Emotion

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Patterns of Emotion-Network Dynamics Are Orthogonal to Mood Disorder Status: An Experience Sampling Investigation

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Individuals differ markedly in how they experience the ebb and flow of emotions. In this study, we used daily experience sampling to examine whether these differences reflect the nature and presence of mood disorders or whether they can better be characterized as distinct dynamic emotion profiles that cut-across diagnostic boundaries. We followed 105 individuals in 2019–2020 with diagnoses of major depression, remitted major depression, bipolar disorder, or no history of disorder, over 14 days ($n = 6{,}543$ experience-sampling assessments). We applied group iterative multiple model estimation, using both diagnosis-based and data-driven methods to investigate similarities in unfolding within-person emotion-network time-courses. Results did not support diagnosis-based subgroupings but rather revealed two significant data-driven subgroups based on dynamic emotion patterns. These data-driven subgroups did not significantly differ in terms of clinical features or demographics, but did differ on key emotion metrics—instability, granularity, and inertia. These data-driven subgroupings, agnostic to diagnostic status, provide insights into the nature of idiographic emotion-network dynamics that cut-across clinical diagnostic divisions.

Keywords: emotion, experience sampling, depression, bipolar, idiographic analysis

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Mood disorders, such as depression and bipolar disorder, are a leading cause of distress and disability worldwide (Alonso et al., 2011; Friedrich, 2017; Grande et al., 2016). They are characterized by core difficulties with negative and positive affect and motivation (Rottenberg, 2005) alongside myriad behavioral, somatic, and cognitive symptoms, including manic or hypomanic episodes in bipolar presentations (American Psychiatric Association, 2013). These characterizations have historically been developed based on comparisons of "disordered" individuals against normative distributions of functioning. This approach has generated a vast corpus of nomothetic (between-person) clinical research whereby individuals diagnosed with a mood disorder are compared, along multiple dimensions, with relevant mentally healthy control groups.

This nomothetic research tradition has generated many valuable insights into the nature of human mood and emotional difficulties. However, there is a long-standing awareness that individuals with mood disorders, in addition to showing marked between-group differences from healthy peers, are also characterized by complex dynamic, *within-person* or possibly even *idiographic* interactive patterns between core symptoms and underlying affective, cognitive, behavioral, and inter-personal processes, that manifest and change over time in response to and in interaction with the environment.

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These results have not been shared in any prior disseminated conferences or publications. Methods and procedures were approved by the Cambridge University Psychology Research Ethics Committee (PRE.2019.040).

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Anonymized data and analysis code are shared openly on GitHub to encourage replication and reproducibility of findings (https://github.com/mkullar/DataDrivenEmotionDynamics). This study was not preregistered.

Monica Kullar served as lead for conceptualization, data curation, formal analysis, investigation, methodology, project administration, validation, visualization, writing–original draft, and contributed equally to funding acquisition. Scott Carter served as lead for software and served in a supporting role for writing–review and editing. Caitlin Hitchcock served in a supporting role for data curation and writing–review and editing. Steve Whittaker served in a supporting role for software and writing–review and editing. Aidan G. C. Wright contributed equally to methodology and served in a supporting role for formal analysis, validation, and writing–review and editing. Tim Dalgleish served as lead for funding acquisition, supervision, and served in a supporting role for conceptualization, formal analysis, investigation, methodology, project administration, resources, and writing–review and editing.

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Indeed, the differences in behavior, affect and cognition that vary within-person across situations can be of comparable magnitude to any differences between individuals. Furthermore, relationships between variables that are valid at the between-person level are not necessarily applicable at the within-person level (Fleeson, 2001; Molenaar, 2004). Thus, although the prototypical between-person research studies that typify the clinical literature can clarify how individual differences are structured in the population, they provide little insight into how behavior, mood, emotions, and cognition are organized idiographically within the individual (Fleeson & Noftle, 2012).[1]

This long-standing awareness of the importance of dynamic intra-individual interactions over time between symptoms, and with events in the environment, is at the heart of established and contemporary psychological theories of mood disorders (e.g., Beck & Haigh, 2014; Borsboom & Cramer, 2013; Smith et al., 2021). These theories characterize mood disorders as emerging through entrenched patterns of relationships within this dynamically unfolding matrix. These theoretical conceptualizations then provide a natural route to the person-specific, idiographic formulations that lie at the heart of clinical practice, whereby the particular dynamic profile of inter-relating factors for each patient is elucidated (e.g., Persons, 2012). These formulations then motivate bespoke intervention protocols that seek to disrupt dysfunctional within-person processes to enable change.

Two further features of these theories merit comment. First, their purview extends beyond the traditional sets of signs and symptoms enshrined within diagnostic manuals to include key biopsychosocial processes deemed to play a causal role in etiology, maintenance, and recovery. For example, the central role of diverse types of maladaptive cognitions within Cognitive Therapy conceptualizations (Beck & Haigh, 2014). Second, these theories often do not respect traditional nosological boundaries between diagnoses. Rather, they are compatible with a transdiagnostic approach (Dalgleish et al., 2020) that seeks to formulate the profile of clinical difficulties for each patient, regardless of whether that profile is best characterized in terms of no clear diagnosis, a single diagnosis, or comorbid diagnoses.

One dynamic within-person processing domain that is central to theoretical, empirical, and clinical approaches to human mood disorders is unfolding emotional experience. Human emotional life is a fluctuating and time-dependent phenomenon (aan het Rot et al., 2012; Bonsall et al., 2012; Crowe et al., 2019; Scherer, 2009) where emotions shift in type and intensity as a result of internal and external events (Frijda, 2017) and where, critically, such within-person fluctuations are distinct from mean levels of emotions aggregated across individuals and/or over time (Eaton & Funder, 2001; Larsen & Diener, 1987; Sperry & Kwapil, 2019).

Historically one barrier to investigating unfolding emotional experience in an ecologically valid manner has been the difficulty in collecting daily-life data at scale, with early research typically residing within the clinical literature and relying on single-case designs (Spencer & Schöner, 2003). However, detailed assessment of such dynamic processes within the naturalistic setting of day-to-day life, is now feasible due to the development of ambulatory assessment methodologies that record information repeatedly during everyday life routines across large samples (Trull & Ebner-Priemer, 2013), and this had led to a burgeoning literature on emotion dynamics.

