Average daily stress was not significantly associated with daytime or bedrest HRV in any model (*p*s > .43), and inclusion of this covariate did not change the significance level of the relationship between network density or inertia and heart rate variability. Model results are displayed in Supplementary Tables S12-S15.

Discussion

This study examined associations between heart-rate variability (HRV) and emotional persistence, which was operationalized as both stability of emotions (emotional inertia) and interconnection of emotions (emotion network density). Hypotheses were partially supported. Although neither negative nor positive emotional stability was associated with cross-sectional well-being (hypothesis 1), participants with more interconnected negative emotions had *lower* daytime and bedrest HRV (hypothesis 2). Interconnection of positive emotions was not associated with HRV. Regarding covariates, interestingly, average levels of negative and positive affect, measured via EMA, were not significantly associated with HRV. Age and antidepressant medication were both negatively associated with HRV, while physical activity was positively associated with HRV, and sex showed no significant association.

The findings that age, antidepressant medication, and physical activity were significantly associated with HRV is consistent with previous research (Jensen-Urstad et al., 1997; O'Regan et al., 2015). The finding that sex was not associated with HRV contrasts from previous research that found lower HRV in women (Jensen-Urstad et al., 1997), however that study noted that age differences were more pronounced than sex differences. Overall, the expected relationships between HRV and age, medication, and physical activity lend credence to the validity of this measure of HRV and methodology.

Negative Emotion Network Density and HRV

In line with our hypotheses, we found that contemporaneous network density of negative emotions was inversely associated with both daytime and bedrest HRV. That is, participants with more interconnected negative emotions within a given two-hour window had lower HRV both during the day and during bedrest during the weeks in which EMA data was collected. This finding held controlling for average levels of negative and positive affect, interconnection of positive emotions, demographic variables, antidepressant medication, physical activity, and daily stress levels. This finding is in line with previous research that has found lower HRV to be related to various psychiatric diagnoses (Beauchaine & Thayer, 2015; Cheng et al., 2022; Koch et al., 2019), neuroticism (Di Simplicio et al., 2012), and slow recovery from external stressors (Cattaneo et al., 2021). The current study extends these previous findings by demonstrating that one aspect of negative emotionality associated with low HRV is the *interconnection* of negative emotions. Individuals with entangled negative emotions may experience multiple negative emotions simultaneously or find that one negative emotion is likely to lead to another within a short time span. Low HRV may represent a biological inflexibility that underlies negative emotional inflexibility and entanglement of negative emotions. Given the cross-sectional nature of our analyses, we cannot determine directionality in our results. Low HRV may contribute to the persistence of negative emotions, or persistent negative emotions may result in biological inflexibility and low HRV. To our knowledge, this is the first study to examine associations between network density and HRV, and one of the first studies to examine associations between emotion dynamics and an externally valid measure of HRV.

Several caveats should be noted. First, we found that contemporaneous, not temporal, network density was associated with HRV. Contemporaneous network density represents relationships among symptoms within the timeframe of one EMA survey (closely occurring, if not simultaneous) and temporal network density represents relationships among symptoms from one timepoint to another. Thus, we can only infer associations between HRV and interconnectedness of negative emotions within a smaller time frame, and not in the longer timescale represented by temporal network density. Additionally, when we conducted sensitivity analyses and used networks created from a smaller set of EMA surveys (restricted to epochs 1-2 or epochs 2-3), the relationship between negative emotion interconnection and HRV held only for median bedrest HRV for epochs 1-2. This suggests that these results may be sensitive to sample size (e.g., EMA surveys per person), and without sufficient data in these sensitivity analyses, we may not have been powered to find an effect. Future studies with larger sample sizes should continue to examine this effect. Regardless, results should be considered cautiously.

Non-Significant Relationships between HRV and Emotions

Negative Emotional Inertia

The nonsignificant relationship between negative emotional stability and HRV was surprising given the established association between HRV and emotion regulatory capacity (Appelhans & Luecken, 2006; Heiss et al., 2021; Karpyak et al., 2014; Luecken et al., 2006; Visted et al., 2017) and slow recovery from external stressors (Cattaneo et al., 2021). HRV has been posited to be indicative of emotion regulatory flexibility (Butler et al., 2006), which is also represented by negative emotional persistence. The contrasting results between analyses examining stability and interconnection suggest that the additional nuance provided by network density may be valuable when examining emotion dynamics and regulation.

Positive Emotional Persistence

Since there is less literature on the relationship between HRV and *positive* emotion dynamics, this relationship was explored for the purposes of specificity analysis, and the lack of a significant finding is less surprising. However, this is still somewhat at odds with previous literature. For example, one study found a relationship between HRV and positive emotion dysregulation at low levels of positive affect (Weiss et al., 2021). Another study found that HRV was inversely related to instability of positive affect (Koval et al., 2013). However, these previous studies measured HRV at rest in a controlled laboratory setting, which may partially account for the differences in findings.

However, there has been some variation in the literature on emotion dynamics and HRV, and several recent studies present findings in line with our null results. For example, Bylsma et al. (2024) found that baseline HRV was not associated with variability in affect, which suggests that emotion dynamics measured via EMA may not correspond to HRV. Other studies have found that HRV was related to shifting attention between affective and nonaffective aspects of certain negative stimuli, but that it was unrelated to processing of positive material (Grol & De Raedt, 2020) or emotion regulation strategies used in a lab task (Grol & De Raedt, 2021).

Average Levels of Affect

The finding that neither average negative affect nor average positive affect was related to HRV was also surprising. This differs from studies that have found associations between HRV and mood or negative emotions in both depressed and general samples (Hamilton & Alloy, 2016; Koch et al., 2019; Paniccia et al., 2017). However, other studies that used EMA to assess emotions and their relationship with HRV revealed somewhat mixed findings. For example, one study found that average negative, but not positive, affect, was associated with HRV (Bylsma et al., 2024). On the other hand, another study found that positive, but not negative, affect was associated with HRV (Määttänen et al., 2021). Further, a study that measured HRV throughout the participants' daily lives in a pilot sample found that there was so much individual variation in the relationship between HRV and daily experiences of stress that there were no overall effects (Yang & Kershaw, 2022). This study noted that individuals may physiologically react to stressors differently, which may explain both our nonsignificant results and the previous mixed literature.

Alternative methodology may better elucidate the nuances of these relationships. Perhaps a cluster analysis identifying subgroups based on physiological reactivity that analyzes the relationship between HRV and EMA-assessed emotion dynamics would be useful in parsing out these relationships. Furthermore, the relationship between HRV and average affect or positive emotional persistence may not be linear, or may only correspond to certain types of affect, as found in a previous study which concluded that contentment was quadratically, but not linearly, related to HRV, and that excitement was not significantly related to HRV (Duarte & Pinto-Gouveia, 2017a). Whether due to individual variation or methodology, the relationship between daily affect, particularly positive affect, and HRV is unsupported.

Strengths

The use of a smartwatch to measure HRV over the course of eight days is a unique component of this study's methodology. Most studies examining the relationship between HRV and emotions use laboratory-based measures of HRV (e.g., Carnevali et al., 2018; Chalmers et al., 2016; Koval et al., 2013), which are measured in a controlled baseline setting over a short period of time. In addition to being controlled, by virtue of being conducted in a research laboratory, it is possible that many of these settings act more as an anticipatory period than a true neutral baseline, as participants may feel anxiety about being evaluated or about upcoming study stressor tasks. Thus, in our study, measuring HRV throughout the participant's day creates more external validity. This study conceptualizes emotional persistence as a trait factor (as opposed to an internal state), and measuring HRV slowly over a longer period better aligns with this conceptualization. Additionally, the eight-day time window used in this study was much longer than the typical baseline window. The more frequent sampling and longer time period from our study may make our study more reliable than studies using a shorter baseline (Heiss et al., 2021).

Limitations

Our study methodology is not without limitations. For example, assessment of different affect items via EMA or in different timescales may have provided different insights. Inclusion of different negative emotions such as anger or shame, or different positive emotions such as gratitude, may have provided a different representation of emotional persistence. Administering EMA surveys on a different timescale may also have provided different results.

The timing mismatch between HRV and EMA measurements may have created additional limitations. HRV was sampled throughout the day or at bedrest for a period of eight days and then calculated across the eight-day period. While the days matched up with days during which participants answered EMA surveys, the timing did not exactly align. There were no surveys during bedrest, and HRV sampling during the day was random and not associated with the exact timing of EMA surveys. Further, the eight-day windows used in this study were not consecutive, occurring six weeks apart, which may also have confounded results. Future studies examining 24 consecutive days may reveal different results.

There were also limitations to the execution of HealthKit's HRV detection. The measure of bedrest HRV was imprecise in that it may not have always captured a participant's exact bedrest window and consisted of missing data for 28% of participants. The time windows for "bedrest" vs "daytime" were delineated based on when a participant set their bedtime in Apple Health, which may not match their activity on a given day. During the day, the sampling frequency was inconsistent and HRV was more likely to record when the watch received a better signal, for example, when participants were at rest. While our method of sampling throughout a participant's daily life provided more external validity, the lack of a controlled resting HRV measure may present additional complications that may confound results.

Finally, the sample size was still relatively small for idiographic networks (Mansueto et al., 2022), and many participants (17% for negative emotion networks, 11% for positive emotion networks) were removed from the analysis due to their networks not converging. Among participants who were retained in the analysis, many had "empty" temporal networks (29% for negative emotion networks and 39% for positive emotion networks), which contained no significant connections. Whether these empty networks represent the true relationships between emotions for these participants or are the result of the network being underpowered is difficult to determine. Increasing the threshold of surveys needed for inclusion in the analysis did not decrease the proportion of empty networks, which suggests they may be indicative of true low-density relationships. However, future studies that incorporate a greater number of surveys per person would provide helpful insight. This high proportion of empty networks may account for the nonsignificant relationship between temporal network density and HRV in our models.

Future Directions

Future studies should continue to examine the mechanisms underlying these relationships and address methodology limitations. To address the limitations of our analysis, studies that incorporate more EMA surveys with different emotions and daytime resting measures of HRV would be valuable. Examining non-linear relationships among HRV and emotion persistence, particularly for positive emotions, may also be valuable. Additionally, future studies could also examine whether other physiological indices such as facial electromyography or salivary cortisol relate to emotional persistence. Furthermore, given the concurrent collection of HRV and EMA data in our study, we cannot discern causality from our results. Future studies should investigate the directionality of the relationship between HRV and negative emotional persistence.

Finally, this study has implications for psychological interventions. Better understanding of mechanisms and directionality will illuminate the most promising paths for intervention. If low HRV contributes to maintenance of negative emotions, HRV biofeedback training, which has been shown to effectively reduce anxiety and stress (Goessl et al., 2017), may be particularly helpful for individuals with interconnected negative emotions. If interconnected negative emotions contributes to low HRV, then interventions that disrupt patterns of negative emotions, such as positive affect treatment, may help target this biological inflexibility (Craske, Meuret, et al., 2019). Future studies should discern directionality of the effects and then examine the effectiveness of corresponding interventions accordingly.

Conclusion

This study examined relationships between measures of emotional persistence and HRV, assessed via smartwatch in increments of eight days. Emotional persistence was operationalized as both emotional stability (emotional inertia) and emotion interconnectedness (emotion network density). We found that higher interconnection of negative emotions was associated with lower daytime and bedrest HRV. Positive emotional persistence was not associated with HRV. This is the first study to examine relationships between these affective dynamics and HRV throughout a participant's daily life. This research has implications for the effectiveness of interventions such as HRV biofeedback training or positive affect treatment for individuals with interconnected negative emotions and low HRV. Future studies should examine the directionality in this relationship and continue to discern physiological mechanisms underlying emotional persistence.

Table S1

Model Results for Sensitivity Analysis #1, Hypothesis 1a

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Daytime HRV	0.01	0.00	0.00	0.01	0.01
Residual Variances					
Negative Affect	6.91	0.09	0.00	6.74	7.09
Positive Affect	5.59	0.07	0.00	5.45	5.72
Between- Level					
HRV on Negative Emotional Inertia	0.06	0.14	0.36	-0.23	0.33
HRV on Positive Emotional Inertia	-0.28	0.20	0.06	-0.69	0.09
HRV on Negative Affect	-0.004	0.01	0.28	-0.02	0.01
HRV on Positive Affect	0.003	0.01	0.40	-0.02	0.02
HRV on Age	-0.02	0.002	0.00	-0.02	-0.01
HRV on Sex	-0.03	0.04	0.25	-0.11	0.05
HRV on Medication	-0.20	0.04	0.00	-0.28	-0.12
HRV on Steps	0.03	0.01	0.00	0.01	0.05
Means					
Negative Affect	11.00	0.20	0.00	10.60	11.41
Positive Affect	9.07	0.13	0.00	8.83	9.33
Negative Emotional Inertia	0.43	0.02	0.00	0.39	0.45
Positive Emotional Inertia	0.35	0.01	0.00	0.33	0.38
Intercepts					
Median Daytime HRV	4.10	0.16	0.00	3.78	4.43
Variances					
Negative Affect	10.38	0.96	0.00	8.72	12.49
Positive Affect	4.39	0.40	0.00	3.72	5.22
Negative Emotional Inertia	0.04	0.01	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.004	0.00	0.02	0.03
Residual Variances					
Median Daytime HRV	0.10	0.01	0.00	0.08	0.12

Table S2

Model Results for Sensitivity Analysis #1, Hypothesis 1b

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					

Median Bedrest HRV	0.02	0.00	0.00	0.02	0.02
Residual Variances					
Negative Affect	6.89	0.09	0.00	6.72	7.08
Positive Affect	5.86	0.07	0.00	5.45	5.72
Between- Level					
HRV on Negative Emotional Inertia	-0.28	0.35	0.23	-0.94	0.43
HRV on Positive Emotional Inertia	-0.11	0.52	0.41	-1.12	0.91
HRV on Negative Affect	-0.004	0.02	0.39	-0.04	0.03
HRV on Positive Affect	-0.01	0.03	0.37	-0.07	0.04
HRV on Age	-0.01	0.004	0.00	-0.02	-0.003
HRV on Sex	-0.09	0.11	0.23	-0.31	0.15
HRV on Medication	-0.22	0.11	0.02	-0.43	-0.02
HRV on Steps	0.06	0.02	0.00	0.03	0.10
HRV on Bedrest Duration	0.06	0.03	0.01	0.01	0.11
Means					
Negative Affect	10.98	0.20	0.00	10.60	11.40
Positive Affect	9.07	0.13	0.00	8.82	9.32
Negative Emotional Inertia	0.42	0.02	0.00	0.39	0.45
Positive Emotional Inertia	0.35	0.01	0.00	0.32	0.38
Intercepts					
Median Bedrest HRV	3.51	0.51	0.00	2.51	4.51
Variances					
Negative Affect	10.42	0.94	0.00	8.90	12.60
Positive Affect	4.38	0.39	0.00	3.69	5.21
Negative Emotional Inertia	0.04	0.01	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.004	0.00	0.01	0.03
Residual Variances					
Median Daytime HRV	0.66	0.06	0.00	0.55	0.80

Table S3

Results for Sensitivity Analysis #1, Hypothesis 2a: Temporal Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	260.84	4.09	0.15	<.001
Negative network density β_{01}	480.65	0.04	0.65	.95
Positive network density β_{02}	481.73	-0.32	0.62	.60
Epoch β_{03}	243.53	0.01	0.01	.36
Average NA β_{04}	249.59	-0.01	0.01	.30
Average PA β_{05}	249.56	0.002	0.01	.78

Age β_{06}	249.87	-0.01	0.002	<.001
Sex β_{07}	249.46	-0.05	0.04	.26
Step Count β_{08}	249.88	0.02	0.01	.01
Medication β_{09}	250.06	-0.22	0.04	<.001
Negative Network Density x Epoch β_{11}	243.46	0.06	0.28	.84
Positive Network Density x Epoch β_{12}	242.88	-0.10	0.27	.71
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.28		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	210.26	3.94	0.23	<.001
Negative network density β_{01}	353.96	-0.68	0.92	.46
Positive network density β_{02}	352.09	-0.48	0.89	.60
Epoch β_{03}	178.19	-0.02	0.03	.39
Average NA β_{04}	196.75	-0.001	0.01	.90
Average PA β_{05}	195.27	0.02	0.01	.10
Age β_{06}	198.79	-0.02	0.002	<.001
Sex β_{07}	197.87	-0.06	0.05	.29
Step Count β_{08}	197.80	0.03	0.01	<.001
Medication β_{09}	196.71	-0.23	0.05	<.001
Bedrest Duration β_{010}	200.95	0.005	0.01	.72
Negative Network Density x Epoch β_{11}	177.91	0.18	0.46	.70
Positive Network Density x Epoch β_{12}	177.83	0.10	0.45	.83
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.09	0.30		
Residual var(e_{ti})	0.03	0.18		

Table S4

Results for Sensitivity Analysis #1, Hypothesis 2b: Contemporaneous Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	275.04	4.16	0.15	<.001
Negative network density β_{01}	481.32	-1.42	1.13	.21
Positive network density β_{02}	482.53	-0.97	0.87	.27
Epoch β_{03}	243.23	0.004	0.02	.85
Average NA β_{04}	249.53	-0.01	0.01	.23
Average PA β_{05}	249.54	0.004	0.01	.64
Age β_{06}	250.03	-0.01	0.002	<.001
Sex β_{07}	249.35	-0.05	0.04	.19
Step Count β_{08}	249.81	0.02	0.01	.01
Medication β_{09}	249.97	-0.22	0.04	<.001
Negative Network Density x Epoch β_{11}	242.64	0.25	0.49	.61
Positive Network Density x Epoch β_{12}	244.11	0.04	0.38	.92
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.28		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	222.43	4.01	0.23	<.001
Negative network density β_{01}	356.17	-3.43	1.64	.04
Positive network density β_{02}	348.98	-0.38	1.35	.78
Epoch β_{03}	178.47	-0.03	0.04	.42
Average NA β_{04}	196.68	-0.002	0.01	.83
Average PA β_{05}	196.02	0.02	0.01	.06
Age β_{06}	198.88	-0.01	0.002	<.001
Sex β_{07}	198.28	-0.07	0.05	.18
Step Count β_{08}	197.88	0.03	0.01	<.001
Medication β_{09}	197.04	-0.24	0.05	<.001
Bedrest Duration β_{010}	201.30	0.002	0.01	.83