This growing body of research indicates that disruptions in emotional fluctuations characterize mood disorders such as major depressive or bipolar disorder with consistent findings revealing higher levels of negative emotion intensity (the average strength of felt emotion across time), lower levels of positive emotion intensity, lower levels of granularity (the ability to make nuanced differentiations between similar emotions) for negative emotion, higher levels of inertia for negative emotions (the extent to which a person's current negative emotion state is predicted by their previous state), and greater emotional instability (fluctuations in emotion intensity over time), relative to both healthy persons and those in remission from depression (aan het Rot et al., 2012; Bonsall et al., 2012; Crowe et al., 2019; Dejonckheere et al., 2018; Ebner-Priemer & Trull, 2009; Gruber et al., 2013; Houben et al., 2015; Koval et al., 2013; Kuppens et al., 2012; Smidt & Suvak, 2015; Thompson et al., 2012, 2021; see Dejonckheere et al., 2019, for an overview). Such disrupted patterns of emotional experience also seem to precede and predict the onset and course of mood disorders over-and-above mean levels of emotion (e.g., Kuppens et al., 2012; van de Leemput et al., 2014; Wichers et al., 2015).

This extant research has tended to focus on relatively straightforward affective metrics assaying how individual emotions, or broader constructs such as valence, develop and change over time (Dejonckheere et al., 2019). An important aspect of emotional experience that has received less empirical attention is what we might characterize as the "affective montage." This is where emotion experiences, examined within a network or matrix (Borsboom & Cramer, 2013) of multiple interacting emotions, self-perpetuate, or morph into different emotions, or where emotions become stuck within maladaptive reciprocal positive or negative feedback cycles, either relatively contemporaneously or over longer time periods ("lagged" affective dynamics; Izard, 1972). For example, specific negative emotions such as sadness can reactively prompt different emotions such as disgust or anger such that those emotions can be thought of as "coupled" (Power & Dalgleish, 2015). Elucidating the affective montage properly thus involves measuring these inter-connected networks of different emotions and how these networks evolve over time, thus going considerably beyond the extant set of established affect metrics discussed above (Dejonckheere et al., 2019).

Breaking or disrupting such dysfunctional emotional patterns is a core focus within the clinic (Greenberg & Watson, 2006; Power, 2010) and so further understanding the nature of these patterns and how they relate to mood disorders is an important research challenge. The present study, therefore, enlisted repeated intensive data collection within everyday life using ambulatory assessment to elucidate person-by-person the dynamic temporal patterns within a core matrix of positive and negative emotions over a two-week period in a sample of patients with and without a history of mood disorders to allow evaluation of changing emotion networks over time.

[1] In fact, insights from between-person data can only help explain within-person patterns when two very strict criteria are satisfied. When the within-person process is (a) stationary; that is, the statistical characteristics such as mean, variance and covariances do not vary over time and (b) homogeneous across subjects; that is, an identical statistical model applies to each individual in the population (Gayles & Molenaar, 2013; Molenaar, 2004).

Within the canon of emotion dynamics research to date, the main focus has been on whether patterns of affective experience reliably differ across groups of individuals classified according to established diagnostic criteria (aan het Rot et al., 2012; Crowe et al., 2019; Ebner-Priemer & Trull, 2009; Houben et al., 2015; Kuppens et al., 2012; Thompson et al., 2021; van de Leemput et al., 2014). However, as already noted, there has been increasing emphasis on examining whether processes fundamental to psychopathology aggregate in ways that do not closely align with traditional diagnoses (Dalgleish et al., 2020). Initiatives such as the Research Domain Criteria (RDoC; Insel et al., 2010) and the Hierarchical Taxonomy of Psychopathology (Kotov et al., 2021) propose interesting and important alternative conceptualizations of symptoms alongside underlying biopsychosocial processes. This raises the question of whether there are important variations in emotion dynamics that do not map directly onto diagnostic status that could be identified using data-driven analysis within ambulatory assessment data. The patterns across such processes might better align with wider sets of disorders, with sets of symptoms that certain disorders have in common, or more radically, may completely diverge from diagnostic or symptom-based divisions altogether (Cicchetti & Rogosch, 1996; Dalgleish et al., 2020). The capacity to detect meaningful sub-groupings that cut-across a priori diagnostic boundaries using the same analytic methodology is an advantage of the data-driven approach within group iterative multiple model estimation (GIMME).

The present study, therefore, sought to examine whether the changing dynamics of emotion networks over time differ reliably across established diagnostic groups, as well as asking whether there are meaningful clusters of individuals, characterized by different emotion-network dynamics, that do not respect those traditional diagnostic boundaries.

To address our study aims what is required is an analytic approach that firstly, can handle networks of inter-related variables and how they change over time and, secondly, allows both top-down diagnosis-aligned evaluations as well as putative data-driven transdiagnostic or adiagnostic evaluations and, finally, that is able to bridge the traditional idiographic-nomothetic divide that has hitherto characterized the literature.

Such an approach would therefore need to provide a personalized analysis of an individual's dynamic associations within networks of emotions, while also nesting these person-specific analyses within a broader nomothetic structure. Importantly, any such approach must also accommodate the inevitably high heterogeneity in the idiographic pathways within the emotion matrix across individuals, while also revealing important commonalities if and when present.

A compelling approach that meets these diverse criteria is GIMME (Gates & Molenaar, 2012). GIMME uses principles of unified structural equation models (uSEMs) and vector autoregression to capture within-person associations between interconnected sets of study variables and how these change over time, while also taking advantage of between-person information across the sample by including group-level information in the final derived individual-level solutions (Beltz & Gates, 2017). This allows GIMME to generate clustered subgroups with similar within-person dynamic process profiles (Gates et al., 2017). An important added benefit is that these subgroupings within GIMME can either be derived in a data-driven manner, based on discovered shared commonalities across individual processes, or they can be evaluated using a confirmatory approach (Henry et al., 2019), whereby potential commonalities across a priori subgroups such as preexisting diagnoses can be assessed (Gates et al., 2017). This allows the same analytic framework to be used to elucidate traditional diagnosis-based commonalities within a study sample, alongside putative data-driven adiagnostic or transdiagnostic subgroupings (Dalgleish et al., 2020; Insel et al., 2010).[2]

Thus, our key research question investigated whether these putative subgroups, based on patterns of emotion dynamics, align with traditional diagnostic groupings, evaluated using confirmatory GIMME, that allows the user to specify the groupings of participants, and/or whether data-driven GIMME, that uses algorithms to search for similar patterns in person-specific models, can identify robust subgroups that cut-across these a priori nosological boundaries.

Having used GIMME to potentially identify robust subgroups that are either aligned with diagnoses and/or exhibit differential data-driven profiles, we can then examine how these putative subgroups potentially differ from one another on key additional demographic (e.g., age, gender), and clinical variables (e.g., symptom frequency, intensity), as well as the established emotion metrics discussed above (see Dejonckheere et al., 2019) including emotion intensity, instability, inertia, and granularity (the degree of differentiation between similar emotions; Smidt & Suvak, 2015).

Specifically, then, the current study gathered naturalistic information about emotion-network dynamics across a 14-day period in a diverse sample who met diagnostic criteria for (a) major depression currently in episode, (b) major depression in remission, (c) bipolar disorder, or (d) no history of mood disorder. We analyzed multiple intraday ratings across a range of specific emotions to elucidate intra-individual and subgroup profiles of associations between emotions.

We evaluated the following three tiers of confirmatory diagnostic subgroupings: two subgroups, one with a mental ill-health history and one with no mental ill-health history (with all three clinical groups collapsed together relative to healthy controls); three subgroups, one with a unipolar depression history (pooling currently depressed and remitted individuals), one with a bipolar history, and healthy controls; and four subgroups comprising currently depressed, remitted-depressed, bipolar disorder,[3] and healthy participants. Various outcomes were plausible for these diagnosis-led analyses and the current state of the empirical and theoretical literature precludes prioritizing any given set of particular predictions over another. For example, those with any mental ill-health history might be expected to show more consolidated patterns of self-reinforcement among the different negative emotions, both contemporaneously and lagged (Selby et al., 2008). This could contrast with similar cascading relationships for positive emotions (Fredrickson, 2001), alongside

[2] Because of these advantages, GIMME is gaining currency within mental health research. A detailed primer on GIMME is beyond our scope here, but the reader is directed to a number of excellent papers introducing and applying the method (Lane et al., 2019; Wright & Zimmermann, 2019).

[3] Participants with bipolar disorder history were not further separated by episode status due to the majority being in depressive episode and no currently manic/hypomanic participants available for participation (see Participants section).

positive affective responses to negative emotions (Garland et al., 2010), in those with no mental ill health history. These patterns could be more established in those with acute symptoms compared to those in remission (Rottenberg, 2017). One might also expect differences between participants with unipolar depression versus bipolar depression, with negative responses to affect putatively more consolidated in the latter group (Edge et al., 2013). As noted already, more specific patterns are also plausible; For example, individual negative emotions such as sadness might reactively prompt other negative emotions such as disgust or anger—patterns that have been characterized in the theoretical literature as emotion "coupling" (e.g., Power & Dalgleish, 2015).

We next also used data-driven analysis within GIMME to cluster person-specific models into possible bottom-up subgroups respecting shared dynamic commonalities that putatively cut-across these a priori diagnostic divisions.

Having derived and extracted information about dynamic associations between positive and negative emotions across diagnostically defined and data-driven subgroups, where indicated we sought to further characterize how any putative subgroups might differ from one another on a range of demographic, clinical, and affective metrics.

Method

Participants

We recruited 114 participants, aged 18–70 to take part in the study during 2019–2020. Participants underwent a diagnostic assessment based on the DSM-5 criteria for mood/anxiety disorders via the Structured Clinical Interview for DSM (First et al., 2015). Recruitment was transdiagnostic in aim within the mood disorders and included individuals with: (a) major depressive disorder (MDD) in episode ($n = 39$); (b) MDD in remission ($n = 28$); (c) bipolar disorder ($n = 14$); and (d) no history of any mood or anxiety disorder ($n = 33$).

Clinical samples were recruited from a patient database at the Cognition and Brain Sciences Unit. Additional inclusion criteria included normal or corrected-to-normal vision, English fluency, and possession of a personal smartphone with SMS service and internet access for experience sampling. Exclusion criteria included current alcohol/substance use disorder, organic brain damage, current psychosis, brain injury, intellectual disabilities, or current requirements for ongoing management of self-injury/suicide risk.

A priori power analysis for time-series approaches have not yet been sufficiently developed, and thus as many participants as possible were enrolled into the study within our time constraints in line with similar studies (Aalbers et al., 2019; Greene et al., 2020). For GIMME analysis, ability to detect effects is determined by the timepoint numbers, rather than sample size per se, with a minimum of 10 participants and 60 timepoints advisable to adequately detect signal from noise and recover accurate models (Gates et al., 2017; Lane et al., 2019). On this basis, it is reasonable to assume we had adequate power for our analysis approach.

Five enrolled participants were excluded from analyses; three completed fewer than 50% of experience sample surveys ($M = 30.67\%$) and two withdrew participation in the first few days due to technical issues. Data from four further participants were set aside due to data quality (see Results section). The analysis sample therefore comprised 105 individuals with a relatively high number of observations ($n = 6{,}543$ fully complete observations across 70 timepoints) compared to other experience-sampling-based studies (e.g., Crowe et al., 2019; Hill & Updegraff, 2012; Ludwig et al., 2020; van Winkel et al., 2015).

Measures

Clinical Information

The Structured Clinical Interview for the DSM-5—Research Version (SCID-5-RV). The SCID is a comprehensive structured interview including modules for mood, anxiety, and stressor disorders, with good reliability, specificity, and clinical validity (First et al., 2015; Osório et al., 2019). Interviews were completed by a trained researcher, and all diagnoses were second-rated blind by a clinical psychologist with 100% agreement.

The Expanded Inventory of Depression and Anxiety Symptoms (IDAS-II). The IDAS-II is a widely used symptom self-report measure spanning 19 transdiagnostic mental health subscales: General Depression, Dysphoria, Lassitude, Insomnia, Suicidality, Appetite Loss, Appetite Gain, Well-Being, Ill Temper, Mania, Euphoria, Panic, Social Anxiety, Claustrophobia, Traumatic Intrusions, Traumatic Avoidance, Checking, Ordering, and Cleaning. The IDAS allowed us to characterize our confirmatory and/or data-driven GIMME subgroups in terms of continuous transdiagnostic symptom dimensions. The IDAS-II is a reliable and valid measure (Watson et al., 2012). Internal reliability in our sample was high across all subscales (Cronbach's αs $= 0.72$–0.94; see online supplemental materials).

The Patient Health Questionnaire-9 (PHQ-9). The PHQ-9 is a severity measure for depression and was included to provide a brief, reliable, and valid (Kroenke et al., 2001) measure of current depression symptom severity over the previous 2 weeks across all participants.

The Generalized Anxiety Disorder-7 (GAD-7). The GAD-7 is a seven-item severity measure for generalized anxiety and was included to provide a brief reliable and valid (Spitzer et al., 2006; Löwe et al., 2008) measure of anxiety symptoms over the previous two weeks across all participants.

Internal consistencies for the PHQ-9 ($\alpha = 0.91$) and GAD-7 ($\alpha = 0.92$) were high in our sample.