Negative Network Density x Epoch β_{11}	176.38	1.09	0.83	.19
Positive Network Density x Epoch β_{12}	180.61	-0.36	0.68	.60
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.09	0.30		
Residual var(e_{ti})	0.03	0.18		

Table S5

Model Results for Sensitivity Analysis #2, Hypothesis 1a

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Daytime HRV	0.01	0.00	0.00	0.01	0.01
Residual Variances					
Negative Affect	5.92	0.08	0.00	5.76	6.07
Positive Affect	4.72	0.06	0.00	4.60	4.83
Between- Level					
HRV on Negative Emotional Inertia	0.004	0.13	0.49	-0.27	0.24
HRV on Positive Emotional Inertia	-0.24	0.20	0.14	-0.62	0.17
HRV on Negative Affect	-0.001	0.01	0.43	-0.02	0.01
HRV on Positive Affect	-0.003	0.01	0.40	-0.03	0.02
HRV on Age	-0.02	0.002	0.00	-0.02	-0.01
HRV on Sex	0.01	0.05	0.42	-0.09	0.11
HRV on Medication	-0.18	0.05	0.00	-0.28	-0.08
HRV on Steps	0.03	0.01	0.00	0.02	0.05
Means					
Negative Affect	11.03	0.23	0.00	10.59	11.49
Positive Affect	8.95	0.14	0.00	8.67	9.22
Negative Emotional Inertia	0.40	0.02	0.00	0.37	0.44
Positive Emotional Inertia	0.36	0.01	0.00	0.32	0.39
Intercepts					
Median Daytime HRV	4.05	0.19	0.00	3.68	4.44
Variances					
Negative Affect	11.87	1.12	0.00	9.89	14.18
Positive Affect	5.02	0.47	0.00	4.18	5.99
Negative Emotional Inertia	0.05	0.01	0.00	0.04	0.07
Positive Emotional Inertia	0.03	0.005	0.00	0.02	0.04
Residual Variances					
Median Daytime HRV	0.14	0.02	0.00	0.11	0.17

Table S6

Model Results for Sensitivity Analysis #2, Hypothesis 1b

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Bedrest HRV	0.02	0.00	0.00	0.02	0.02
Residual Variances					
Negative Affect	5.92	0.08	0.00	5.78	6.09
Positive Affect	4.72	0.06	0.00	4.60	4.85
Between- Level					
HRV on Negative Emotional Inertia	0.32	0.33	0.17	-0.34	0.95
HRV on Positive Emotional Inertia	-0.64	0.47	0.07	-1.56	0.24
HRV on Negative Affect	-0.02	0.02	0.16	-0.05	0.02
HRV on Positive Affect	0.01	0.03	0.30	-0.04	0.06
HRV on Age	-0.01	0.004	0.02	-0.02	-0.001
HRV on Sex	0.02	0.11	0.41	-0.25	0.18
HRV on Medication	-0.25	0.11	0.01	-0.47	-0.05
HRV on Steps	0.05	0.02	0.01	0.01	0.09
HRV on Bedrest Duration	0.12	0.03	0.00	0.07	0.17
Means					
Negative Affect	11.02	0.22	0.00	10.59	11.44
Positive Affect	8.96	0.15	0.00	8.69	9.26
Negative Emotional Inertia	0.40	0.02	0.00	0.37	0.44
Positive Emotional Inertia	0.36	0.02	0.00	0.33	0.39
Intercepts					
Median Bedrest HRV	2.83	0.46	0.00	1.88	3.71
Variances					
Negative Affect	11.85	1.07	0.00	10.02	14.07
Positive Affect	5.05	0.47	0.00	4.29	6.07
Negative Emotional Inertia	0.05	0.01	0.00	0.04	0.07
Positive Emotional Inertia	0.03	0.004	0.00	0.02	0.04
Residual Variances					
Median Daytime HRV	0.65	0.07	0.00	0.53	0.79

Table S7

Results for Sensitivity Analysis #2, Hypothesis 2a: Temporal Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	244.17	4.28	0.17	<.001
Negative network density β_{01}	383.57	-0.12	0.79	.88
Positive network density β_{02}	380.98	-1.38	0.86	.11
Epoch β_{03}	212.20	-0.03	0.02	.04
Average NA β_{04}	220.69	-0.01	0.01	.32
Average PA β_{05}	220.02	0.001	0.01	.91
Age β_{06}	219.90	-0.02	0.002	<.001
Sex β_{07}	219.22	-0.04	0.05	.43
Step Count β_{08}	219.84	0.02	0.01	.05
Medication β_{09}	219.60	-0.24	0.04	<.001
Negative Network Density x Epoch β_{11}	211.56	0.16	0.26	.53
Positive Network Density x Epoch β_{12}	212.04	0.27	0.28	.34
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.29		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	188.60	4.12	0.25	<.001
Negative network density β_{01}	259.70	-0.77	1.16	.51
Positive network density β_{02}	258.40	-1.63	1.26	.20
Epoch β_{03}	165.30	-0.04	0.02	.14
Average NA β_{04}	168.40	-0.0004	0.01	.96
Average PA β_{05}	170.20	0.01	0.01	.41
Age β_{06}	168.80	-0.02	0.002	<.001
Sex β_{07}	169.40	-0.06	0.06	.31
Step Count β_{08}	169.70	0.03	0.01	.01
Medication β_{09}	169.80	-0.25	0.06	<.001
Bedrest Duration β_{010}	167.40	0.006	0.02	.69

Negative Network Density x Epoch β_{11}	164.00	0.35	0.40	.39
Positive Network Density x Epoch β_{12}	164.60	0.32	0.44	.46
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.11	0.33		
Residual var(e_{ti})	0.03	0.17		

Table S8

Results for Sensitivity Analysis #2, Hypothesis 2b: Contemporaneous Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	269.00	4.22	0.17	<.001
Negative network density β_{01}	380.75	0.14	1.48	.93
Positive network density β_{02}	384.79	0.73	1.15	.52
Epoch β_{03}	212.84	-0.003	0.02	.90
Average NA β_{04}	220.77	-0.01	0.01	.32
Average PA β_{05}	219.94	0.001	0.01	.93
Age β_{06}	219.96	-0.02	0.002	<.001
Sex β_{07}	219.38	-0.04	0.05	.36
Step Count β_{08}	220.00	0.02	0.01	.05
Medication β_{09}	219.51	-0.24	0.04	<.001
Negative Network Density x Epoch β_{11}	212.25	-0.14	0.48	.77
Positive Network Density x Epoch β_{12}	212.20	-0.33	0.38	.38
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.09	0.29		
Residual var(e_{ti})	0.02	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	226.50	3.90	0.26	<.001
Negative network density β_{01}	262.30	2.29	2.13	.28

Positive network density β_{02}	266.20	3.30	1.74	.06
Epoch β_{03}	168.60	0.06	0.04	.10
Average NA β_{04}	178.70	-0.001	0.01	.92
Average PA β_{05}	180.40	0.01	0.01	.49
Age β_{06}	179.00	-0.02	0.002	<.001
Sex β_{07}	179.50	-0.06	0.06	.31
Step Count β_{08}	180.00	0.03	0.01	.01
Medication β_{09}	180.00	-0.25	0.06	<.001
Bedrest Duration β_{010}	177.70	0.004	0.02	.78
Negative Network Density x Epoch β_{11}	168.20	1.04	0.74	.16
Positive Network Density x Epoch β_{12}	170.60	-1.12	0.61	.07
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.10	0.32		
Residual var(e_{ti})	0.03	0.17		

Table S9

Results for Sensitivity Analysis #3, Hypothesis 1

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept	314.60	3.95	0.45	<.001
Negative Emotional Inertia β_{01}	325.80	0.30	0.49	.54
Positive Emotional Inertia β_{02}	317.30	0.09	0.95	.92
Epoch β_{03}	286.30	-0.01	0.03	.76
Average NA β_{04}	306.14	0.00	0.02	.99
Average PA β_{05}	305.50	0.09	0.38	.81
Age β_{06}	307.00	-0.02	0.001	<.001
Sex β_{07}	306.70	-0.02	0.04	.61
Step Count β_{08}	306.80	0.02	0.01	<.001
Medication β_{09}	306.80	-0.22	0.04	<.001
Negative Emotional Inertia x Epoch β_{11}	288.27	0.01	0.04	.81
Positive Emotional	285.60	0.01	0.06	.87

Inertia x Epoch β_{12}				
Negative Emotional Inertia x Average NA β_{13}	306.10	-0.01	0.04	.82
Positive Emotional Inertia x Average PA β_{14}	305.50	-0.03	0.10	.75
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.09	0.30		
Epoch var(r_{1i})	0.001	0.03		
Residual var(e_{ti})	0.02	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	274.84	4.00	0.57	<.001
Negative Emotional Inertia β_{01}	293.97	-0.28	0.63	.66
Positive Emotional Inertia β_{02}	276.21	0.64	1.24	.61
Epoch β_{03}	214.25	0.001	0.05	.98
Average NA β_{04}	261.90	-0.01	0.02	.73
Average PA β_{05}	254.55	0.02	0.05	.68
Age β_{06}	252.92	-0.02	0.002	<.001
Sex β_{07}	256.23	-0.02	0.05	.68
Step Count β_{08}	252.68	0.03	0.01	<.001
Medication β_{09}	251.82	-0.25	0.05	<.001
Bedrest Duration β_{010}	262.96	0.002	0.01	.87
Negative Emotional Inertia x Epoch β_{11}	224.67	0.10	0.08	.25
Positive Emotional Inertia x Epoch β_{12}	214.20	-0.17	0.12	.16
Negative Emotional Inertia x Average NA β_{13}	264.92	0.02	0.05	.69

Positive Emotional Inertia x Average PA β_{14}	254.53	-0.04	0.13	.75
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.13	0.36		
Epoch var(r_{1i})	0.01	0.08		
Residual var(e_{ti})	0.03	0.18		

Table S10

Results for Sensitivity Analysis #3, Hypothesis 2a- Temporal Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept	258.20	4.19	0.16	<.001
Negative Network Density β_{01}	263.53	0.25	0.01	.93
Positive Network Density β_{02}	264.55	-1.09	1.73	.53
Epoch β_{03}	244.21	0.002	0.01	.85
Average NA β_{04}	254.78	-0.01	0.01	.27
Average PA β_{05}	253.91	-0.001	0.01	.91
Age β_{06}	254.16	-0.02	0.002	<.001
Sex β_{07}	254.08	-0.03	0.04	.43
Step Count β_{08}	254.23	0.02	0.01	.02
Medication β_{09}	254.22	-0.22	0.04	<.001
Negative Network Density x Epoch β_{11}	240.23	0.01	0.16	.93
Positive Network Density x Epoch β_{12}	239.59	-0.16	0.15	.27
Negative Network Density x Average NA β_{13}	253.70	0.05	0.18	.79
Positive Network Density x Average PA β_{14}	253.19	0.09	0.21	.65
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.27		
Epoch var(r_{1i})	0.0003	0.02		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	214.00	4.04	0.23	<.001
Negative Network Density β_{01}	227.00	-0.04	2.44	.99
Positive Network Density β_{02}	219.90	-2.99	2.15	.16
Epoch β_{03}	185.50	-0.01	0.01	.37
Average NA β_{04}	208.50	-0.002	0.01	.83
Average PA β_{05}	203.40	0.01	0.01	.42
Age β_{06}	204.50	-0.02	0.002	<.001
Sex β_{07}	206.10	-0.03	0.05	.51
Step Count β_{08}	205.00	0.03	0.01	.002
Medication β_{09}	204.60	-0.22	0.05	<.001
Bedrest Duration β_{010}	209.20	0.005	0.01	.68
Negative Network Density x Epoch β_{11}	185.40	<.001	0.28	.99
Positive Network Density x Epoch β_{12}	182.80	0.17	0.26	.52
Negative Network Density x Average NA β_{13}	213.10	0.05	0.22	.82
Positive Network Density x Average PA β_{14}	200.50	0.39	0.26	.13
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.11	0.33		
Epoch var(r_{1i})	0.005	0.07		
Residual var(e_{ti})	0.03	0.17		

Table S11

Results for Sensitivity Analysis #3, Hypothesis 2b- Contemporaneous Network Density

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept	258.77	4.39	0.21	<.001
Negative Network Density β_{01}	263.72	-4.57	3.57	.20

Positive Network Density β_{02}	259.55	-2.92	3.37	.39
Epoch β_{03}	246.40	-0.02	0.01	.06
Average NA β_{04}	253.82	-0.01	0.01	.19
Average PA β_{05}	253.66	-0.01	0.02	.46
Age β_{06}	254.26	-0.01	0.001	<.001
Sex β_{07}	254.15	-0.03	0.04	.43
Step Count β_{08}	254.28	0.02	0.01	.01
Medication β_{09}	254.36	-0.22	0.04	<.001
Negative Network Density x Epoch β_{11}	247.79	0.52	0.30	.08
Positive Network Density x Epoch β_{12}	244.22	0.14	0.21	.51
Negative Network Density x Average NA β_{13}	253.60	0.16	0.32	.62
Positive Network Density x Average PA β_{14}	253.72	0.37	0.36	.30
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.07	0.27		
Epoch var(r_{1i})	0.0002	0.02		
Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	211.16	4.14	0.28	<.001
Negative Network Density β_{01}	221.26	-1.27	4.40	.77
Positive Network Density β_{02}	212.34	-2.53	4.09	.54
Epoch β_{03}	181.81	-0.05	0.02	.01
Average NA β_{04}	206.97	0.002	0.01	.82
Average PA β_{05}	200.54	0.01	0.02	.61
Age β_{06}	203.77	-0.01	0.002	<.001
Sex β_{07}	205.39	-0.04	0.05	.45
Step Count β_{08}	203.65	0.03	0.01	.001
Medication β_{09}	203.54	-0.21	0.05	<.001
Bedrest Duration β_{010}	209.27	0.004	0.01	.74

Negative Network Density x Epoch β_{11}	177.11	0.80	0.53	.13
Positive Network Density x Epoch β_{12}	178.68	0.30	0.39	.44
Negative Network Density x Average NA β_{13}	207.28	-0.25	0.40	.53
Positive Network Density x Average PA β_{14}	201.69	0.25	0.43	.56
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.10	0.32		
Epoch var(r_{1i})	0.01	0.06		
Residual var(e_{ti})	0.03	0.17		

Table S12

Adding Stress as a Covariate for Hypothesis 1a- Daytime HRV

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Daytime HRV	0.01	0.00	0.00	0.01	0.01
Residual Variances					
Negative Affect	6.57	0.07	0.00	6.44	6.72
Positive Affect	5.29	0.06	0.00	5.18	5.40
Between- Level					
HRV on Negative Emotional Inertia	0.08	0.13	0.28	-0.18	0.35
HRV on Positive Emotional Inertia	-0.25	0.18	0.08	-0.60	0.07
HRV on Negative Affect	0.00	0.02	0.50	-0.03	0.03
HRV on Positive Affect	0.004	0.01	0.36	-0.02	0.02
HRV on Age	-0.02	0.002	0.00	-0.02	-0.01
HRV on Sex	-0.01	0.04	0.39	-0.10	0.07
HRV on Medication	-0.21	0.04	0.00	-0.29	-0.14
HRV on Steps	0.03	0.01	0.00	0.01	0.04
HRV on Stress	-0.02	0.06	0.38	-0.14	0.11
Means					
Negative Affect	10.99	0.20	0.00	10.61	11.35
Positive Affect	9.03	0.13	0.00	8.77	9.27
Negative Emotional Inertia	0.44	0.02	0.00	0.41	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.39

Intercepts					
Median Daytime HRV	4.12	0.17	0.00	3.80	4.44
Variances					
Negative Affect	10.52	0.92	0.00	8.87	12.52
Positive Affect	4.55	0.41	0.00	3.86	5.48
Negative Emotional Inertia	0.04	0.005	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Median Daytime HRV	0.09	0.01	0.00	0.08	0.11

Table S13

Adding Stress as a Covariate for Hypothesis 1b- Bedrest HRV

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Median Bedrest HRV	0.03	0.00	0.00	0.03	0.03
Residual Variances					
Negative Affect	6.58	0.07	0.00	6.44	6.71
Positive Affect	5.28	0.06	0.00	5.17	5.40
Between- Level					
HRV on Negative Emotional Inertia	0.06	0.25	0.40	-0.44	0.55
HRV on Positive Emotional Inertia	-0.35	0.32	0.15	-0.98	0.31
HRV on Negative Affect	0.02	0.03	0.26	-0.04	0.07
HRV on Positive Affect	0.02	0.02	0.16	-0.02	0.06
HRV on Age	-0.01	0.003	0.00	-0.02	-0.01
HRV on Sex	0.02	0.08	0.40	-0.14	0.18
HRV on Medication	-0.28	0.08	0.00	-0.44	-0.13
HRV on Steps	0.05	0.01	0.00	0.02	0.08
HRV on Bedrest Duration	0.04	0.02	0.03	0.00	0.07
HRV on Stress	-0.04	0.11	0.35	-0.26	0.16
Means					
Negative Affect	10.98	0.21	0.00	10.59	11.36
Positive Affect	9.02	0.14	0.00	8.77	9.30
Negative Emotional Inertia	0.44	0.01	0.00	0.42	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.40
Intercepts					
Median Bedrest HRV	3.42	0.37	0.00	2.67	4.13
Variances					
Negative Affect	10.50	0.97	0.00	8.90	12.54
Positive Affect	4.54	0.43	0.00	3.78	5.48
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.05
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03