Ambulatory Assessment

To collect naturalistic dynamics ratings, a novel web-based platform was developed and used for signal-contingent data collection. Experience sampling collection was employed via personalized survey links sent to participants' mobile phones by SMS at pre-programmed times. Participants were prompted for 14 days with five daily signals beginning at 10:00 am and continuing every 2 hr. To avoid formulaic responses to expected collection times, signals were delivered within a 30-min window (e.g., the first signal was sent at a randomized time between 9:45 am and 10:15 am).

Emotion Self-Report. To assess the unfolding dynamics of emotional experience for each individual across time, at each prompt, participants were asked to rate the present intensity of nine emotions (enthusiastic, happy, pleased, relaxed, nervous, sad, angry, irritated, and stressed) on 7-point Likert scales from 1 (*not at all*) to 7 (*extremely*) (see online supplemental materials for

emotion term selection methods). Emotions were selected to represent the complete bi-dimensional space of positive to negative valence and high to low and arousal. Following each set of emotion ratings, participants rated the chronometry of their overall current emotion state by estimating how long it had lasted (in minutes). Participants also provided a yes/no response as to whether they were thinking about something other than what they were currently doing (Chaieb et al., 2021).[4]

Given that limited information is added when investigating covariance across time when emotion terms very frequently co-occur, we examined post hoc patterns of repeated measures inter-correlations (r_{rm}) between positive- and negative-valence emotions, and collapsed the highest inter-correlating positive emotions—"happy" and "pleased" hereafter referred to as "Happy"; r_{rm} (6,446) = .71, $p < .001$ and negative emotions—"angry" and "irritated" hereafter referred to as "Angry," r_{rm} (6,444) = .63, $p < .001$ to single terms. The between-person Spearman correlation confirmed they were the highest correlating valence pairs—Happy-Pleased $r(103) = .95$, $p < .001$ and Angry-Irritated $r(103) = .88$, $p < .001$. Seven final emotion terms (happy, angry, enthusiastic, relaxed, nervous, sad, and stressed) were therefore used in the final analysis to maintain a granular set of emotion terms while mitigating the influence of highly correlating items (see online supplemental materials). The affective dynamics of emotional intensity, instability, granularity, and inertia were calculated from the collected emotion time courses of participants. Each metric was calculated separately for positively and negatively valenced emotion, following prior work (Houben et al., 2015; Pond et al., 2012; Thompson et al., 2021) and the added benefit to compare differential emotion functioning (see Results section).

Additional daily diary measures were collected each evening as part of a wider study.

Procedures

Methods and procedures were approved by the Cambridge University Psychology Research Ethics Committee (PRE.2019.040). This study was not preregistered. Participants attended an initial session where they were briefed on study procedures and provided informed consent and then completed clinical measures (SCID-5, IDAS-II, PHQ-9, and GAD-7) and were introduced to the experience sampling platform which commenced the following day. At the end of the 14-day experience sampling period, participants were debriefed, paid, and thanked.

Analytic Plan

Group Iterative Multiple Model Estimation. GIMME was estimated in the R statistical language with *gimme*, which allows options to assess for confirmatory and exploratory subgroup analyses. Data-driven subgroup solutions were assessed for robustness using *perturbR* (Gates et al., 2019; Lane & Gates, 2017). GIMME estimates uSEMs for each individual, which can be understood to be networks of regression paths, both contemporaneous and lagged (lag-1). GIMME provides an emergent group-level model/structure (i.e., the set of paths that will be freely estimated for all individuals) across participants, and person-specific (idiographic) models for each individual. Group-level structure was determined through modification indices that identified the contemporaneous and lagged paths that significantly (Bonferroni corrected by the number of participants, $p \leq .05/N$) improved model fit for the majority ($\geq$75%) of the sample iteratively a cutoff determined to be optimal for signal-to-noise detection in simulation studies (Gates et al., 2017). This process iterates until no further relations significantly improve the models of the sample majority (see online supplemental materials for further details). For GIMME, preprocessing included assessing missingness, constant variables, linear trends, and inclusion of hypothesized outside (exogenous; Arizmendi et al., 2021) influences on the model like diurnal "time of day" (see online supplemental materials for further details).

For the confirmatory analysis, as noted in the Introduction, subgroup assignments were based on our a priori diagnostic groupings, identifying whether any significant paths exist for the majority of participants (51%) within these predetermined subgroups provided as input in *gimme*. For our exploration of putative data-driven subgroups, subgroup assignments were determined for clusters of individuals with similar dynamic processes (i.e., patterns of contemporaneous and lagged emotion associations). To do this, similarity matrices were generated with *gimme* based on person-specific models, and a community detection algorithm (*Walktrap*) based on random walks between pairwise person-specific similarity matrices searched for possible clusters (Pons & Latapy, 2006). Subgroup-level analysis continued to iterate for paths that significantly ($p \leq .05$) improve model fit for the majority ($\geq$51%) of the subgroup, a cutoff determined to be optimal for subgroups (Gates et al., 2017). S-GIMME has been shown to provide accurate subgroup identification and path recovery at various sample sizes, including smaller subgroups where $n < 25$ (Gates et al., 2017; Simoes et al., 2022).

Finally, to return to the person-specific level models, structure was established for each participant using modification indices to determine the contemporaneous and lagged relations that significantly improve model fit for the participant, iterating until there are no more significant relations, with nonsignificant relations removed. Thus, each final person-specific model is a combination of the group structure (i.e., paths present in the majority of the sample), subgroup structure (i.e., paths identified as present in the majority of the sub-group), and person-specific structure (i.e., paths that are present only in the individual or in a minority of participants). All estimated paths have weights unique to each individual (Gates et al., 2017).

Evaluation of GIMME Solution Robustness. For both the confirmatory and putative data-driven subgroupings, a modularity value (Q) was generated for the overall solution. Q indicates the extent to which there is greater similarity between individuals within a subgroup, compared to between subgroups, than would be expected by chance (i.e., calculated as the summation of the number of edges falling within subgroups, minus the expected number in an equivalent network with edges placed at random; Gates et al., 2017; Newman, 2006). A positive Q value, therefore, indicates the presence of community structure (Newman, 2004, 2006) while a negative Q value means there are fewer edges within a subgroup than expected by chance and may be interpreted as "anti-modular." A negative Q value indicated that solutions are not robust and in that

[4] Six additional follow-up items reported on the nature of the extraneous thought content only if participants reported "yes" to this latter probe, as part of a separate study. These items were therefore not used in this analysis for theoretical and methodological reasons (see online supplemental materials).

eventuality, no further solution evaluations are applied (Hintze & Adami, 2010; Newman, 2006).

Further evaluation of the robustness of subgroups with acceptable Q values then includes: perturbing the paths relating to individual similarity matrices within subgroups incrementally to test stability of the subgroup clusters; examining the variance of information (VI) as the distance between resulting subgroups in comparison to a random distribution; and calculating an adjusted rand index (ARI) as a cluster validation measure of agreement on subgroup partitions (Gates et al., 2019).

Transparency and Openness

We report how we determined our sample size, all data exclusions, and provide all data and analysis code shared openly on GitHub to encourage replication and reproducibility of findings (github.com/mkullar/DataDrivenEmotionDynamics). This study was not preregistered.

Results

Demographics

As noted, data from four participants were set aside due to constant self-report of "1" across all timepoints for "Nervous" or "Angry," since the uSEM framework of GIMME cannot assess constant variables for which there is no variance as is the case with all association-based analyses (Lane & Gates, 2017). This provided a final analysis sample of $n = 105$. Clinical groups were not significantly different for age, gender, ethnicity, income, and education (see Table 1). As expected, depressed and bipolar participants had the highest ratings of depression and anxiety, followed by lower levels in remitted participants, and very low levels in healthy participants, PHQ-9—$p < .001$, $\eta_p^2 = 0.51$, 95% CI [0.40, 0.65]; GAD-7—$p < .001$, $\eta_p^2 = 0.41$, [0.26, 0.55]; see Figure 2. For additional diagnostic information, see online supplemental materials.

The total missingness of all intraday experience sampling measures was low at 10.62% missing timepoints across the sample, and 0.35% partially missing timepoints. The average number of complete timepoints across the sample appeared sufficiently powered for GIMME ($M = 62.31$, $SD = 8.11$). There was no significant difference in missingness across the diagnostic groups, $\chi^2(3, 109) = 3.72$, $p = .29$. Given the relatively low level of data missingness in the sample, we moved forward with a full information maximum likelihood approach utilized by GIMME that can handle missing values (Beltz & Gates, 2017).

GIMME Outcomes

Confirmatory Analyses Examining A Priori Diagnostic Sub-Groups

As outlined in the Introduction, three levels of theoretically-based confirmatory subgroupings were modeled: (a) two subgroups with all clinical participants combined ($n = 76$) compared to healthy controls ($n = 29$); (b) three subgroups with current/past major depression ($n = 65$), bipolar disorder ($n = 11$), and healthy controls ($n = 29$); and (c) four subgroups with currently depressed ($n = 37$), remitted depressed ($n = 28$), bipolar disorder ($n = 11$), and healthy controls ($n = 29$). All participant person-specific models loaded successfully, except for one participant whose individual solution estimation failed to converge with the subgroup solution.

For all three levels of confirmatory subgroupings based on diagnosis, the modularity of the subgroupings was negative (two subgroups $Q = -0.0049$; three subgroups $Q = -0.0042$, four subgroups $Q = -0.0106$). As noted, such negative modularity implies there are fewer edges between sub-grouped participants than expected by chance (Hintze & Adami, 2010; Newman, 2006) indicating these subgroupings were not robust. There was therefore no support for any of the three levels of a priori diagnostic subgroupings in the data and neither further assessments of subgroup robustness, nor additional analyses characterizing the subgroups, were conducted.

Data-Driven Subgroups

Next, we proceeded with the data-driven approach of putatively clustering participants to subgroups based on dynamic emotion-network patterns rather than clinical diagnostic status. This uncovered two approximately equal-sized subgroups (Subgroup 1, $n = 53$; Subgroup 2, $n = 51$).

In contrast to the confirmatory diagnostic subgroups, the modularity of this data-driven two-subgroup solution was positive $Q = 0.1008$ and indicative of potentially robust community structure in the clustering solution. Further validity checks were therefore conducted.

The two data-driven subgroups were evaluated through comparisons between the solutions from the produced matrix against possible random solutions obtained by perturbing path weights incrementally (Gates et al., 2019). This involved three tests for solution robustness; evaluating whether the solution modularity (Q) was significantly higher than that of a null distribution (critical value for significance; $Q_{95} = 0.0641$), the VI, and the ARI (see online supplemental materials). All three tests indicated that the quality of the data-driven two-subgroup solution was significantly acceptable and robust (modularity: $Q_{\text{solution}} = 0.1008 > Q_{95} = 0.0641$); VI = 0.433, $\alpha > 0.20$; ARI = 0.627, $\alpha > 0.20$. VI shows 43.31% of the obtained two-subgroup solution paths would need to be changed in order to be as different as when 20% of participant subgroup assignments are switched. In contrast, a randomized solution at chance would only need as few as 2% of paths perturbed if groupings were altered. ARI supports this finding, similar confirming a significantly higher level of perturbation is required for the solution than the near immediate drop in a randomized solution at chance (see online supplemental materials; Figure S2 in the online supplemental materials).

The clustering of participants across these two subgroups is displayed in Figure 1a. Here, individuals (represented as nodes) with more similar person-specific dynamic emotion models are displayed closer together, based on their underlying similarity matrices.[5] These clusters were determined through random walks, based on the robust mathematical basis that random walks along a graph

[5] Similarity matrices consist of the counts of all significant possible and estimated paths shared and in the same direction for all pairwise individuals (Gates et al., 2017). A unique aspect of GIMME is that it does not force all participants into subgroups if the fit for a given participant is more heterogenous than uncovered subgroups. On this basis, one participant was not clustered to either subgroup, reflecting a relatively high degree of idiosyncrasy in his/her individual temporal model (see Figure 1a).

Table 1
Demographic Sample Characteristics for the Diagnostic Groups and Healthy Controls