Residual Variances					
Median Bedrest HRV	0.33	0.04	0.00	0.27	0.41

Table S14

Adding Stress as a Covariate for Hypothesis 2a

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	258.60	4.16	0.15	<.001
Negative network density β_{01}	255.00	0.72	0.60	.23
Positive network density β_{02}	250.80	-0.35	0.55	.53
Epoch β_{03}	244.20	-0.002	0.01	.85
Average NA β_{04}	254.33	-0.01	0.01	.30
Average PA β_{05}	253.90	0.001	0.01	.95
Age β_{06}	254.20	-0.02	0.002	<.001
Sex β_{07}	254.20	-0.03	0.04	.45
Step Count β_{08}	254.30	0.02	0.01	.02
Medication β_{09}	254.30	-0.22	0.04	<.001
Stress β_{010}	254.10	0.03	0.06	.57
Negative Network Density x Epoch β_{11}	240.30	0.01	0.16	.93
Positive Network Density x Epoch β_{12}	239.60	-0.16	0.15	.27
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.08	0.27		
Epoch var(r_{1i})	0.0003	0.02		
Residual var(e_{ti})	0.01	0.13		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	213.35	3.99	0.22	<.001
Negative network density β_{01}	200.15	0.65	0.85	.44
Positive network density β_{02}	191.72	0.07	0.78	.93
Epoch β_{03}	185.30	-0.01	0.01	.37
Average NA β_{04}	208.49	0.01	0.02	.58
Average PA β_{05}	202.94	0.02	0.01	.10
Age β_{06}	204.04	-0.02	0.002	<.001

Sex β_{07}	206.24	-0.04	0.05	.43
Step Count β_{08}	204.75	0.03	0.01	.003
Medication β_{09}	204.66	-0.23	0.05	<.001
Bedrest Duration β_{010}	209.79	0.004	0.01	.74
Stress β_{011}	205.05	-0.05	0.08	.49
Negative Network Density x Epoch β_{11}	185.23	0.003	0.28	.99
Positive Network Density x Epoch β_{12}	182.64	-0.17	0.26	.51
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.11	0.33		
Epoch var(r_{1i})	0.004	0.07		
Residual var(e_{ti})	0.03	0.17		

Table S15

Adding Stress as a Covariate for Hypothesis 2b

Median Daytime HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	263.40	4.24	0.15	<.001
Negative network density β_{01}	254.00	-2.88	1.09	.01
Positive network density β_{02}	254.80	0.41	0.79	.61
Epoch β_{03}	246.70	-0.02	0.01	.06
Average NA β_{04}	254.00	-0.02	0.01	.17
Average PA β_{05}	254.00	0.0002	0.01	.98
Age β_{06}	254.30	-0.01	0.002	<.001
Sex β_{07}	254.20	-0.03	0.04	.47
Step Count β_{08}	254.40	0.02	0.01	.01
Medication β_{09}	254.40	-0.21	0.04	<.001
Stress β_{010}	254.10	0.05	0.06	.43
Negative Network Density x Epoch β_{11}	248.10	0.52	0.30	.08
Positive Network Density x Epoch β_{12}	244.50	0.14	0.21	.52
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.07	0.27		
Epoch var(r_{1i})	0.0002	0.02		

Residual var(e_{ti})	0.01	0.12		

Median Bedrest HRV				
Fixed Effects	*Df*	*B*	*SE*	*p-value*
Intercept β_{00}	215.03	4.13	0.22	<.001
Negative network density β_{01}	185.06	-3.79	1.56	.02
Positive network density β_{02}	189.09	-0.28	1.15	.81
Epoch β_{03}	181.73	-0.05	0.02	.01
Average NA β_{04}	206.83	0.004	0.02	.79
Average PA β_{05}	202.12	0.02	0.01	.11
Age β_{06}	203.41	-0.02	0.002	<.001
Sex β_{07}	205.69	-0.04	0.05	.44
Step Count β_{08}	203.97	0.03	0.01	.002
Medication β_{09}	203.97	-0.22	0.05	<.001
Bedrest Duration β_{010}	208.44	0.004	0.01	.76
Stress β_{011}	203.93	-0.04	0.07	.61
Negative Network Density x Epoch β_{11}	177.04	0.80	0.53	.13
Positive Network Density x Epoch β_{12}	178.63	0.30	0.39	.44
Random Effects	*Variance*	*SD*		
Intercept var(r_{0i})	0.10	0.32		
Epoch var(r_{1i})	0.004	0.06		
Residual var(e_{ti})	0.03	0.17		

Study 3: Linguistic Substrates of Emotional Inertia and Network Density

Abstract

Emotional inertia and emotion network density represent emotional persistence and are associated with higher levels of anxiety and depression. Studies investigating these metrics in relation to objective indicators of mental health, while important for ascertaining mechanisms, are scarce. The constructionist approach conceptualizes language as a component of emotional experiences and linguistic indicators such as positive and negative sentiment have been identified as related to emotions. Thus, language is one path of interest. In this study, adults with moderate-to-severe depression completed three eight-day epochs of ecological momentary assessment (EMA) assessing negative and positive affect. Emotional inertia and idiographic networks were calculated separately for negative and positive affect. Following the final EMA epoch, participants were interviewed using scripted, open-ended questions. Transcripts were evaluated for probability of positive and negative sentiment using natural linguistic processing (NLP) tools. Sentiment scores were combined into a difference score representing tendency towards positive (over negative) sentiment. Associations among emotional inertia, emotion network density, and tendency for positive sentiment were assessed using nested comparison tests and Bayesian multilevel models. Emotional persistence was not associated with sentiment. EMA-rated average positive affect was positively associated with trend towards positive sentiment from the interview. Overall, this study suggests that NLP of a brief dialogue may provide valuable insight into a person's average positive emotions in daily life, and that positive affect is more related to NLP than is negative affect. Future research should examine the mechanisms and directionality underlying these relationships and continue to investigate whether other aspects of emotion regulation and dynamics are associated with language.

Introduction

Emotional inertia and emotion network density, which capture symptom dynamics, are generally considered to be associated with higher levels of anxiety and depression. Inertia, or the stability of emotions, in negative emotions has been found to be related to markers of psychopathology or poor psychological well-being, including depression, rumination, and neuroticism (Koval et al., 2012). Network density, which uses the network modeling approach to psychopathology (Borsboom & Cramer, 2013), similarly represents persistence of emotions but incorporates relationships between different symptoms instead of simply aggregating symptom scores. Both emotional inertia and emotion network density are considered to be measures of emotional flexibility. Individuals with higher network density for negative emotions and lower network density for positive emotions have been shown to have a greater likelihood of diagnosis of major depressive disorder or generalized anxiety disorder (Shin et al., 2022).

However, studies investigating emotional inertia and network density in relation to more objective indicators of well-being are scarce. In fact, the network analysis literature in general lacks research on how networks interact with or relates to objective measures (McNally, 2021). Further investigation of the relationship between these constructs of symptom dynamics and objective indicators would provide additional insight into the role of emotional inertia and emotion network density as potential indicators of transdiagnostic well-being. One such objective indicator of well-being is linguistic sentiment.

Language and Emotions

The constructionist approach to language identifies a connection between language and emotion. This model suggests that words are predictive models for how individuals make meanings of sensations (Lindquist, 2017). Specifically, the constructionist approach identifies that language is critical to one's perception of their emotions. This is supported by research indicating that brain regions that support language are also involved in emotions (Lindquist, MacCormack, et al., 2015) and experimental research showing that impairing access to the meaning of emotion words impairs the ability to perceive emotion faces (Lindquist, MacCormack, et al., 2015; Lindquist, Satpute, et al., 2015; Nook et al., 2022). Furthermore, researchers have posited that vocabulary may provide a window into mental habits, as vocabulary may relate to the concepts that one thinks about (Vine et al., 2020).

Sentiment analysis is a method of analyzing language that provides helpful insight into patterns in one's written or spoken language use. This method is a branch of natural language processing (NLP) that focuses on analyzing emotions and perspectives.

Negative Emotion Words

Previous studies on sentiment analysis have found that the use of negative emotion words relates to negative indicators of mental health. For example, use of negative emotion vocabulary in a writing exercise was found to be associated with both trait neuroticism and depression as well as state negative mood after writing (Vine et al., 2020). In another study, individuals assigned to use more negative words in a writing exercise, even to describe a positive experience, reported higher negative affect following the writing exercise (Knuppenburg, 2021). A correlational study asking participants to write about their thoughts and feelings also found a negative correlation between negative emotion words and life satisfaction (Song & Zhao, 2023). Similarly, extant research links neuroticism and negative language use. Social media users with higher neuroticism had higher negative sentiment in their Facebook posts (Shen et al., 2015). They also used more negative sentiment and fewer positive sentiment words in tweets (Qiu et al., 2012). Neuroticism was also associated with more negative and less positive sentiment words in personal essays (Resnik et al., 2013).

Positive Emotion Words

Fewer studies have investigated the relationship between use of positive emotion words and mental health. Participants who used more positive emotion words in an essay about thoughts and feelings reported higher life satisfaction (Song & Zhao, 2023). Another study found that using more positive words in a stream of consciousness self-reflective essay correlated with higher extraversion, agreeableness, and overall health, and less neuroticism and depression (Vine et al., 2020). Using more positive words for this essay also predicted feeling more positively after writing (Vine et al., 2020). Conversely, another study found that individuals assigned to use more positive words in a writing exercise did not report differences in positive affect compared to those assigned to use more negative words (Knuppenburg, 2021).

The abovementioned literature suggests that language use and sentiment may be thought of as an indicator for general psychological well-being. In addition to its relationship with general well-being, there is reason to believe that language sentiment may be associated with emotional inertia and emotion network density. Language sentiment, emotional inertia, and emotion network density have all demonstrated associations with neuroticism and depression (Bringmann et al., 2016; Koval et al., 2016; Shin et al., 2022; Vine et al., 2020). Additionally, emotional inertia has been found to be related to rumination, a negative-focused pattern of repetitive thinking that often involves use of negative language (Blanke et al., 2021). However, to our knowledge, no study has examined whether emotional inertia and emotion network density correspond to objective linguistic measures such as sentiment analysis. This study examined the association between emotional inertia and emotion network density and sentiment analysis as an objective indicator of well-being.

Study Aims and Hypotheses

The aim of this study was to investigate the relationship between sentiment of language in a spoken reflection task and both inertia and network density of emotions. Specifically, we investigated the relationship between tendency towards positive sentiment from an interview and both negative and positive emotional inertia and density in daily life.

Hypothesis 1: Greater inertia of negative emotions will be associated with lower tendency towards positive sentiment, controlling for average level of negative emotions.

Hypothesis 2: Greater inertia of positive emotions will be associated with greater tendency towards positive sentiment, controlling for average level of positive emotions.

Hypothesis 3: Greater density in negative emotion networks will be associated with less tendency towards positive sentiment, controlling for average level of negative emotions.

Hypothesis 4: Greater density in positive emotion networks will be associated with greater tendency towards positive sentiment, controlling for average level of positive emotions.

Methods

Participants

Study 3 used the same sample as Studies 1 and 2. See Study 1 for a description of the sample. A total of N=270 participants completed the interview and were included in this study. Of the 270, N=209 participants had enough data for both negative and positive emotion networks to converge and were thus included in the network analysis.

Procedure

As described in Study 1, the study lasted about three and a half months and consisted of 12 weeks of weekly surveys assessing various symptoms. Participants attended one in-person visit, which occurred around week 12 or 13, depending on participant scheduling constraints. This visit occurred directly after the last day of EMA epoch 3. During the in-person visit, participants completed additional surveys and tasks, including a task in which they spent 10 minutes participating in a recorded interview over Zoom. During this interview, a study team member asked participants open-ended interview questions such as "Did anything happen last week that made you feel good?". Interviewers were provided with a script with instructions to read questions verbatim to participants, only breaking up two-part questions for participants who struggled to respond to the entire question. Interviewers were instructed not to respond to participants with empathetic or affirming language, but to thank them for their response and to continue to the next prompt. Interview questions are displayed in Table 1.

Table 1.

List of Interview Questions

Question Number	Question Content
1	How are you feeling today?
2	Did anything happen this week that made you feel angry, stressed, or sad? If yes, describe what happened and how you felt.
3	Did anything happen this week that made you feel good? If yes, describe what happened and how you felt.
4	Is there something you are worrying about? If yes, please describe what is it you're worrying about and how it makes you feel.
5	Is there something good you expect will happen soon that you are looking forward to? If yes, what is it and how does it make you feel?
6	Have you been planning or working towards a positive future event or experience? If yes, what is it and what have you been doing?
7	Tell me about your happiest memory.

Measures

EMA Measures. EMA measures were the same affect subscales, sent five times per day for 8 days over three different epochs, as described in Study 1. EMA responses from all three epochs were used for this study such that completers had 120 responses.

Emotional Inertia: Emotional inertia was calculated using the same procedures as Study 2. Data from all three EMA epochs was included.

Emotion Network Density: Emotion network density was calculated using the same procedure as Study 2. Data from all three EMA epochs was included.

Sentiment Analysis: Participants' spoken responses to the questions during the Zoom interview were transcribed, and the transcriptions were processed using Bidirectional Encoder Representations for Transformers (BERT) (Acheampong et al., 2021). We used the roBERTa-base model, which was trained on tweets of varying sentiment levels (Barbieri et al., 2020). BERT provided three sentiment analysis variables for each participant's response to each of seven questions: probability of negative sentiment, probability of positive sentiment, and probability of neutral sentiment. The three values summed to 1 for each question.

Tendency towards positive sentiment. Since the estimates for probability of positive and negative sentiment were not independent, we used difference scores to combine them into one metric. For each question, each participant's probability of negative sentiment was subtracted from their probability of positive sentiment. The average difference score across responses to all seven interview questions was calculated for each participant. This difference score represented a participant's tendency towards positive sentiment over negative sentiment. Positive scores indicated that participants' responses usually contained more positive than negative sentiment, and lower, negative scores indicated that the participant's responses usually contained more negative than positive sentiment.

Exploratory Analysis Covariates:

Depression. For our exploratory analyses, we added depression, as measured on the interview day (Week 12 or 13, the end of epoch 3). Depression was measured using the fourteen-item Patient Health Questionnaire-14 (PHQ-14) (see Depression Symptom Response (DSRP) Project OSF site: https://osf.io/j6r3q/), which is a derivation of the PHQ-9, with compound symptoms disaggregated (Kroenke et al., 2002). This scale is a self-report questionnaire where participants rate each of the DSM-IV criteria for depression from 0 ("not at all") to 3 ("nearly every day") as they pertain to the previous two weeks. Scores were totaled such that higher scores reflect greater depression symptom severity.

Data Analysis

All analyses were preregistered on Open Science Framework (registration DOI: https://doi.org/10.17605/OSF.IO/TK4P2). The only notable change from the pre-registered analyses is the use of a difference score to represent tendency towards positive sentiment. The pre-registered plan noted the intention to separately test relationships between emotional persistence and probability of positive and negative sentiment. We chose to combine these two indicators into one difference score for two reasons: first, this seemed more appropriate given that the two metrics were not entirely independent of each other, and second, this decreased risk of type I error by halving the number of total models in our study. All other aspects of the analytical plan either match the pre-registration or are noted as exploratory hypotheses.

Emotional Inertia and Emotion Network Density

See Study 1 for description of how emotional inertia and emotion network density were calculated. As with Study 1, all main analyses pertaining to emotional inertia were conducted in MPLUS Version 8.10 (Muthen & Muthen, 2017) and all analyses pertaining to network density were conducted in RStudio Version 4.3.2.

Hypotheses 1 and 2: Emotional Inertia Hypotheses

Bayesian dynamic structural equation models with noninformative prior distributions for all parameters in the model were used to examine the association between emotional inertia from EMA epochs 1-3 and linguistic sentiment from the interview following Week 12. Affect was regressed onto lag-1 affect to model emotional inertia, and this parameter was allowed to vary across participants. We regressed tendency towards positive sentiment onto these parameters and included random intercepts of negative and positive affect.

Hypotheses 3 and 4: Network Density Hypotheses

Nested multiple linear regression models were used to examine the association between network density from EMA epochs 1-3 and sentiment from the interview after Week 12. Network density was entered as the predictor and average levels of negative and positive affect were entered as covariates. Tendency towards positive sentiment was entered as the outcome. The null model consisted of only average levels of affect and sentiment. A log-likelihood ratio test was used to compare the model containing network density to the simpler null model to test whether network density was associated with probability of sentiment above and beyond mean levels of affect.

Exploratory Hypothesis: Sentiment Constancy

Given that measures of inertia and network density represent persistence of emotion, we conducted exploratory hypotheses examining associations between emotional inertia and network density and constancy of sentiment throughout the interview. This exploratory analysis was designed to examine whether changes in daily emotions correspond to changes in language patterns.

The interview consisted of seven questions that elicited varied emotional valence from participants. That is, the first question was neutral, questions two and four were negative, and questions three, five, six, and seven were positive. For these exploratory analyses, we restricted the data to sentiment measures from the first five questions, which asked the participants about events of alternating valence (i.e., negative, then positive, then negative). The two questions we removed from these exploratory analyses did not alternate valence. We restricted the questions in this way to capture participants' sentiment in response to *changing* prompts.

These analyses separately examined persistence of positive and negative sentiment and did not use difference scores. Using BERT sentiment scores from the first five questions, we calculated the autocorrelation coefficient for each participant for their probability of negative sentiment and positive sentiment (separately) for each question. We used these autocorrelations to represent constancy of sentiment. We then examined the association between individual negative/positive sentiment constancy and emotional inertia and density.

Emotional Inertia and Sentiment Constancy. Bayesian dynamic structural equation models with noninformative prior distributions for all parameters in the model were used to examine the association between emotional inertia from EMA epochs 1-3 and constancy of linguistic sentiment from the interview following Week 12. Affect was regressed onto lag-1 affect to model emotional inertia, and this parameter was allowed to vary across participants. We regressed sentiment constancy onto this parameter and included random intercepts of negative and positive affect, and total negative (exploratory hypothesis 1) and positive (exploratory hypothesis 2) sentiment.