n	Whole sample 105	Depressed 37	Remitted 28	Bipolar disorder 11	Healthy controls 29	Statistic
Demographics						
Age, years: *M* (*SD*)	40.32 (13.56)	40.41 (12.59)	43.36 (13.29)	35.27 (12.49)	39.21 (15.26)	$F = 1.04$, $p = .38$
Female	76 (72.38%)	27 (72.97%)	24 (85.71%)	8 (72.72%)	17 (58.62%)	$p = .16$*
Male	29 (27.62%)	10 (27.03%)	4 (14.29%)	4 (30.77%)	13 (41.94%)	
Ethnicity						$p = .74$*
White (British)	94 (89.52%)	32 (86.49%)	26 (92.86%)	10 (90.91%)	26 (89.66%)	
White (other)	5 (4.76%)	3 (8.11%)	1 (3.57%)	—	1 (3.45%)	
Asian	4 (3.81%)	2 (5.40%)	1 (3.57%)	—	1 (3.45%)	
Black	1 (0.95%)	—	—	—	1 (3.45%)	
Mixed White/Asian	1 (0.95%)	—	—	1 (9.09%)	—	
Income (£)						$p = .39$*
<10,000	23 (21.90%)	8 (21.62%)	6 (21.43%)	4 (36.36%)	5 (17.24%)	
10,000–29,999	48 (45.71%)	20 (54.05%)	14 (50.00%)	4 (36.36%)	10 (34.48%)	
30,000–49,999	16 (15.24%)	5 (13.51%)	4 (14.29%)	1 (9.09%)	6 (20.69%)	
50,000–69,999	5 (4.76%)	1 (2.70%)	1 (3.57%)	2 (18.18%)	1 (3.45%)	
Preferred not to say	13 (12.38%)	3 (8.11%)	3 (10.71%)	—	7 (24.14%)	
Highest education level						$p = .54$*
GCSE	9 (8.57%)	5 (13.51%)	4 (14.29%)	—	—	
A-levels	15 (14.29%)	4 (10.81%)	3 (10.71%)	3 (27.27%)	5 (17.24%)	
HND/BTEC/NVQ levels	14 (13.33%)	5 (13.51%)	5 (17.86%)	2 (18.18%)	2 (6.90%)	
Bachelor's degree	38 (36.19%)	13 (35.14%)	8 (28.57%)	4 (36.36%)	13 (44.83%)	
Master's degree	21 (20.00%)	6 (16.22%)	5 (17.86%)	2 (18.18%)	8 (27.59%)	
Doctoral degree	8 (7.62%)	4 (10.81%)	3 (10.71%)	—	1 (3.45%)	

Note. GCSE = General Certificate of Secondary Education; A-Level = Advanced level; HND = Higher National Diploma; BTEC = Business and Technology Education Council; NVQ = National Vocational Qualifications.
* Fisher's exact test was used with *p*-value noted.

between nodes tend to stay within the same cluster (Harel & Koren, 2001). Paths between individual nodes were not interpreted. Figure 1b depicts shared group and subgroup pathways for the two subgroups.

The overall group majority shared path (valid across both subgroups) is displayed in bolded black. This indicated that for more than 75% of the whole sample, experiencing the emotion "Happy" influenced experiencing the emotion "Enthusiastic" at the contemporaneous level. The figure also shows bolded green subgroup-level paths shared by the majority (≥51%) of participants within a subgroup. These subgroup-specific paths showed notable differences across the two subgroups. Within Subgroup 1, there was a robust contemporaneous pathway with feeling "Angry" influencing the experience of "Sad," but this was not a robust path in Subgroup 2. Other paths linked the same emotion pairs across the two subgroups, but indicated that the emotions influenced each other in opposing directions, as indicated by the directional arrowheads of pathways. For instance, in Subgroup 1, the experience of "Stress" influences the experience of "Angry," whereas the direction of influence is reversed for Subgroup 2. It is important to note that the subgroup paths plotted here are those that apply to the *majority of participants* within each subgroup.

Some pathways will be shared by smaller proportions of individuals within each subgroup that are not plotted as a majority shared path (≥51% of the subgroup). These nonmajority subgroup similarities still contribute to the robustness of the overall two subgroup solution, given that the clustering solution draws upon all person-specific similarity matrices. To visualize this level of information, the plots therefore also display individual-level paths in faded gray to illustrate the underlying heterogeneity among person-specific paths; the thicker gray lines indicate greater numbers of individuals showing that within-person relationship. We walk through some sample person-specific paths to illustrate the richness and heterogeneity of the data in the online supplemental materials.

Further Characterizing the Two Data-Driven Subgroups. Our next step was to test for any diagnostic, clinical, or emotion summary metric differences across these two data-driven subgroups.

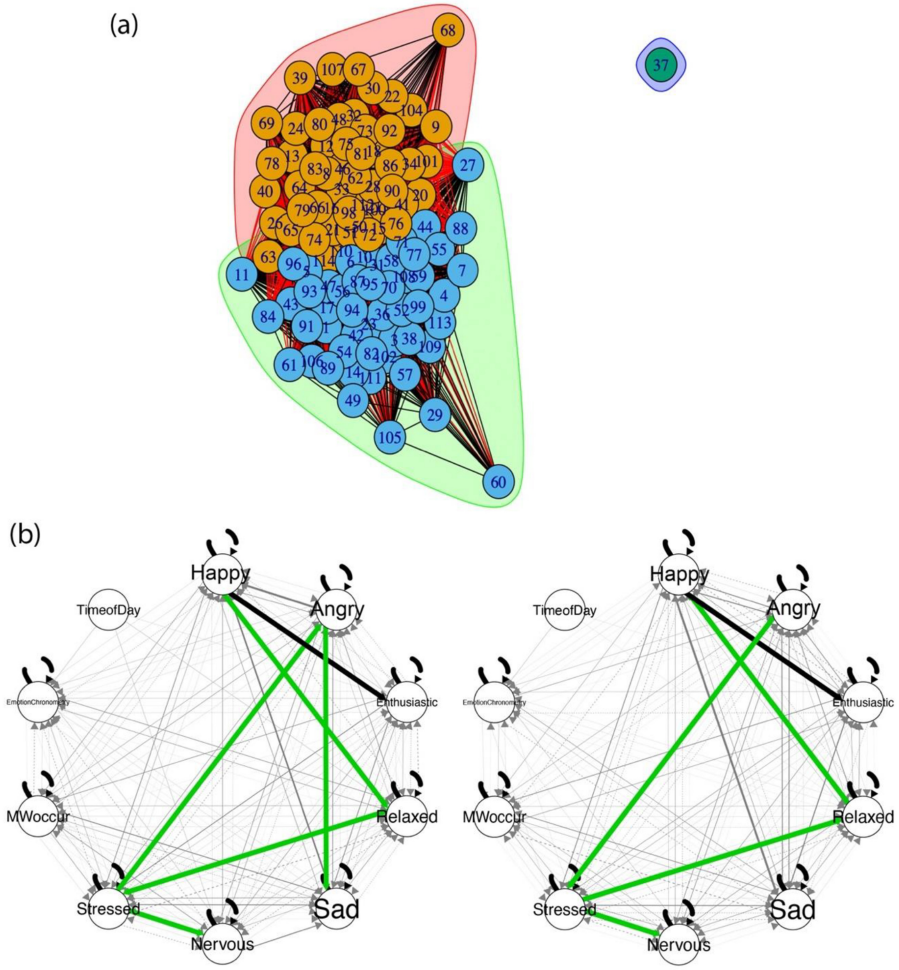
We first examined whether the two subgroups differed in terms of demographic characteristics. There was no support for demographic differences: age—$F(1, 102) = 1.57$, $p = .21$, sex—χ^2 $(1) = 0.30$, $p = .59$, ethnicity ($p = .27$), income ($p = .99$), education level ($p = .91$; see Table S5 in the online supplemental materials).