Network Density and Sentiment Constancy. Nested multiple linear regression models were used to examine the association between network density from EMA epochs 1-3 and constancy of sentiment from the interview after Week 12. Network density was entered as the predictor. Average levels of negative and positive affect and total sentiment (corresponding to the valence used in the sentiment constancy calculation) were entered as covariates. Sentiment constancy was entered as the outcome. The null model consisted of only average levels of affect, total sentiment, and constancy of sentiment. A log-likelihood ratio test was used to compare the model containing network density to the simpler null model to test whether network density is associated with sentiment constancy above and beyond mean levels of affect.

Sensitivity Analysis

Because the sample size needed to detect this effect is unknown, sensitivity analysis for the main hypotheses was conducted using inertia and density calculated only using EMA from the final two epochs (weeks 6 and 12). Additionally, sensitivity analysis incorporating interaction terms for emotional persistence and average levels of affect was also conducted. See Study 1 for more information.

Results

Descriptives

Table 2 displays the descriptive statistics for emotional inertia, emotion network density, and descriptive statistics for the results of the BERT sentiment analysis. See Study 1 for histograms of emotional inertia and emotion network density.

Table 2

Descriptive statistics for emotional inertia, emotion network density, and BERT results

Variable	Mean	SD	Range
Negative Emotional Inertia	0.46	0.13	0.01-0.86
Positive Emotional Inertia	0.38	0.09	0.11-0.66
Negative Temporal Network Density	0.03	0.04	0-0.23
Positive Temporal Network Density	0.03	0.04	0-0.31
Negative Contemporaneous Network Density	0.03	0.02	0-0.15
Positive Contemporaneous Network Density	0.03	0.03	0-0.22

Tendency Towards Positive Sentiment (BERT)	0.22	0.24	-0.56-0.81

Changing Network Threshold

Visual inspection of the idiographic networks revealed that about one third of temporal networks were “empty”, or consisting of no significant edges between nodes. Additionally, about 10-15% of networks consisted of at least one negative edge. In both cases, this may be representative of true relationships among symptoms. However, this may also be indicative of overfitting due to low power (Bulteel et al., 2018) or low sensitivity to detect true edges, which is more likely in networks with a small number of measurements (Mansueto et al., 2022).

There are no clear guidelines for power in multilevel VAR networks such as those used in this study. Participants with less than 25 surveys were excluded from the main analysis to retain power. Previous studies have found sufficient sensitivity and specificity for VAR networks with eight nodes and 50 measurements per person (Epskamp, Waldorp, et al., 2018). We chose to set the threshold at 25 because these networks had fewer nodes (five for negative affect networks and four for positive affect networks), which increases sensitivity (Mansueto et al., 2022) and because our nodes were expected to be highly correlated. With this threshold, included participants had a median of 60.5 total measurements, which is in line with or above previous studies with more nodes (Epskamp, Waldorp, et al., 2018; Shin et al., 2022).

To examine whether empty networks may have been due to lack of power, we tried increasing the threshold to 40 surveys per person, and then to 60 surveys per person. In both cases, the proportion of participants with empty networks or negative edges remained at about one third. Thus, there was not sufficient evidence to believe that the empty networks were a sign of low power. For all analyses reported below, networks that converged for all participants with at least 25 total surveys were included, as initially planned.

Hypotheses 1 and 2: Emotional Inertia Hypotheses

Model results are displayed in Table 3. Given the data, the probability that the relationship between negative emotional inertia and tendency towards positive sentiment is negative is 0.37, which does not give us enough confidence to be sure that the relationship is positive. The mean of the posterior distribution is 0.03 (CI [-0.15, 0.24). Similarly, the probability that the relationship between positive emotional inertia and tendency towards positive sentiment is positive is 0.25, which does not give us enough confidence to be sure that the relationship is negative (Mean= -0.01, 95% CI [-0.37, 0.19]). Additionally, according to the model, the probability that the relationship between average negative affect and tendency towards positive sentiment is positive is 0.08, which does not give us enough confidence to be sure that the relationship is negative (Mean=-0.01, 95% CI[-0.02, 0.03]). The model did provide evidence for a positive relationship between average positive affect and tendency towards positive sentiment (Mean=0.03, 95% CI [0.01, 0.04]).

Table 3

Model Results for Hypothesis 1 and 2

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Tendency to Positive Sentiment	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	6.80	0.07	0.00	6.67	6.95
Positive Affect	5.48	0.06	0.00	5.38	5.59
Between- Level					
Sentiment on Negative Emotional Inertia	0.03	0.10	0.37	-0.15	0.24
Sentiment on Positive Emotional Inertia	-0.10	0.14	0.25	-0.37	0.19
Sentiment on Negative Affect	-0.01	0.01	0.08	-0.02	0.003

Sentiment on Positive Affect	0.03	0.01	0.002	0.01	0.04
Means					
Negative Affect	10.94	0.20	0.00	10.55	11.32
Positive Affect	9.06	0.13	0.00	8.81	9.29
Negative Emotional Inertia	0.44	0.01	0.00	0.41	0.47
Positive Emotional Inertia	0.36	0.01	0.00	0.34	0.39
Intercepts					
Sentiment	0.05	0.11	0.35	-0.16	0.27
Variances					
Negative Affect	9.78	0.88	0.00	8.26	11.69
Positive Affect	4.30	0.41	0.00	3.60	5.22
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.04
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Sentiment	0.05	0.01	0.00	0.04	0.06

Note: "Sentiment" refers to the average difference score between positive and negative sentiment; representing a person's average tendency toward positive over negative sentiment.

Hypotheses 3 and 4: Network Density Hypotheses

All model results for Hypotheses 3 and 4 are displayed in Table 4.

Temporal Network Density

We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 2.68, *p*=.26). In both models, average positive affect was significantly associated with tendency towards positive sentiment (β=0.25, *p*<.001). Neither temporal negative affect network density (β=-0.05, *p*=.44) nor temporal positive affect network density (β=0.10, *p*=.14) was significantly associated with tendency towards positive sentiment. Average negative affect was also not significantly associated with tendency towards positive sentiment (β=-0.09, *p*=.20).

Contemporaneous Network Density

We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 0.72, *p*=.70). In both models, average positive affect was significantly associated with tendency towards positive sentiment (β=0.25, *p*<.001). Neither contemporaneous negative affect network density (β=-0.06, p=.41) nor contemporaneous positive affect network density (β=0.003, p=.96) was significantly associated with tendency towards positive sentiment. Average negative affect was also not significantly associated with tendency towards positive sentiment (β=-0.09, p=.19).

Table 4

Results for Hypotheses 3 and 4

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	0.02	0.11	0.22	.82
	Negative Network Density	-0.36	0.46	-0.77	.44
	Positive Network Density	0.67	0.45	1.48	.14
	Average Negative Affect	-0.01	0.01	-1.30	.20
	Average Positive Affect	0.03	0.01	3.64	<.001
Contemporaneous Network Density					
	Intercept	0.05	0.11	0.47	.64
	Negative Network Density	-0.69	0.84	-0.83	.41
	Positive Network Density	0.03	0.57	0.05	.96
	Average Negative Affect	-0.01	0.01	-1.31	.19
	Average Positive Affect	0.03	0.01	3.54	<.001

Note: Estimates represent unstandardized estimates.

Exploratory Hypothesis: Sentiment Constancy

Emotional Inertia and Sentiment Constancy

Exploratory Hypothesis 1: Emotional Inertia and Constancy of Negative Sentiment. Given the data, the probability that the relationship between negative emotional inertia and constancy of negative sentiment is positive is 0.50, which does not give us enough confidence to be sure that the relationship is negative. The mean of the posterior distribution is -0.001 (95% CI [-0.20, 0.23]). Additionally, the probability that the relationship between positive emotional inertia and constancy of negative sentiment is negative is 0.46, which does not give us enough confidence to be sure that the relationship is positive (Mean=0.02, 95% CI [-0.27, 0.29]). Further, according to the model, the probability that the relationship between average negative affect and constancy of negative sentiment is negative is 0.23, which does not give us enough confidence to be sure that the relationship is positive (Mean=0.003, 95% CI [-0.01, 0.01]). The model did provide strong evidence that there is a negative association between constancy of negative sentiment and both total negative sentiment across the five questions (Mean= -0.21, 95%CI [-0.24, -0.17]) and average positive affect from the EMA (Mean=-0.03, 95% CI [-0.04, -0.01]). Results are displayed in Supplementary Table S1.

Exploratory Hypothesis 2: Emotional Inertia and Constancy of Positive Sentiment. Given the data, the probability that the relationship between negative emotional inertia and constancy of positive sentiment is positive is 0.37, which does not give us enough confidence to be sure that the relationship is negative (Mean= -0.03, 95% CI [-0.19, 0.13]). Additionally, the probability that the relationship between positive emotional inertia and constancy of positive sentiment is negative is 0.29, which does not give us enough confidence to be sure that the relationship is positive (Mean= 0.06, 95% CI [-0.16, 0.28]). Further, according to the model, the probability that the relationship between average negative affect and constancy of positive sentiment is positive is 0.27, which does not give us enough confidence to be sure that the relationship is negative (Mean= -0.002, 95% CI [-0.01, 0.01]). The model did provide strong evidence that there is a negative association between constancy of positive sentiment and both total positive sentiment from the interview (Mean=-0.21, 95% CI [-0.23, -0.19]) and average positive affect from the EMA (Mean=-0.01, 95% CI [-0.03, -0.003]). Results are displayed in Supplementary Table S2.

Hypotheses 3 and 4: Network Density Hypotheses

Exploratory Hypothesis 3: Emotion Networks and Constancy of Negative Sentiment. All model results for Exploratory Hypothesis 3 are displayed in Supplementary Table S3.

Temporal Network Density. We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 0.02, p=.99). In both models, total negative sentiment (β=-0.18, p=.01) and average positive affect (β=-0.23, p=.002) were significantly inversely associated with constancy of negative sentiment. Temporal negative emotion network density (β=0.004, p=.89), temporal positive emotion network density (β=0.001, p=.99), and average level of negative affect (β=-0.02, p=.79) were all nonsignificantly associated with constancy of negative sentiment.

Contemporaneous Network Density. We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 0.37, p=.83). In both models, total negative sentiment (β=-0.18 p=.01) and average positive affect (β=-0.23 p=.002) were significantly inversely associated with constancy of negative sentiment. Contemporaneous negative emotion network density (β=-0.02, p=.77), contemporaneous positive emotion network density (β=0.04 p=.56), and average levels of negative affect (β=-0.02, p=.77) were all nonsignificantly associated with constancy of negative sentiment.

Exploratory Hypothesis 4: Emotion Networks and Constancy of Positive Sentiment. All model results for Exploratory Hypothesis 4 are displayed in Supplementary Table S4.

Temporal Network Density. We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 3.30, p=.19). In both models, total positive sentiment (β=-0.50, p<.001) and average positive affect (β=-0.14, p=.03) were significantly inversely associated with constancy of positive sentiment. Temporal negative emotion network density (β=-0.04, p=.51), temporal positive emotion network density (β=0.10, p=.09), and average levels of negative affect (β=-0.03, p= .67) were all nonsignificantly associated with constancy of positive sentiment.

Contemporaneous Network Density. We failed to reject the hypothesis that the data was equally likely under both models, according to the log-likelihood test (χ^2 (2) = 0.20, p=.91). In both models, total positive sentiment (β=-0.50, p<.001) and average positive affect (β=-0.15, p=.03) were significantly inversely associated with constancy of positive sentiment. Contemporaneous negative emotion network density (β=-0.02, p=.76), contemporaneous positive emotion network density (β=0.02, p=.71), and average levels of negative affect (β=-0.02, p= .70) were all nonsignificantly associated with constancy of positive sentiment.

Exploratory Analyses: Addition of Depression Score as Covariate

We re-ran the main analyses including depression as a covariate. Depression was assessed using the PHQ-14 on the same day as the interview. While the survey asked participants about their symptoms over the past week, we expected participants' answers to be heavily influenced by their current levels of mood and thus used this analysis as a proxy to examine whether previous results held over and above this proxy for current mood and depression symptoms.

Model results can be seen in Supplementary Tables S5-S6. The addition of the new covariate did not meaningfully change previous results. That is, EMA-rated average positive affect was still positively associated with tendency towards positive sentiment in all three models. Depression score was not significantly associated with tendency towards positive sentiment. All other inferences remained unchanged.

Sensitivity Analyses

Sensitivity Analysis 1: Restricting to using EMA data from Epochs 2 & 3

We repeated the analysis for all main hypotheses in MPLUS (hypotheses 1-2) and R (hypotheses 3-4), this time using EMA data from epochs 2 and 3 (instead of 1, 2, and 3). All other methodology remained the same as described above. Results for all four hypotheses did not meaningfully differ from the results of the main analysis. Model results are displayed in Supplementary Tables S7-S8.

Sensitivity Analysis 2: Adding Interaction Term

We repeated the analysis for all main hypotheses in RStudio, including interaction terms between emotional persistence and average level of affect (e.g., one interaction between average negative affect and negative emotional persistence and one interaction between average positive affect and positive emotional persistence). Emotional inertia was calculated as described in Study 1 sensitivity analyses. The interaction term was not significant in any model, and significance levels and inferences from the main analyses remained unchanged. Model results for all models are displayed in Supplementary Tables S9-S10.

Discussion

This study examined associations between emotional persistence and linguistic sentiment from a structured interview. Emotional persistence was operationalized in two ways: emotional inertia measured stability of emotions over time, while emotion network density measured the interconnectedness of emotions over time. We did not find support for any of our hypotheses. That is, no measure of emotional persistence (neither emotional stability nor emotional interconnectedness) during weeks 1, 6, and 12 was associated with tendency towards positive sentiment from an interview administered after week 12. Neither negative nor positive emotional persistence was significantly associated with linguistic sentiment. Thus, overall, we found that no index of emotional persistence from daily life predicted sentiment expressed during a subsequent structured interview.

Regarding covariates, we did find that levels of positive affect measured throughout a participant's daily life related to tendency towards positive sentiment during the interview. That is, participants who reported higher levels of positive affect throughout their day in EMA surveys administered during weeks 1, 6, and 12 of the study were found to have higher levels of positive relative to negative sentiment during their interview at the end of the study. Average level of negative affect from the EMA surveys was not associated with interview sentiment. Finally, exploratory analysis revealed that that average positive affect reported via EMA was negatively associated with the degree to which levels of sentiment remained constant over the first five interview questions. That is, participants who reported lower levels of positive affect throughout their day in the EMA surveys had more stable levels of both positive and negative sentiment during the interview.

Implications

Emotional Persistence is Not Related to Sentiment

Counter to our hypotheses, no measure of emotional persistence was related to a participant's linguistic sentiment during the interview. This is surprising given research that has found that both linguistic sentiment and emotional inertia are related to neuroticism and depression (Koval et al., 2016; Vine et al., 2020) and research that has found idiographic network density to be associated with anxiety and depression (Shin et al., 2022), which suggests that emotional persistence might at least be indirectly related to linguistic sentiment. To our knowledge, this was the first study to examine associations between linguistic sentiment and emotion dynamics, so there is no pre-established relationship between the two. One possible explanation for the null findings regarding emotional persistence is that this affective dynamic does not provide any additional information about linguistic sentiment above and beyond average levels of positive affect, which *was* found to be related to tendency towards positive sentiment. Another possible explanation for our null findings is the mismatched timing and setting of the surveys and the interview. Emotional persistence was measured as a process occurring over the course of several days, which may not correspond to sentiment in a controlled 10-minute interview.

Average Affect and BERT Sentiment Results

The finding that average levels of positive affect from EMA were significantly associated with tendency towards positive sentiment from BERT analysis of interview responses is relatively in line with the current literature. These results suggest that language expressed during an interview about positive and negative experiences and emotions is associated with daily emotions measured over the course of several weeks. This connection between positive sentiment and positive mood aligns with the prior research finding that positive emotion words correspond to higher life satisfaction (Song & Zhao, 2023). These findings suggest that sentiment analysis based on a controlled task such as an interview may be a useful indicator of daily emotions as they occur in the natural environment.

The EMA was collected before the interview, suggesting that the data captured during EMA represents a pattern that impacts the valence of a person's language. However, directionality of the effects is uncertain, since in general, daily language may contribute to daily affect as much as daily affect contributes to language. This would be somewhat consistent with the psychological constructionist view, which suggests that language shapes emotions (Lindquist, 2017) and is somewhat supported by studies finding that impairing access to language alters emotion perception (Lindquist, MacCormack, et al., 2015; Lindquist, Satpute, et al., 2015; Nook et al., 2015). In this case, participants' linguistic sentiment in their daily life *before* completing the interview may have contributed to their reports of daily affect via EMA. Their interview sentiment may thus have either been influenced by their daily affect (indicating bidirectional effects) or simply been indicative of their previous linguistic sentiment. Future research is needed to parse these effects. It is also interesting that these results held controlling for current levels of depression, suggesting that above and beyond current mood state at the time of the interview, there is a relationship between daily positive emotions and the language used during an interview.

That *only* positive affect from EMA, and not average levels of negative affect, was significantly associated with linguistic sentiment was surprising. Positive affect was associated with tendency towards positive sentiment, a difference score that incorporates both positive and negative sentiment, over and above the effects of average negative affect. This suggests that the approach/appetitive system, which is associated with positive affect and emotions, may be more involved in language than its counterpart, the withdrawal/defense system, which contains negative emotions (Shankman & Klein, 2003). The *interpersonal* nature of the interview task may have contributed to the results, in that positive affect may play a more dominant role than negative affect when people present themselves to others. However, to our knowledge, there is no support for this dominant role of positive affect in the literature, and it merits future study.

Exploratory Hypotheses: Examining Relationships with Constancy of Sentiment

In a set of exploratory analyses, we examined relationships between emotional persistence and sentiment constancy to identify whether patterns of language use across the interview questions corresponded to patterns of emotion dynamics throughout the week. There were no significant relationships between emotional inertia or emotion network density and sentiment constancy. Constancy of either positive or negative sentiment indicates a similarity of sentiment levels across the context of different interview questions, which switched between asking about positive and negative aspects of participants' lives. The finding that sentiment constancy did not relate to emotional persistence suggests that linguistic patterns may be unrelated to patterns of emotion dynamics in individuals with depression.