We next evaluated any differences on clinical metrics. Although the a priori diagnostic groupings did not lead to robust subgroupings within GIMME, it remained possible or even likely that the subgroups differed on aspects of their clinical structure. However, the clinical diagnoses were distributed evenly across the two subgroups (Figure 2a) and the proportions of participants from each diagnostic category did not significantly differ from the overall sample proportions in either Subgroup 1—$\chi^2(3) = 3.41$, $p = .33$ or Subgroup 2—$\chi^2(3) = 3.54$, $p = .32$. Similar comparability across the subgroups was evident across our continuous symptom measures with no significant subgroup differences for depression and anxiety severity: IDAS–General Depression ($p = .71$); IDAS–Dysphoria ($p = .73$); PHQ-9 ($p = .84$); GAD-7 ($p = .59$; Figure 2b), nor on any other IDAS-II subscales (all ps $> .05$; see online supplemental materials).

Affective Dynamics. For a descriptive view of the aggregate group emotion time courses across the length of the study, see

Figure 1

(a) The Resulting Two Data-Driven Subgroups Using GIMME. Each Node Represents an Individual, Shaded by Subgroup, and Provides the Distribution of Individual Similarity Matrices. More Similar Individuals Are Displayed Closer Together, Paths and Specific Node Distance Were Not Manually Interpreted. (b) The Paths Within the Resulting Subgroup Emotion Time-Course Changes; Subgroup 1 on the Left and Subgroup 2 on the Right



Note. Each gray line represents a path present in an individual's data, thicker lines represent more total counts of individuals experiencing that path. Solid black (dark) lines indicate group-level paths, and green (light) lines represent subgroup-level paths. Arrow directions indicate the direction of influence. "MWoccur" = whether an individual was thinking about something other than their current setting, "EmotionChronometry" = reported duration of that emotional experience, "TimeofDay" = the exogenous variable of diurnal time; GIMME = group iterative multiple model estimation. See the online article for the color version of this figure.

Figure 3a. To formally analyze affective dynamics, we next compared the two data-driven subgroups on our pre-specified emotion indices: intensity, instability, granularity, and inertia, across aggregated sets of positive and negative emotions. For these analyses, positive (happy, enthusiastic, and relaxed) and negative emotion ratings (angry, sad, nervous, stressed) were therefore averaged within-individuals. Cross-subgroup comparisons for intensity, instability, and granularity employed Wilcoxon tests due to nonparametric data distributions while cross-subgroup comparisons for inertia employed a multilevel model due to the nested data structure. We applied a Bonferroni-corrected α to adjust for the eight comparisons (critical $p = .00625$).

Emotion intensity was calculated per person as the average rating for their self-reported emotion intensity across timepoints. There were no significant group differences in overall intensity of positive ($Z = 2.02$, $p = .04$) or negative emotion ($Z = 0.20$, $p = .85$; Figure 3b).

To measure emotion instability, we calculated the mean sum of squared differences (MSSD) between data timepoints (Houben et al., 2015). Subgroup 1 showed significantly higher positive ($Z =$

3.72, $p < .001$) and negative emotion instability ($Z = 4.49$, $p < .001$) than Subgroup 2 (Figure 3b), with moderate effect sizes —$r = .37$, 95% CI [0.19, 0.53], $r = .44$, [0.27, 0.59], respectively.

Emotion granularity was measured by computing intraclass correlations (ICC; Pond et al., 2012). High ICC scores suggest that emotion terms of a similar valence were strongly correlated across time; coefficients were reverse coded to facilitate interpretation, such that higher scores represent greater granularity. Subgroup 2 showed significantly higher positive ($Z = 3.86$, $p < .001$) and negative emotion granularity ($Z = 4.55$, $p < .001$) than Subgroup 1 with moderate effect sizes—$r = .38$, 95% CI [0.2, 0.54], $r = 45$, [0.27, 0.61], respectively; Figure 4b.

For emotion inertia, we used multilevel modeling due to the nested structure of the data in assessing how emotion at time t may be predicted from time $t - 1$ for each individual and subgroup (Thompson et al., 2021). Predictor variables were person-mean centered at Level-1 (within-person emotion) with subgroup as a moderator at Level-2 (between-person subgroup assignment). Subgroup 2 significantly differed from Subgroup 1 showing greater inertia for both positive—$b = 0.11$, $SE = 0.03$, $t(104) = 4.41$, $p < .001$ and negative emotions—$b = 0.19$, $SE = 0.03$, $t(104) = 0.66$, $p < .001$; Figure 3b; see online supplemental materials for all model statistics.

Overall, although showing no significant clinical or demographic differences, the two identified subgroups were delineated in terms of the summary emotion metrics of emotion instability, granularity, and inertia (Figure 3). Importantly, these differences were robust for both positive and negative emotions. This opposing interplay between instability and granularity in the two data-driven subgroups was further probed using Bonferroni-corrected ($\alpha = 0.025$) correlations, which revealed an inverse relationship in these emotion metrics across the whole sample for both positive ($r = -0.56$, $p < .001$) and negative ($r = -0.54$, $p < .001$) emotions (see Figure 4). Although the diagnostic subgroups did not yield robust solutions with GIMME, we still compared them on these affective features to complement past literature, replicating clinical diagnostic differences on emotion intensity, instability, and inertia, though not granularity (see online supplemental materials).

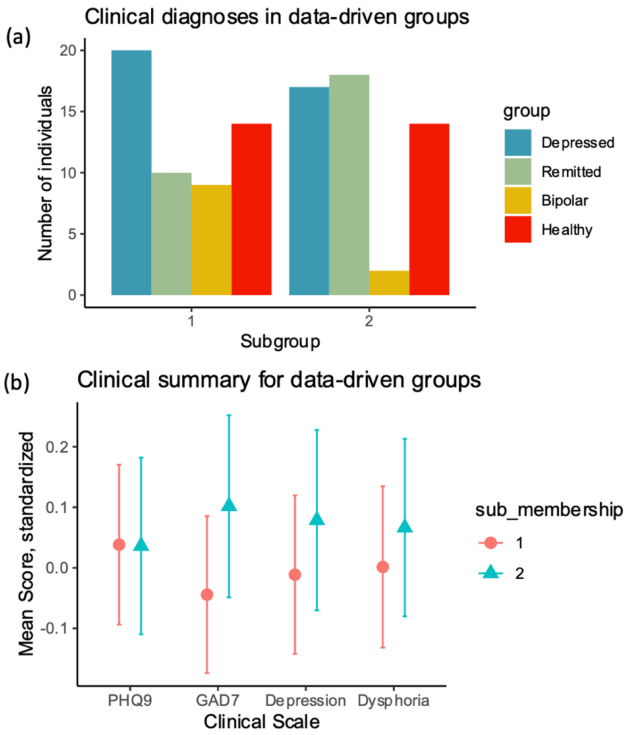
Discussion

This study used GIMME to examine person-specific (idiographic) patterns of within-person daily emotion-network dynamics collected via experience sampling for a large group of participants with and without a history of mood disorders. Our research question probed whether putative subgroups of participants derived from this set of person-specific models in this important dynamic processing domain would either align with traditional diagnostic groupings, evaluated using confirmatory subgroup GIMME, and/or whether data-driven subgroup GIMME would identify robust subgroups that potentially cut-across these a priori diagnostic boundaries.