Additionally, we found that participants reporting lower average positive affect in the EMA had higher constancy of both positive and negative sentiment during the interview. This suggests that participants with higher constancy of sentiment may have demonstrated a blunted response to the content of the question. That is, they may have maintained low positive and high negative sentiment in response to positive questions instead of flexibly adjusting their sentiment in response to the specific question. Future research is needed to understand when constancy of positive and negative sentiment might be maladaptive, and to clarify their relationship with both average levels of affect and emotional persistence.

Sensitivity Analysis

We repeated the main analysis with networks and emotional inertia calculated using only EMA data from the second two epochs. There were no differences from the results of the main analyses. This suggests relative stability over time and with smaller sample sizes for idiographic networks. However, given the relative infancy of this field of research, future research should continue to investigate how network stability changes with sample size, and work to create more specific guidelines about sample size.

Additionally, the second set of sensitivity analyses added an interaction term to the main hypotheses to examine whether the relationship between emotional persistence and linguistic sentiment depended on average levels of affect. The results did not differ from the main analyses. This suggests that the correlates of emotional persistence may not depend on average levels of emotions. To our knowledge, this dissertation is the first set of studies that has examined whether the impact of emotional persistence depends on which *level* of affect is persistent. This analysis was limited by methodological constraints, as inertia values were saved for each participant and included in a separate moderation model that did not include residual error values for the inertia estimates. Future research should use more precise methods to continue to investigate this question. Investigation of other possible moderators should also be considered.

Limitations

This study is not without limitations. First, the EMA data was collected before the interview was conducted, which limits exploration of any bidirectional effects. The specifics of the controlled interview further limit external validity. The interview questions alternated between negative and positive content and restricted what participants spoke about. How participants spoke in the interview may differ from how they speak in their typical day-to-day life at work or with friends and family. For example, participants may have tried to present themselves as more positive and professional, and limited their use of negative language.

An additional limitation pertains to the specifics of the BERT program for linguistic analysis. BERT provided three scores for each participant: the "probability of negative valence", "probability of positive valence", and "probability of neutral valence". These three metrics added up to a total of 1. Thus, if BERT detected more positive sentiment in a participant's response, it would inherently lower the participant's probability of negative sentiment such that the totals still added to one. While the inclusion of neutral sentiment partially addressed this problem, positive and negative valence were still tied to each other in this program. Because of this, we chose to use one difference score to represent positive and negative sentiment instead of viewing them separately. The dependent nature of the positive and negative sentiment measure differs from much of the literature on positive and negative valence systems (i.e., reward/approach vs avoidance), which views the positive and negative valence systems separately (Craske et al., 2016).

Finally, there were limitations pertaining to the calculation of emotional persistence. EMA surveys were delivered approximately every two hours, but emotional persistence may occur on a different scale. Additionally, inclusion of additional or different emotions, such as guilt, shame, calmness, or gratitude, may also have led to different results. Most notably, the sample size was still relatively small for idiographic networks. As a result, many (17% for negative emotion networks, 11% for positive emotion networks) participants were removed from the analysis due to their networks not converging, and of the participants who were retained, many had "empty" temporal networks (29% for negative emotion networks and 39% for positive emotion networks), which contained no significant connections. These empty networks may represent the true relationship between emotions for these participants, or for some, they may be a result of the network being underpowered. Likewise, some networks unexpectedly had negative edges between symptoms, and parsing out whether this was due to misestimation or a true representation of the participant's experience is difficult. While changing the threshold of minimum surveys required for analysis did not change the proportion of empty networks or negative edges in the dataset, future studies that replicate these analyses with more data per person would clarify these questions.

Future Directions

Future studies should continue to investigate these questions, addressing some of this study's methodological limitations. Specifically, studies that analyzed spoken language from a naturalistic setting over a longer period may find different results due to better alignment of sentiment analysis and EMA data. Additionally, future studies should use longitudinal or experimental designs to parse out the directionality of and mechanisms underlying the relationship between linguistic sentiment and positive affect. Finally, this was the first study to our knowledge to examine emotional persistence in relation to linguistic factors. Future studies should examine other linguistic or behavioral markers that are associated with emotional persistence. It is also worthwhile to investigate other aspects of emotion dynamics and regulation that are associated with language.

Conclusion

This study examined relationships between measures of emotional persistence and estimates of positive and negative valence provided by linguistic sentiment analysis. Emotional persistence was operationalized in two different ways, as both emotional inertia and emotion network density, for both negative and positive emotions. We found that no measure of emotional persistence was associated with linguistic sentiment. However, average level of positive affect from EMA data was associated with a tendency towards positive sentiment, a measure which incorporated both positive and negative sentiment, during an interview. This held when controlling for PHQ-14 scores, an approximation of current mood. This research has implications for understanding connections between language and low positive mood. Future research should address methodological limitations and examine the directionality behind these relationships.

Table S1
Model Results for Exploratory Hypothesis 1

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Residual Variances					
Negative Affect	6.77	0.06	0.00	6.65	6.88
Positive Affect	5.27	0.05	0.00	5.18	5.36
Between- Level					
Negative Sentiment Persistence on Negative Emotional Inertia	-0.001	0.11	0.50	-0.20	0.23
Negative Sentiment Persistence on Positive Emotional Inertia	0.02	0.15	0.46	-0.27	0.29
Negative Sentiment Persistence on Negative Affect	0.003	0.01	0.23	-0.01	0.01
Negative Sentiment Persistence on Positive Affect	-0.03	0.01	0.001	-0.04	-0.01
Negative Sentiment Persistence on Total Negative Sentiment	-0.21	0.02	0.00	-0.24	-0.17
Means					
Negative Affect	11.06	0.18	0.00	10.70	11.40
Positive Affect	9.07	0.12	0.00	8.85	9.31
Total Negative Sentiment	1.15	0.05	0.00	1.05	1.24
Negative Emotional Inertia	0.45	0.01	0.00	0.42	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.39
Intercepts					
Negative Sentiment Persistence	0.04	0.11	0.36	-0.18	0.24
Variances					
Negative Affect	10.04	0.80	0.00	8.66	11.78
Positive Affect	4.35	0.36	0.00	3.72	5.13
Total Negative Sentiment	0.75	0.06	0.00	0.64	0.88
Negative Emotional Inertia	0.03	0.004	0.00	0.03	0.04
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Negative Sentiment Persistence	0.07	0.01	0.00	0.06	0.08

Table S2

Model Results for Exploratory Hypothesis 2

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Residual Variances					
Negative Affect	6.77	0.06	0.00	6.65	6.88
Positive Affect	5.27	0.05	0.00	5.17	5.36
Between- Level					
Positive Sentiment Persistence on Negative Emotional Inertia	-0.03	0.08	0.37	-0.19	0.13
Positive Sentiment Persistence on Positive Emotional Inertia	0.06	0.11	0.29	-0.16	0.28
Positive Sentiment Persistence on Negative Affect	-0.002	0.004	0.27	-0.01	0.01
Positive Sentiment Persistence on Positive Affect	-0.01	0.01	0.003	-0.03	-0.003
Positive Sentiment Persistence on Total Negative Sentiment	-0.21	0.01	0.00	-0.23	-0.19
Means					
Negative Affect	11.05	0.17	0.00	10.71	11.40
Positive Affect	9.07	0.12	0.00	8.85	9.30
Total Positive Sentiment	1.73	0.06	0.00	1.60	1.85
Negative Emotional Inertia	0.45	0.01	0.00	0.42	0.47
Positive Emotional Inertia	0.37	0.01	0.00	0.35	0.39
Intercepts					
Positive Sentiment Persistence	0.10	0.08	0.13	-0.05	0.27
Variances					
Negative Affect	10.01	0.78	0.00	8.59	11.66
Positive Affect	4.35	0.36	0.00	3.72	5.13
Total Positive Sentiment	1.29	0.10	0.00	1.13	1.52
Negative Emotional Inertia	0.03	0.004	0.00	0.03	0.04
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Positive Sentiment Persistence	0.04	0.003	0.00	0.04	0.05

Table S3

Model Results for Exploratory Hypothesis 3 (Constancy of Negative Sentiment)

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-0.12	0.14	-0.85	.40
	Negative Network Density	-0.07	0.55	-0.13	.89
	Positive Network Density	0.01	0.53	0.01	.99
	Average Negative Affect	-0.001	0.01	-0.27	.79
	Average Positive Affect	-0.03	0.01	-3.15	<.001
	Total Negative Sentiment	-0.07	0.03	-2.62	<.001
Contemporaneous Network Density					
	Intercept	-0.12	0.14	-0.86	.39
	Negative Network Density	-0.29	1.02	-0.29	.77
	Positive Network Density	0.39	0.67	0.58	.56
	Average Negative Affect	-0.002	0.01	-0.29	.77
	Average Positive Affect	-0.03	0.01	-3.21	.002
	Total Negative Sentiment	-0.07	0.03	-2.61	.01

Note: Estimates represent unstandardized estimates.

Table S4

Model Results for Exploratory Hypothesis 4 (Constancy of Positive Sentiment)

Model	Variable	Estimate	Std Error	T value	P value

Temporal Network Density					
	Intercept	0.03	0.11	0.26	.79
	Negative Network Density	-0.30	0.46	-0.65	.51
	Positive Network Density	0.77	0.45	1.72	.09
	Average Negative Affect	-0.002	0.01	-0.43	.67
	Average Positive Affect	-0.02	0.01	-2.12	.04
	Total Positive Sentiment	-0.17	0.02	-8.04	<.001
Contemporaneous Network Density					
	Intercept	0.04	0.12	0.36	.72
	Negative Network Density	-0.26	0.85	-0.31	.76
	Positive Network Density	0.21	0.57	0.37	.71
	Average Negative Affect	-0.002	0.01	-0.39	.70
	Average Positive Affect	-0.02	0.01	-2.25	.03
	Total Positive Sentiment	-0.17	0.02	-7.88	<.001

Note: Estimates represent unstandardized estimates.

Table S5

Model Results for Exploratory Analyses #2, Emotional Inertia

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level *Variances*					

Tendency to Positive Sentiment	0.00	0.00	0.00	0.00	0.00
Depression	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	6.80	0.07	0.00	6.66	6.94
Positive Affect	5.50	0.05	0.00	5.39	5.60
Between- Level					
Sentiment on Negative Emotional Inertia	0.02	0.11	0.45	-0.16	0.25
Sentiment on Positive Emotional Inertia	-0.07	0.14	0.34	-0.36	0.20
Sentiment on Negative Affect	-0.003	0.01	0.34	-0.01	0.01
Sentiment on Positive Affect	0.03	0.01	0.00	0.01	0.04
Sentiment on Depression	-0.01	0.004	0.13	-0.01	0.003
Means					
Negative Affect	10.96	0.19	0.00	10.59	11.34
Positive Affect	9.04	0.13	0.00	8.78	9.33
Depression	12.47	0.30	0.00	11.93	13.09
Negative Emotional Inertia	0.44	0.01	0.00	0.41	0.47
Positive Emotional Inertia	0.36	0.01	0.00	0.34	0.39
Intercepts					
Sentiment	0.08	0.11	0.26	-0.15	0.30
Variances					
Negative Affect	9.61	0.86	0.00	8.10	11.56
Positive Affect	4.29	0.39	0.00	3.60	5.13
Depression	21.83	1.90	0.00	18.58	25.91
Negative Emotional Inertia	0.04	0.004	0.00	0.03	0.04
Positive Emotional Inertia	0.02	0.003	0.00	0.02	0.03
Residual Variances					
Sentiment	0.05	0.01	0.00	0.04	0.06

Note: "Sentiment" refers to the average difference score between positive and negative sentiment; representing a person's average tendency toward positive over negative sentiment.

Table S6

Results for Exploratory Analyses #2, Emotion Network Density

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	0.05	0.11	0.48	.63
	Negative Network Density	-0.42	0.46	-0.91	.36

	Positive Network Density	0.63	0.45	1.40	.16
	Average Negative Affect	-0.002	0.01	-0.28	.78
	Average Positive Affect	0.03	0.01	3.23	.001
	Depression	-0.004	0.004	-0.96	.34
Contemporaneous Network Density					
	Intercept	0.08	0.12	0.65	.52
	Negative Network Density	-0.59	0.83	-0.71	.48
	Positive Network Density	-0.07	0.57	-0.12	.90
	Average Negative Affect	-0.002	0.01	-0.31	.76
	Average Positive Affect	0.03	0.01	3.19	.002
	Depression	-0.004	0.004	-0.89	.38

Table S7

Model Results for Sensitivity Analysis #1, Hypotheses 1-2

	Estimate	Posterior SD	One-Tailed P-Value	Lower 2.5% Credible Interval	Upper 2.5% Credible Interval
Within-Level					
Variances					
Tendency to Positive Sentiment	0.00	0.00	0.00	0.00	0.00
Residual Variances					
Negative Affect	6.02	0.08	0.00	5.87	6.16
Positive Affect	4.91	0.07	0.00	4.78	5.05
Between- Level					
Sentiment on Negative Emotional Inertia	-0.02	0.10	0.41	-0.21	0.17
Sentiment on Positive Emotional Inertia	-0.04	0.14	0.39	-0.31	0.23

Sentiment on Negative Affect	-0.01	0.01	0.10	-0.01	0.003
Sentiment on Positive Affect	0.03	0.01	0.00	0.01	0.04
Means					
Negative Affect	10.96	0.21	0.00	10.55	11.38
Positive Affect	9.01	0.14	0.00	8.72	9.28
Negative Emotional Inertia	0.42	0.02	0.00	0.39	0.45
Positive Emotional Inertia	0.36	0.02	0.00	0.33	0.39
Intercepts					
Sentiment	0.07	0.10	0.27	-0.15	0.26
Variances					
Negative Affect	11.05	1.03	0.00	9.27	13.33
Positive Affect	4.78	0.45	0.00	4.04	5.80
Negative Emotional Inertia	0.05	0.01	0.00	0.04	0.06
Positive Emotional Inertia	0.03	0.004	0.00	0.02	0.04
Residual Variances					
Sentiment	0.05	0.01	0.00	0.04	0.06

Note: "Sentiment" refers to the average difference score between positive and negative sentiment; representing a person's average tendency toward positive over negative sentiment.

Table S8

Model Results for Sensitivity Analysis #1, Hypothesis 3-4

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	0.01	0.11	0.13	.90
	Negative Network Density	-0.22	0.34	-0.66	.51
	Positive Network Density	-0.001	0.37	0.00	>.99
	Average Negative Affect	-0.003	0.01	-0.71	.48
	Average Positive Affect	0.03	0.01	3.53	<.001
Contemporaneous Network Density					
	Intercept	0.003	0.11	0.03	.98

	Negative Network Density	0.59	0.67	0.87	.39
	Positive Network Density	-0.07	0.51	-0.14	.89
	Average Negative Affect	-0.004	0.005	-0.75	.46
	Average Positive Affect	0.03	0.01	3.41	<.001

Table S9

Model Results for Sensitivity Analysis #2, Hypothesis 1-2

Variable	Estimate	Std Error	T value	P value
Intercept	-0.34	0.35	-0.98	.33
Negative Emotional Inertia	0.05	0.39	0.13	.90
Positive Emotional Inertia	0.98	0.75	1.30	.19
Average Negative Affect	-0.01	0.02	-0.62	.54
Average Positive Affect	0.08	0.03	2.60	.01
Negative Emotional Inertia*Average Negative Affect	0.01	0.03	0.16	.88
Positive Emotional Inertia*Average Positive Affect	-0.13	0.08	-1.71	.09

Table S10

Model Results for Sensitivity Analysis #2, Hypothesis 3-4

Model	Variable	Estimate	Std Error	T value	P value
Temporal Network Density					
	Intercept	-0.05	0.13	-0.04	.97
	Negative Network Density	1.64	1.74	0.94	.35

	Positive Network Density	-0.68	2.17	-0.32	.75
	Average Negative Affect	-.001	0.01	-0.16	.87
	Average Positive Affect	0.03	0.01	2.67	.01
	Negative Network Density*Average Negative Affect	-0.20	0.16	-1.20	.23
	Positive Network Density*Average Positive Affect	0.16	0.24	0.65	.51
Contemporaneous Network Density					
	Intercept	-0.11	0.17	-0.65	.52
	Negative Network Density	-0.87	3.19	-0.28	.78
	Positive Network Density	4.94	2.81	1.76	.08
	Average Negative Affect	-0.01	0.01	-0.93	.35
	Average Positive Affect	0.05	0.01	3.61	<.001
	Negative Network Density*Average Negative Affect	0.02	0.31	0.06	.95
	Positive Network Density*Average Positive Affect	-0.54	0.30	-1.79	.08

General Discussion

The aim of this dissertation was to investigate negative and positive emotional persistence, as represented by two separate metrics: emotional inertia and emotion network density. Emotional inertia represented *stability* of emotions, while emotion network density represented *interconnection* of emotions. Associations between both positive and negative emotional persistence and subjective and objective markers of well-being[2] were examined. Specifically, the three studies were designed to address gaps in the literature pertaining to the implications of positive emotional persistence, longitudinal relationships between emotional persistence and well-being, and inclusion of outcome measures that were transdiagnostic, continuous, or objective.

Study 1 examined cross-sectional and longitudinal relationships between emotional persistence and self-reported psychological well-being. We found that positive emotions that were highly influenced by previous levels of positive emotions (positive emotional inertia) were associated with lower well-being six weeks later, while co-occurrence of multiple positive emotions within the same timeframe (positive contemporaneous emotion network density) was associated with higher well-being six weeks later. In this study, negative emotional persistence was not longitudinally related to well-being and there were no significant cross-sectional relationships between (negative or positive) emotional persistence and well-being. Average EMA-reported affect was both cross-sectionally and longitudinally associated with well-being such that participants with higher negative affect throughout the day reported lower well-being and those with higher positive affect reported higher well-being. Overall, this study suggests that

[2] Hereafter, the phrase "subjective and objective markers of well-being" refers to the self-report, physiological, and linguistic indicators of transdiagnostic psychological well-being included across the three studies.

both metrics of positive emotional persistence may indicate susceptibility to experience change in well-being in the future.

Study 2 examined relationships among heart-rate variability (HRV) and emotional persistence. We found that interconnectivity of negative emotions (e.g., contemporaneous network density) was inversely associated with HRV such that participants with denser networks of negative emotions during weeks 1, 6, and 12 of the study had lower HRV during the same time period. Surprisingly, average level of negative affect was not related to HRV. No measure of positive emotional persistence, nor average positive affect, was related to HRV. Altogether, this study supports the idea that there may be a biological inflexibility underlying negative emotional inflexibility, which may have treatment implications.

Finally, Study 3 examined relationships between emotional persistence and results of natural linguistic processing analysis from a ten-minute interview about emotions and experiences over the past week. We found that emotional persistence was not related to sentiment during the interview. However, average level of positive affect from EMA was associated with a tendency towards positive sentiment in the interview. That is, participants who reported higher levels of daily positive affect during weeks 1, 6, and 12 of the study used more positive and less negative language during the interview after week 12. All in all, while this study did not provide support for a relationship between emotional persistence and language, the results suggest that NLP of a brief encounter may provide insight into a person's average daily levels of positive emotions.

Emotional Inertia

Emotional inertia, the within-person autocorrelation of emotion, captures the stability of a person's levels of positive or negative emotions, and is thought to be related to mental health in that individuals with stable, persistent levels of negative emotions are thought to experience more mental health difficulties (Houben et al., 2015; Koval et al., 2016). On the other hand, stable, persistent levels of positive emotions have demonstrated mixed relationships with mental health indicators (Höhn et al., 2013; Koval et al., 2016). Some researchers argue that stability of any emotion over time is indicative of blunted emotional responses, while others suggest that stable persistence of positive emotions would be related to higher positive emotionality.

The results of these studies provide insight into the relationship between emotional inertia (i.e., stability) and psychological well-being. Previous research generally found that negative emotional inertia is related to current and future depression (Koval et al., 2016), while research on positive emotional inertia was more mixed, with some studies finding positive relationships with depression (Koval et al., 2016) and others finding inverse relationships with depression (Höhn et al., 2013). Partially in line with the research finding that emotional inertia is positively related to depression, Study 1 found that positive emotional inertia was associated with lower subsequent well-being, but that negative emotional inertia was not related to psychological well-being. Meanwhile, Study 2 found no relationships between positive or negative emotional inertia and HRV, and Study 3 found no relation between positive or negative emotional inertia and linguistic sentiment from NLP. The inverse relationship between positive emotional inertia and well-being from Study 1 aligns with the idea that affective blunting is associated with lower psychological well-being; that is, individuals with internalizing disorders such as depression demonstrate reduced emotional reactivity to contextual stimuli (Bylsma et al., 2008). Because of this reduced reactivity, their levels of positive emotions may remain relatively stable and impervious to new information and external or internal attempts at regulation. For example, someone with low emotional reactivity (and high emotional inertia) may have their mood for the whole day set by the outcome of their morning meeting. However, this result does contrast from previous work that uses EMA to measure positive emotional inertia with a continuous outcome variable (Höhn et al., 2013).

One possible reason for the mixed results from this set of studies is that emotional inertia cannot account for the relationships among different types of affect (e.g., anger and sadness) because it uses sum scores and represents overall stability of negative or positive affect. Emotional inertia does not discern between relationships among different types of emotions and the stability of a single emotion, while network density parses out these relationships. Thus, while emotional inertia requires less intra-individual data and is simpler to calculate, the results of this study suggest that this metric may not be as sensitive as network density. This difference is important because the progression from one negative or positive emotion to another may be a key mechanism underlying the process of emotional inflexibility and persistence.

While emotional inertia is easier to calculate than network density (in that it requires less data), these results suggest that, when calculated for aggregated emotion scores, it may be a flawed measure. However, a clearer sense of the mechanisms underlying positive emotional inertia and whether they truly represent a different process than network density may still be worthwhile given the results of Study 1. Additionally, inertia of individual emotions would be less susceptible to the limitations of the aggregated measure and may be a path for future study.

Network Density

Idiographic emotion network density, a representation of the interconnectedness of an individual's emotions, is thought to be related to mental health in that individuals with more strongly connected negative emotions may experience a "contagion effect" of negative emotions and endorse lower levels of psychological well-being (Borsboom, 2008; Robinaugh, Hoekstra, et al., 2020). While the network density of positive emotion networks has been less studied, one previous study suggests that interconnectivity of positive emotions may be indicative of positive mental health outcomes (Shin et al., 2022).

The studies in this dissertation further the literature on network density and psychological well-being. Previous research has primarily focused on nomothetic network density, finding it to be positively related to depression and neuroticism, among other mental health-related variables (Bringmann et al., 2016; Pe et al., 2015). Studies of idiographic network density have been less common, but may be more useful in discerning mechanisms at the individual level, as the results of idiographic and nomothetic networks are not interchangeable (Bringmann et al., 2013). Insights into individual-level mechanisms may have eventual implications for personalized treatment, and thus, idiographic network density was the focus of these three studies. Study 1 found that contemporaneous idiographic network density of positive emotions was related to subsequent well-being, such that participants with higher network density of positive emotions endorsed higher well-being six weeks later. In this study, negative emotion network density was not significantly related to psychological well-being. In Study 2, contemporaneous idiographic network density of negative emotions was inversely related to HRV, such that participants with more interconnected negative emotions had lower median HRV during both daytime and bedrest. In this study, positive emotion network density was not significantly related to HRV. Study 3 found no significant relationships between network density and linguistic sentiment.

The differing results for contemporaneous and temporal network density is notable. These two types of networks represent two different constructs: contemporaneous network density represents relationships among symptoms within the same EMA window, while temporal network density represents relationships among symptoms from one time window to the next

(Epskamp, van Borkulo, et al., 2018). Connectivity of emotions may represent different emotion regulation strategies or capabilities when measured within versus across time frames and thereby provide different results. For example, these studies suggest that experiencing multiple *positive* emotions in a short window or simultaneously (contemporaneous network density of positive emotions) may relate to general well-being, whereas experiencing multiple *negative* emotions in a short window or simultaneously (contemporaneous network density of negative emotions) may relate to psychophysiology. The null findings with regard to temporal network density suggest that interconnection of emotions across several hours may not be as relevant to these measures of psychological well-being and physiological adaptability. However, contemporaneous networks need a smaller sample size to achieve sufficient power relative to temporal networks, and as such it is possible that in these studies the temporal networks were underpowered (Mansueto et al., 2022). All in all, there is evidence that contemporaneous network density may provide valuable insight into emotion dynamics, and more research on temporal network density is needed. With a sufficiently powered sample, continuing to consider the differences between these two metrics to determine how each is related to objective and subjective markers of psychological well-being will be an important next step.

Overall, the results of these studies are broadly in line with literature suggesting that denser negative emotions correspond to maladaptive processes (i.e., lower HRV as a biological index of poorer emotion regulation), while denser positive emotions correspond to beneficial psychological well-being (Shin et al., 2022). However, the fact that positive and negative emotion network density did not relate to the same indices suggests that the relationship between idiographic emotion networks and subjective and objective markers of well-being may be more complex. This may be due to idiographic differences, such as identifying which emotions are most important for different participants, or due to methodological specifications, such as sample size. This may also be due to mechanistic differences, as discussed below.

Positive vs. Negative Emotional Persistence

This dissertation found different results for measures of positive and negative emotional persistence. Study 1 found that only positive emotional persistence (both inertia/stability and density/interconnectedness) was related to later well-being, while negative emotional persistence was not. Study 2 found that only negative network density was related to HRV, while positive network density was unrelated to HRV. Previous work has identified two different systems that contribute to psychological well-being and mood and anxiety disorders by regulating thoughts and behavior (Shankman & Klein, 2003). One system is an approach/appetitive system, which may relate more strongly to positive emotions. The other is the withdrawal/defense system, which may engage more negative emotions (Shankman & Klein, 2003). These different systems may impact subjective and objective markers of well-being differently. The results of this dissertation suggest that positive emotional persistence and average daily positive affect, as part of the approach/appetitive system, may have more influence on subjective report of well-being and language during a structured interpersonal interview. Meanwhile negative emotional connectivity, as part of the withdrawal/defense system, may be more related to biological markers of emotional flexibility and adaptability. Overall, these differing results suggest that dynamics of both positive and negative emotions are important to study separately, as they provide unique insight. However, as all participants in this sample had moderate-to-severe depression, variance in negative emotion dynamics may have been especially limited which thereby limits power to detect results that would generalize to the general population. Future research that examines these concepts in a sample of nondepressed individuals is imperative for further insight, as these samples may have more variance in their emotion dynamics, and thus more power to detect differences.

Objective Indicators of Well-Being

One of the main aims of this set of studies was to examine relationships between emotional persistence and objective, non-self-reported, metrics of psychological well-being. Studies 2 and 3 addressed this aim. Study 2 found that HRV was related only to negative emotional connectivity, not positive emotional connectivity, positive or negative emotional stability, or average levels of affect from EMA. Study 3 found that linguistic sentiment was related only to average levels of positive affect and not related to emotional persistence. To our knowledge, these are the first studies to identify relationships between emotional persistence and physiology, and to identify associations between daily affect and NLP constructs. These findings lend support to our self-report assessments of emotions and network density as a measure of emotional persistence and interconnectivity.

Overall, these studies provided moderate evidence for relationships between emotional persistence extracted from self-reported emotions and objective indicators of well-being. Given the nonsignificant relationships between emotional persistence and linguistic sentiment, and the nonsignificant relationships between average affect and HRV, these results should still be considered cautiously. There are several possible reasons that we did not find stronger evidence. One possibility is the methodological constraint that the timing of the EMA surveys did not perfectly align with the timing of the objective indicators. EMA was collected five times during the day, over eight days, on three separate occasions separated by six weeks. We used HRV estimates from the same days that EMA was collected, but the sample times (i.e., the moment when a survey was sent and the moment when the smartwatch sampled HRV) were not synced.

Additionally, the HRV index that best resembled HRV at rest was collected during bedrest during these same days, but EMA was not collected during bedrest hours, and sample timing within that period varied. NLP analysis was performed on transcripts of an interview conducted after the final EMA epoch ended. We may have found different results if we had HRV or NLP estimates with timing matched more precisely to the EMA surveys. On the other hand, observing relationships despite different timings would have been a strength of the study and indeed was a strength of the observed relationship between negative emotional connectivity and HRV. Additionally, other methodological restrictions, including that participants answered specific prescribed questions in their interviews and that HRV sampling was variable and dependent on participant compliance with the AppleWatch, may also have limited our ability to detect significant relationships.

Alternatively, it is possible that emotion dynamic measurements from self-reported data and linguistic processing are so different that we are unable to observe coherence across them. There is some precedent for this in other studies where coherence across different units of analysis is expected and not observed. For example, one study using self-report, behavioral, psychophysiological, and neuroimaging data found that group factor analysis did not identify any factors loading across different units of analysis (Peng et al., 2021). Additionally, previous work has found that cognitive tasks and self-report measures hypothesized to measure the same construct are often uncorrelated (Enkavi & Poldrack, 2021). This may be, in part, because assessment of psychometrics for different units of analysis varies widely. However, this does not mean that these metrics are not useful in examining subjective and objective psychological well-being. Understanding *which aspects* of the variance in subjective and objective markers of well-being are represented by the different types of data (e.g., self-report, psychophysiological, linguistic) and what other processes might be relevant in considering the unexplained variance, instead of just looking at overall relationships, may be useful in contextualizing this information and enriching our understanding of emotion dynamics (Enkavi & Poldrack, 2021).

Challenges in Results Interpretation & Limitations

Ultimately, an additional takeaway from this program of research is that interpreting conflicting results in the face of minimal additional studies is difficult. While relationships with mental health-related constructs have been identified (Lydon-Staley et al., 2019; Shin et al., 2022), idiographic emotion dynamic research, particularly that for network density, is still very recent. Additionally, some of the literature on emotional persistence, particularly that for positive emotional inertia, provides contrasting results.

One possible explanation for these contrasting results is that the relationship between emotional persistence and well-being may depend on certain moderators. This dissertation tried partially investigating this explanation by examining possible interaction effects between average levels of affect and emotional inertia, though no significant moderation was observed. Future research should further investigate this effect and consider other possible moderators that may illuminate these relationships further. Examples of such moderators may include external stressors and intentional use of regulation strategies. For example, positive emotional stability or connectivity may be adaptive when it represents that participants actively engage in savoring practices (Growney et al., 2025), and maladaptive when it represents dampened emotional reactivity and that participants struggle to respond to attempts to regulate their emotions (Kuppens et al., 2012). Examining external stressors as a moderating factor would allow researchers to identify whether participants show flexible or persistent emotions in response to stressors, thereby illuminating whether participants are demonstrating dampened emotional reactivity or resilience (Waugh et al., 2011).

Another possibility is that persistence of only particular emotions (e.g., not all negative emotions, but just sadness and anger) may be related to well-being, and that this relationship is obscured when too many emotions are examined. That is, it is possible that we may have seen different results if we had examined inertia of each individual emotion assessed via EMA or chosen different emotions to include in the networks. This would be in line with a previous study that separately calculated inertia for angry and dysphoric behavior, and found associations between inertia of both emotions and depression (Kuppens et al., 2012). Our measure of inertia combined all five negative emotions together and all four positive emotions together, which is a method that has precedent in prior research (Koval et al., 2012). However, it is possible that dynamics of only certain emotions are related to subjective and objective markers of well-being, and that alternative methods would have illuminated these relationships.

Null results are equally difficult to interpret in this study, given the many methodological considerations and limitations. On the one hand, nonsignificant effects may represent that persistence of self-reported emotions is simply unrelated to certain markers of psychological well-being. On the other hand, methodological constraints such as low sample size may ultimately be driving the effects. That network density and emotional inertia do not aptly capture emotional persistence or regulation is also possible given the limited research on this topic so far. Future work may benefit from using the same dataset to test different operationalizations (e.g., using different emotions or survey timing) to examine whether small methodological changes provide different results, or if emotional persistence is simply unrelated to certain metrics of psychological well-being.

A notable feature of this study is that measures of emotional persistence were based off of self-reported emotions through EMA. While EMA is partially used to minimize retrospective recall bias and considered to be a better method for studying emotion dynamics and flexibility (Armey et al., 2015), this method comes with its own set of challenges and is still subject to potential responder biases. Respondents may misinterpret questions, struggle to accurately measure their own emotions, or even try to “help” researchers by providing answers that they think researchers are looking for (Stone et al., 2023). Respondents may answer according to slightly different timeframes (e.g., responding based off of how they felt in the past hour versus “right now”) or use different points of comparison (e.g., reporting how happy they feel compared to their own average versus their perception of the global average level of happiness). There is also a risk of sampling error, in that the moments in which data were collected for an individual participant may not be representative of their typical emotions or emotion dynamics (Stone et al., 2023). Additionally, participants had a 30-minute window to respond to questions after receiving the initial notification. It is likely that participants responded during moments that were more convenient, which may also be likely to have less intense levels of emotion (Stone et al., 2023). Finally, the repeated nature of the EMA prompts may have fatigued participants and led to decreased attention and mindfulness about providing accurate responses. These limitations bring into question whether EMA should be the gold standard for emotion flexibility. Inertia and network density may at best measure conscious or verbal relationships between symptoms, but not true emotional relations. While the minimizing of retrospective recall bias and increased volume of data inherent in EMA provide considerable benefits, it is worth considering that there are likely multiple different facets for emotional shifts, including subjective and physiological facets. While no facet is a perfect encapsulation of emotional shifts, subjective report of emotions may be one important piece of the puzzle, but not the only piece or the gold standard. Continuing to study emotional persistence using a multimodal approach is thus important.

In addition to the features and biases of the self-reported nature of the data, it is crucial to note that all studies had a somewhat limited sample size for idiographic networks, which may have resulted in underpowered analyses. Finally, all participants in this study had moderate to severe levels of depression, and results thus do not necessarily generalize to the population at large.

Future Directions

Future research should address these limitations and continue to clarify the relationship between emotional persistence and psychological well-being. One important area for future research is to clarify the mechanisms behind the observed relationships between positive emotional persistence and well-being. Are participants with denser positive emotion networks engaging in more mindfulness or savoring practices that prolong their emotions? Are participants with higher positive emotional inertia struggling to flexibly employ emotion regulation strategies? Further understanding of these mechanisms, and clarity on why inertia and network density provide opposing results, will be important to inform potential interventions. Similarly, clarification of the mechanisms, including directionality, behind the relationship between negative emotional connectivity and biological inflexibility is warranted. Additionally, as Study 1 was the first study to our knowledge that examined longitudinal relationships between network density and well-being, this concept should be studied further. The results of Study 1 suggest that, given that network density and inertia are related to *future* well-being, they may be a relatively stable trait measure. Later studies should examine this assumption and identify timeframes in which these metrics remain relatively stable. These research directions will contribute to a fourth future research aim: to incorporate emotional persistence research into treatment and prevention settings. For example, identifying whether idiographic network density or inertia changes from before to after treatment may provide insight into effective treatment mechanisms. These metrics may also be used to identify individuals who are at greater risk for decreases in their psychological well-being and provide interventions accordingly.

Conclusion

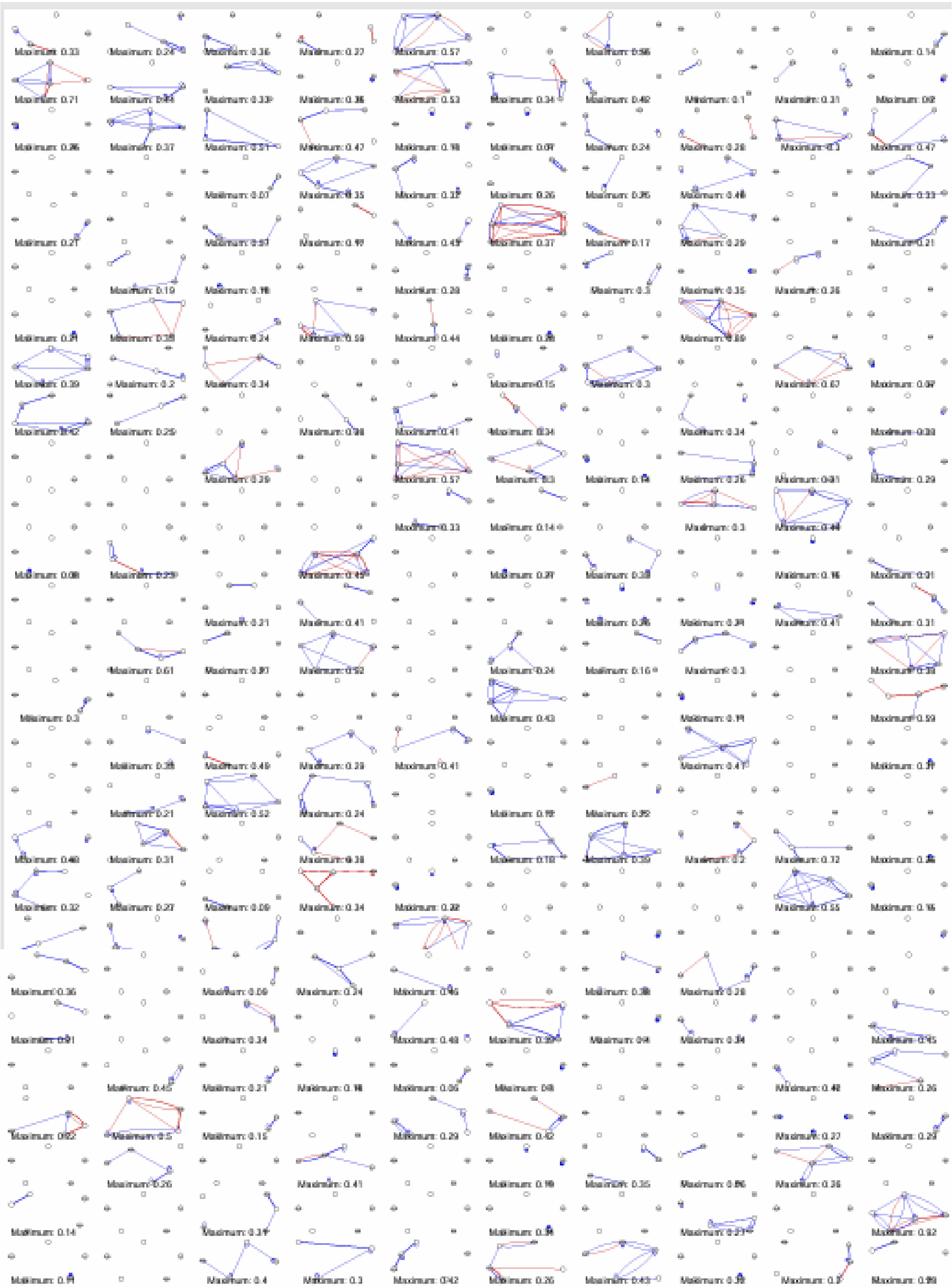
Overall, the purpose of this study was to investigate associations between positive and negative emotional persistence and various transdiagnostic measures of well-being. We found that positive inertia and network density were related to future, but not concurrent, reports of well-being. Negative emotional connectivity was inversely related to HRV. Finally, no measure of emotional persistence was related to linguistic sentiment from a 10-minute interview, but average daily positive affect was associated with tendency towards positive sentiment (higher positive and lower negative sentiment) during the interview. These studies provide insight into how emotional inertia and emotion network density, while thought to represent similar constructs, are distinctly different concepts. The results also highlight the different pathways by which positive and negative emotional persistence relate to mental health. Future research should clarify the mechanisms underlying emotional persistence, continue to address methodological shortcomings such as low sample size, and investigate emotional persistence in the context of treatment and intervention for anxiety and depressive disorders.

Appendix A: Ecological Momentary Assessment Questionnaires

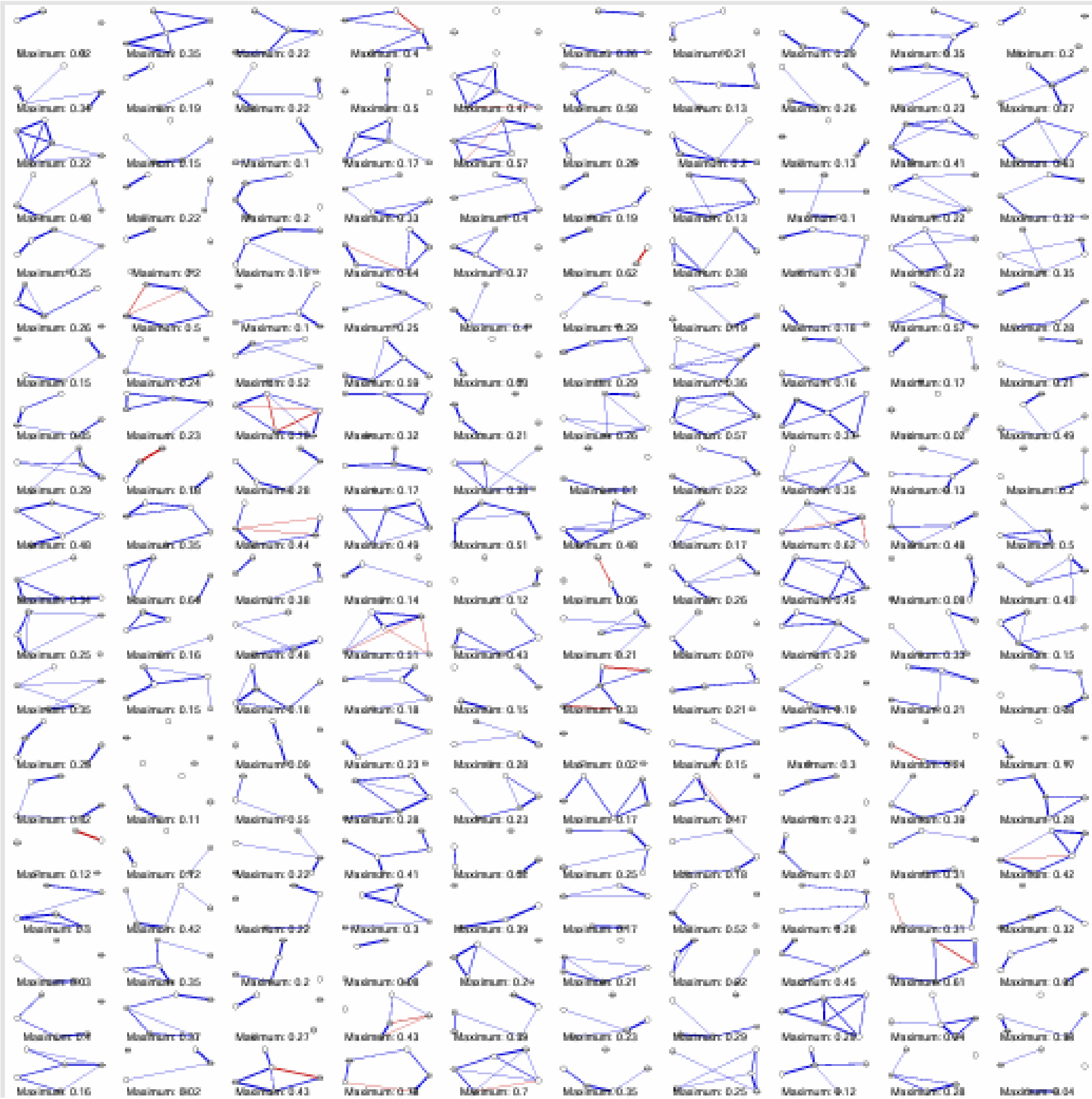
	1 Not at all	2 Slightly	3 Moderately	4 Very	5 Extremely
How sad do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How stressed do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How anxious do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How annoyed/irritated do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How energetic do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How happy do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How motivated do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How engaged do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5
How lonely do you feel right now?	□ 1	□ 2	□ 3	□ 4	□ 5

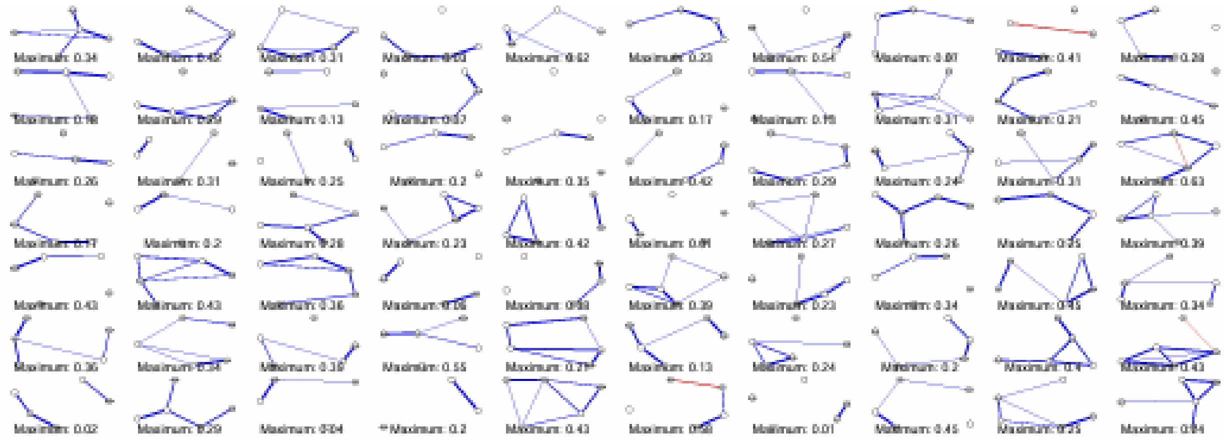
Appendix B: Visuals of Idiographic Networks

Negative Affect Temporal Networks, Epochs 1-2

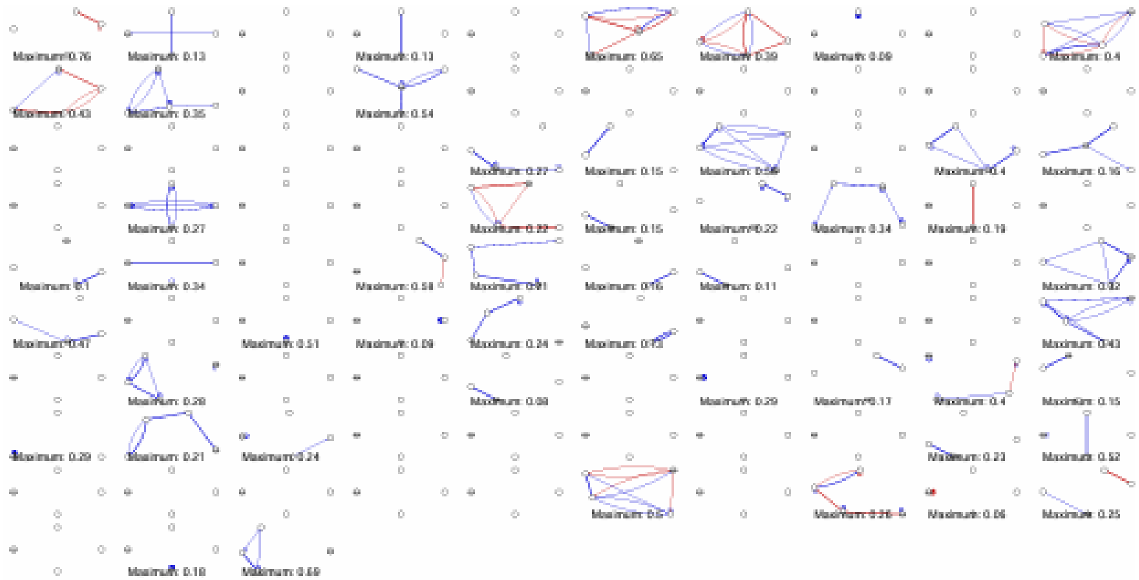


Negative Affect Contemporaneous Networks, Epochs 1-2

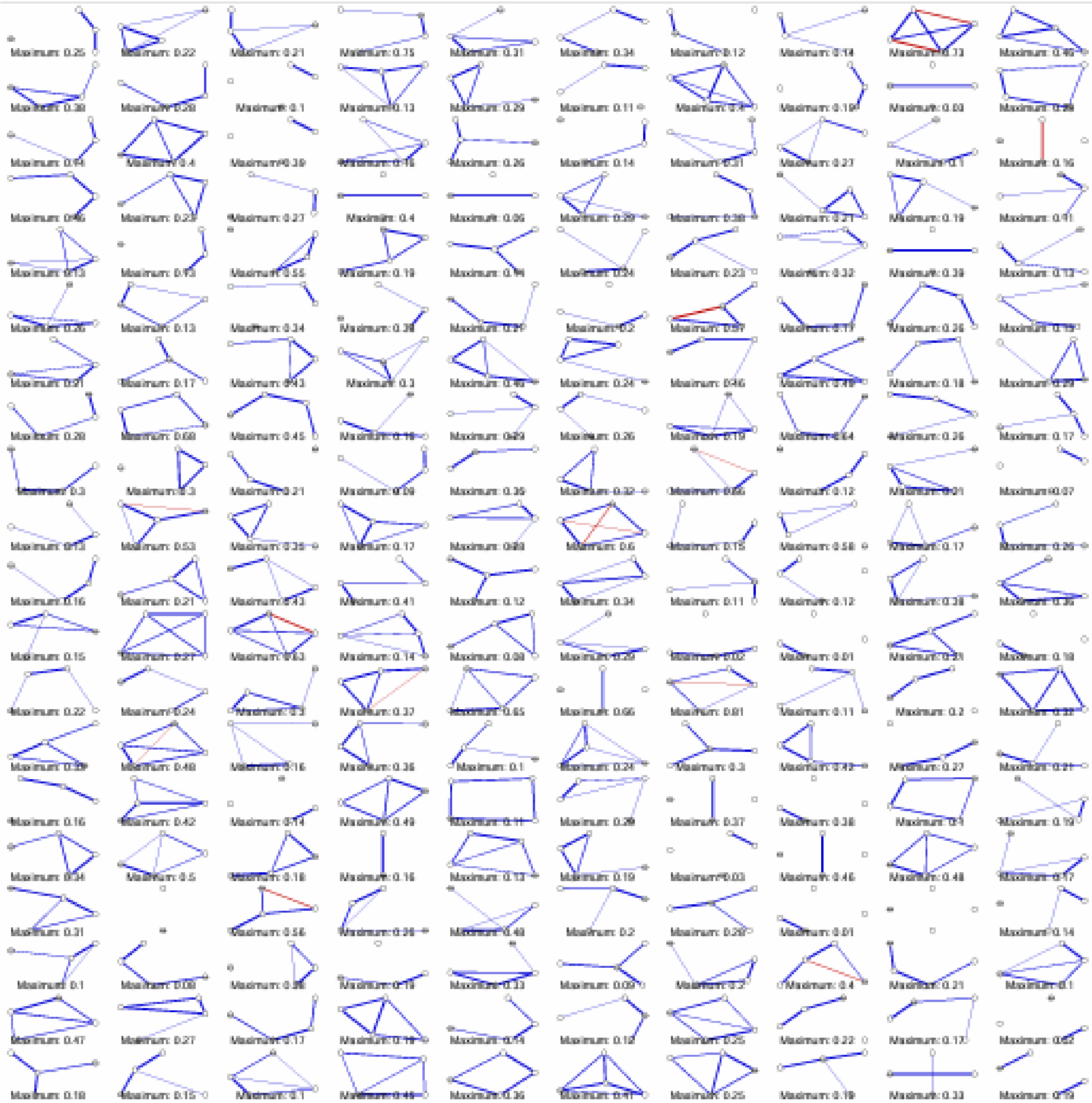


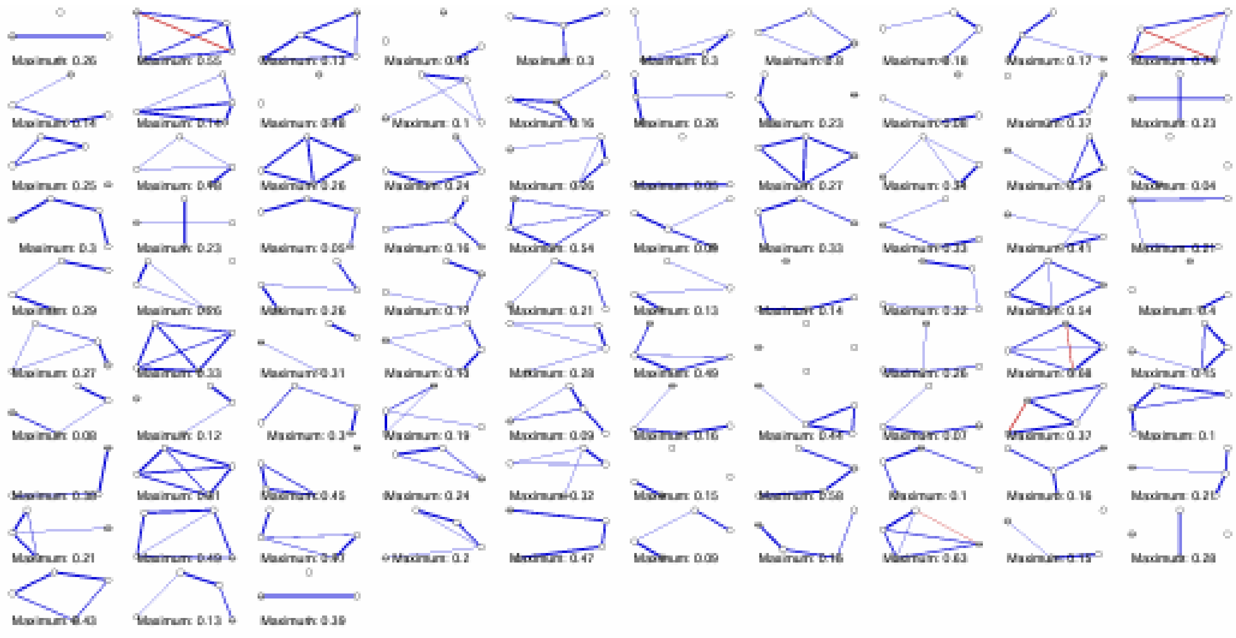


Positive Affect Temporal Networks, Epochs 1-2

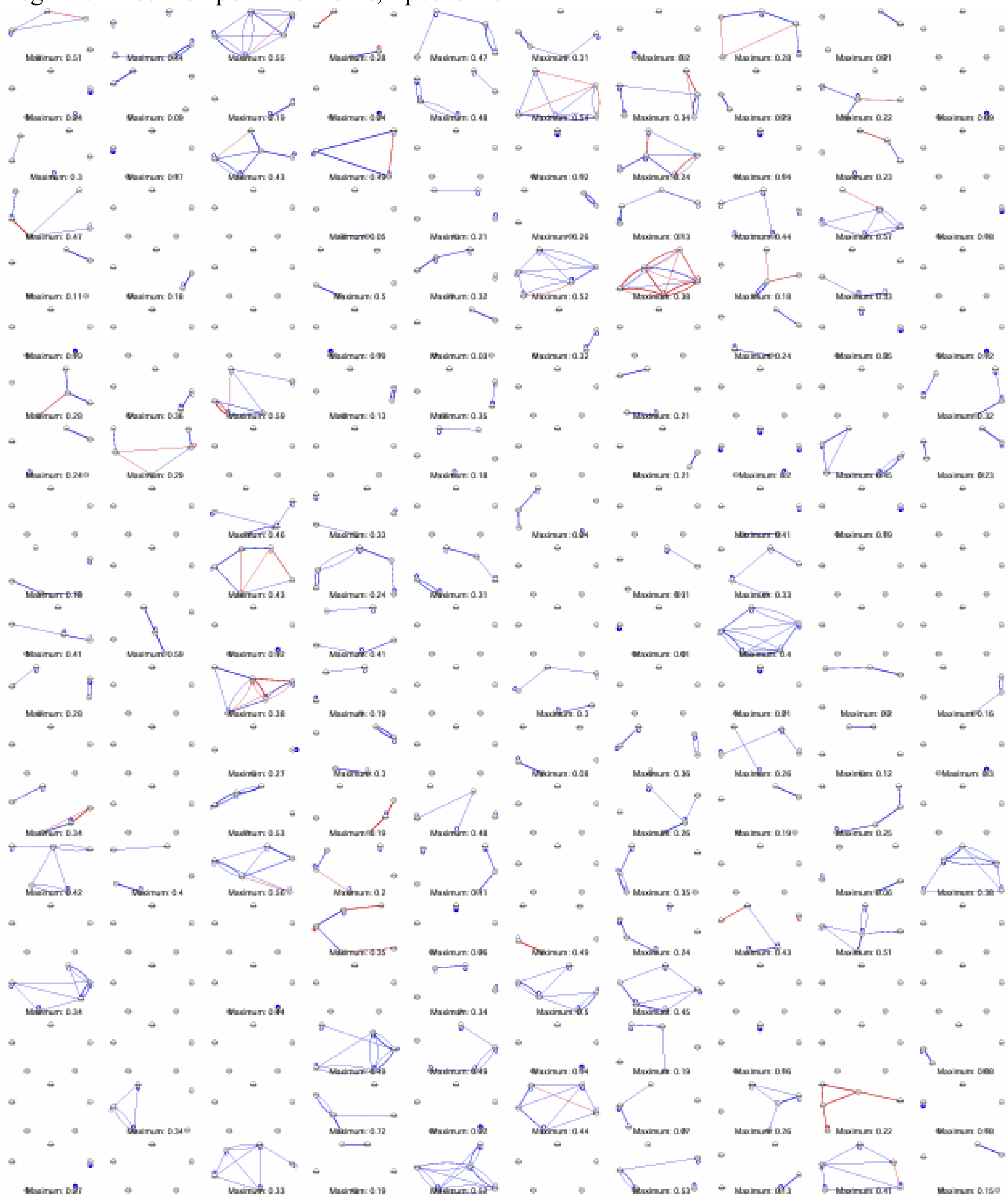


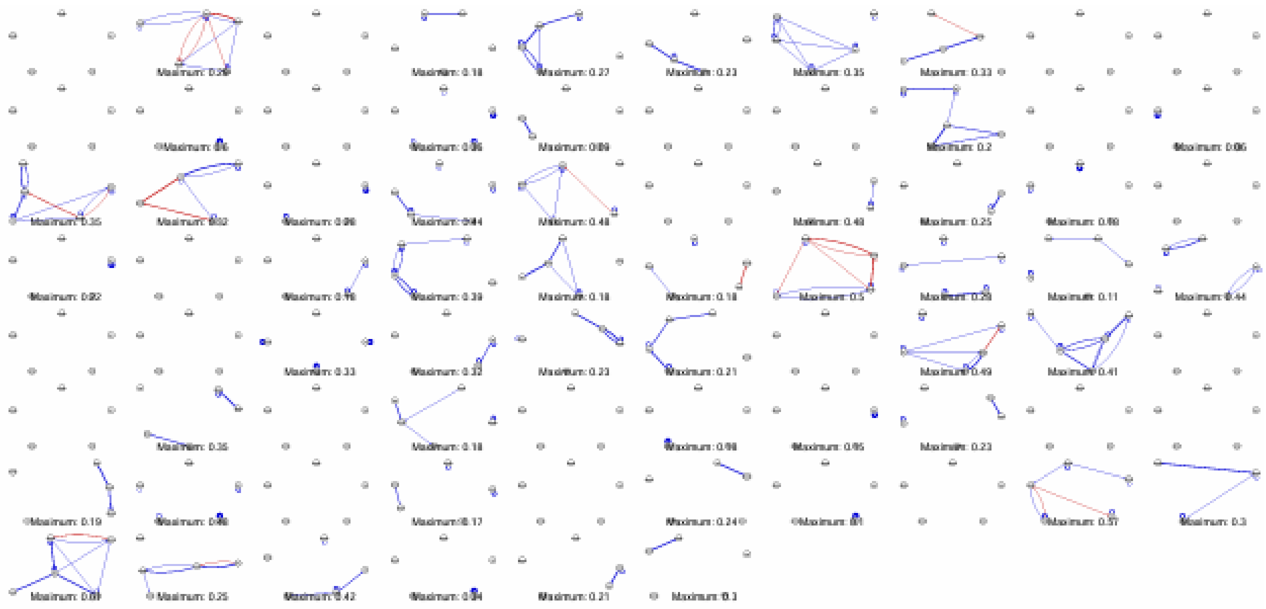
Positive Affect Contemporaneous Networks, Epochs 1-2



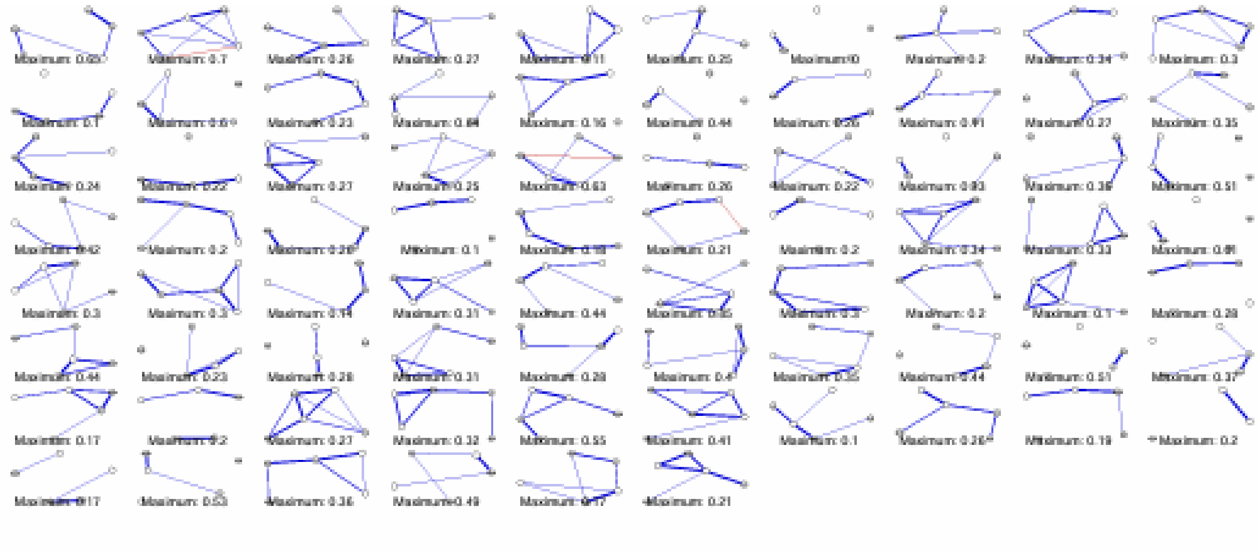


Negative Affect Temporal Networks, Epochs 1-3

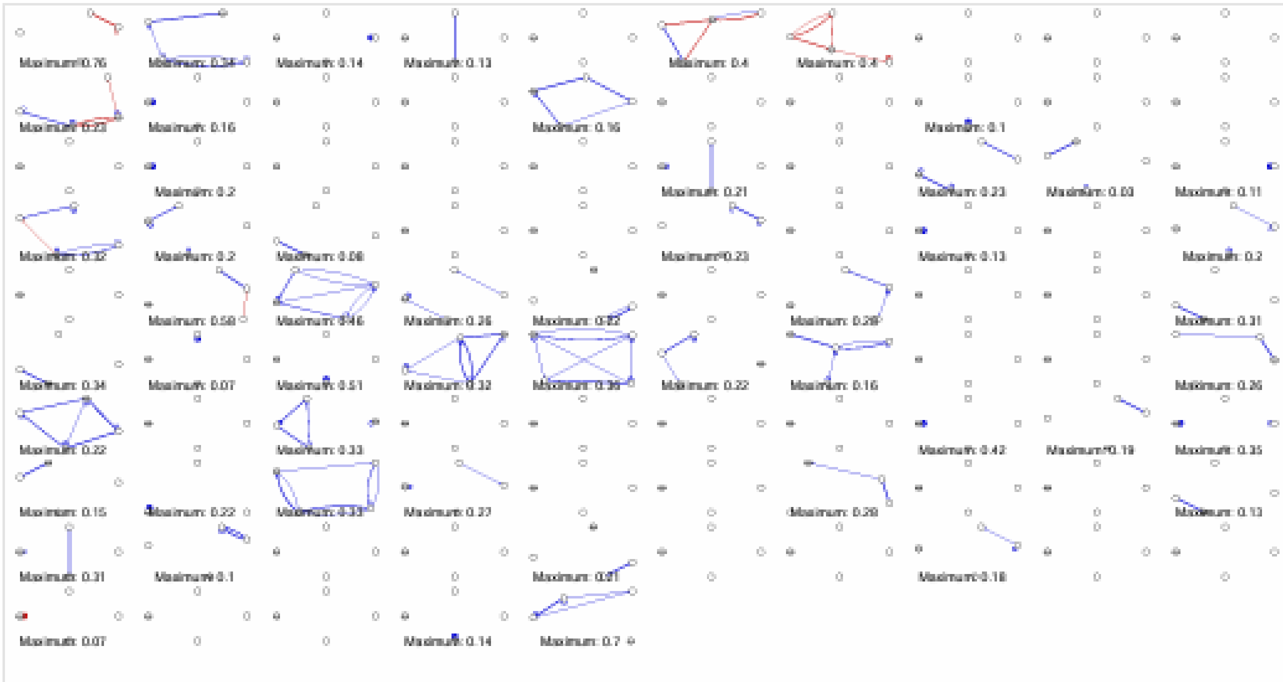




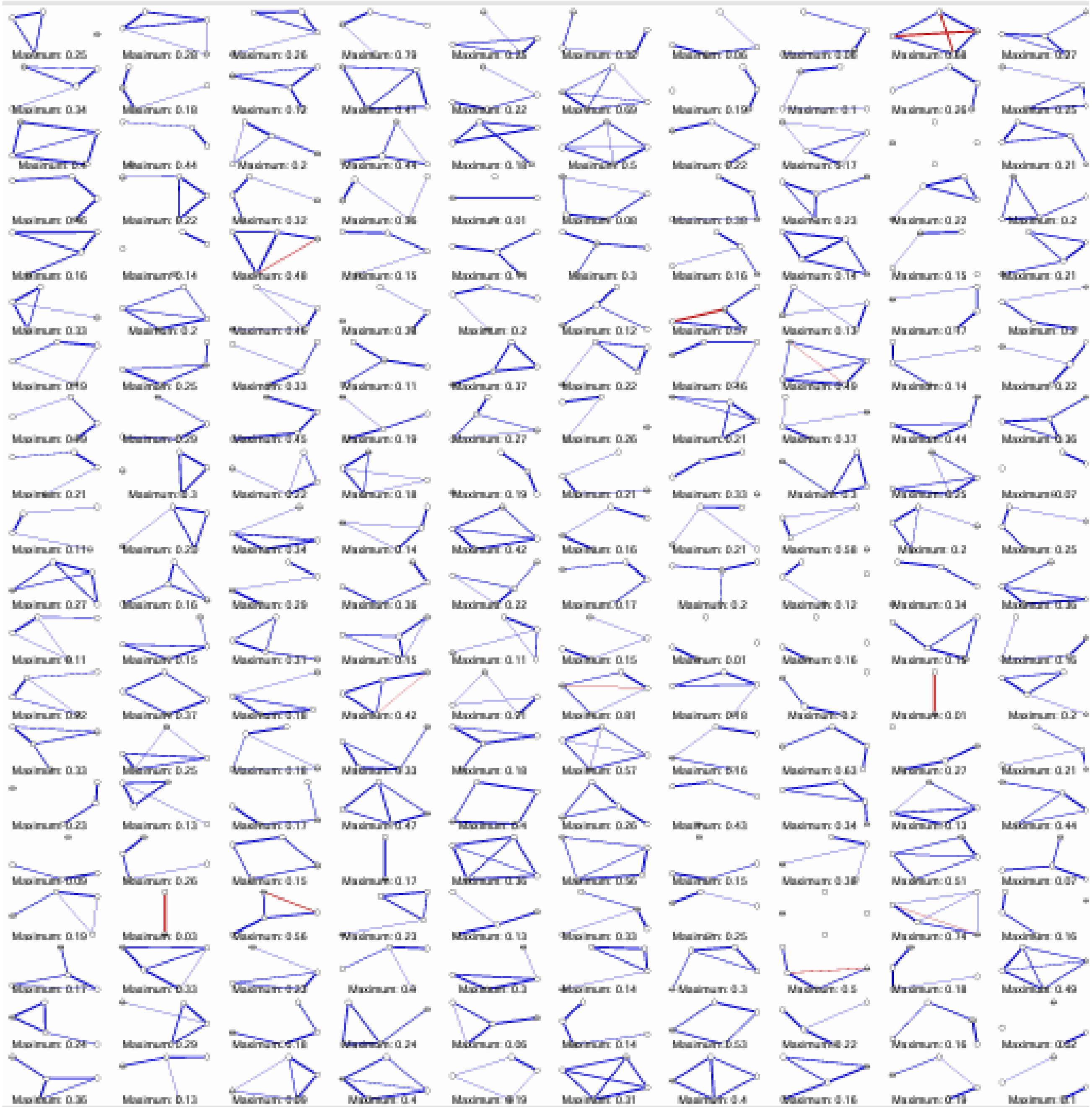
Negative Affect Contemporaneous Networks, Epochs 1-3

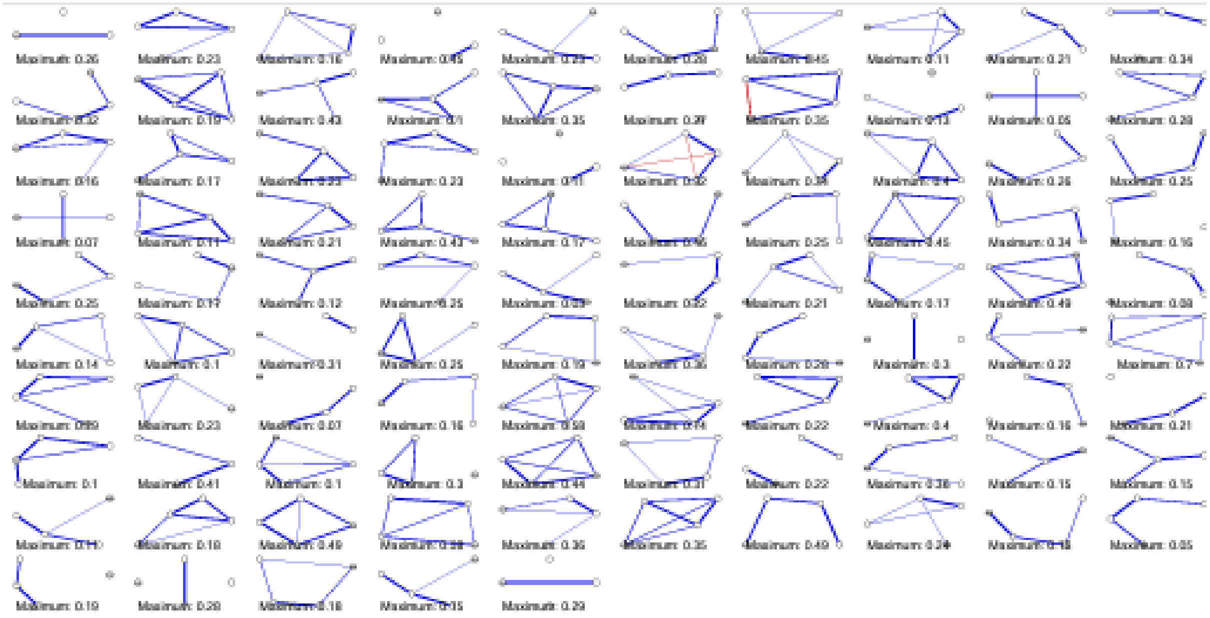


Positive Affect Temporal Networks, Epochs 1-3



Positive Affect Contemporaneous Networks, Epochs 1-3





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