For our three sets of a priori diagnostic groupings; two subgroup (all clinical vs. healthy), three subgroup (all with depression history, bipolar disorder history, and healthy), and four subgroup (currently depressed, remitted depressed, bipolar history, and healthy), GIMME yielded nonsignificant, nonrobust model fits that represented a poorly differentiated partitioning of the dynamic emotion-network data. Contrary to our expectations, this indicates that any differences in the profiles of within-person emotion-network dynamics across time were not well captured by any arrangement

Figure 2

Clinical Characteristics for the Two Data-Driven Subgroups



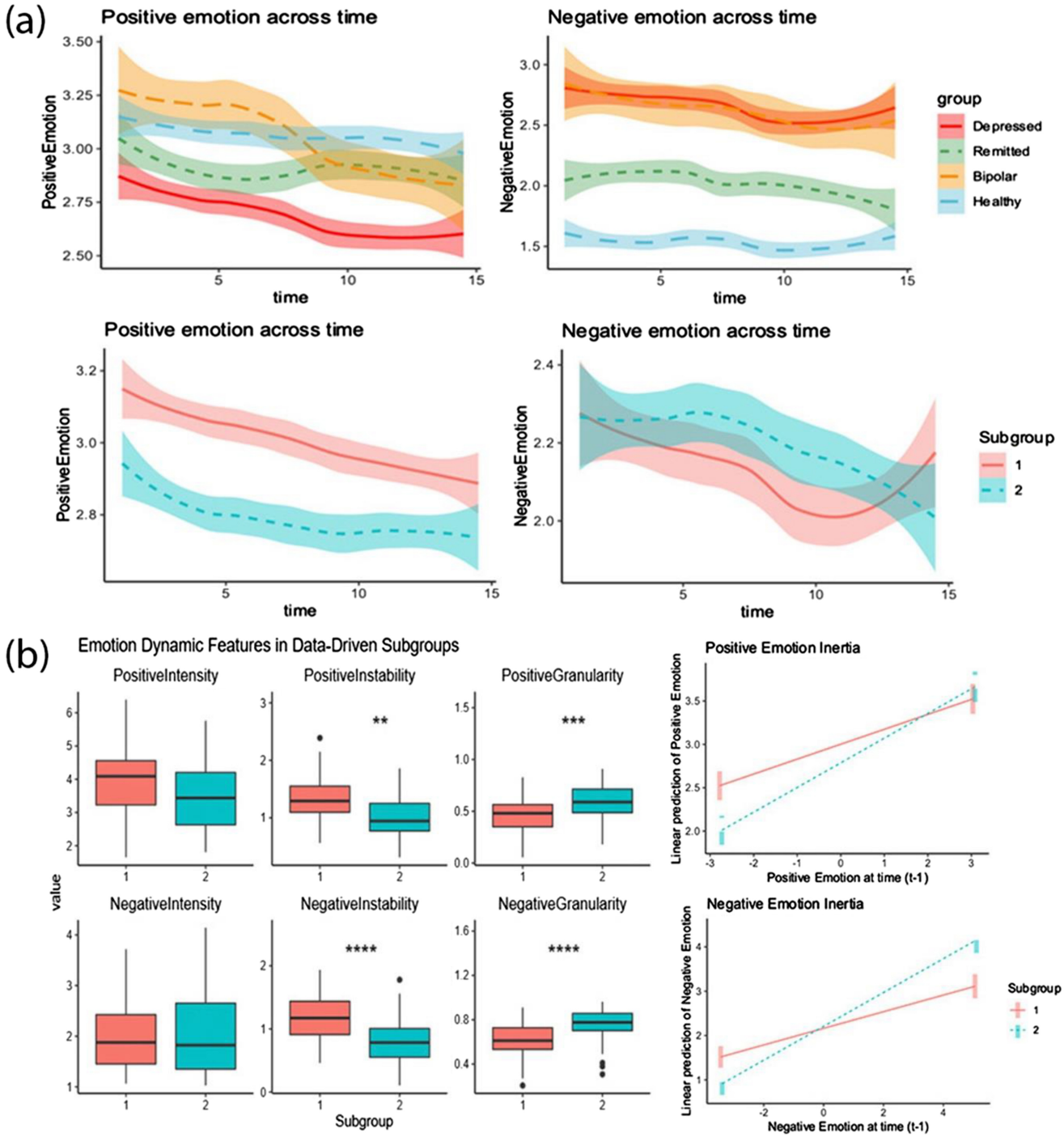
Note. (a) The distribution of diagnoses of participants in each data-driven subgroup. (b) The standardized group means and standard errors for the symptom measures for the data-driven subgroups (sub_membership). PHQ-9 = Patient Health Questionnaire-9; GAD-7 = General Anxiety Disorder-7; Depression = IDAS general depression subscale; Dysphoria = IDAS dysphoria subscale. See the online article for the color version of this figure.

of clinical diagnostic subgroups. This suggests that, in terms of the particular emotion networks under investigation here, there are no clear dynamic patterns emergent over a two week-time period that might represent a clinical target for prevention or intervention. This does not mean however that longer timeframes would not have revealed such patterns. It may also be the case that networks linking emotions to aspects of behavior, cognition, or the environment may be more fruitful in elucidating diagnosis-aligned patterns. These are questions for future research.

However, this did not mean that there were no robust subgroups within the data. Applying a data-driven approach identified a robust two-subgroup partition of the intraday emotion-network data patterns reflecting distinctions between the two subgroups in their members' shared patterns of contemporaneous and lagged directional associations across the network of emotions. A small number of these shared within-subgroup pathways were present in the majority of subgroup members and these subgroup-level shared paths differed across the two subgroups in both direction and composition. Interestingly, these data-driven subgroups did not appear to be delineated by differences in their clinical diagnostic composition, with proportions of diagnoses instead being distributed evenly across the two subgroups. There were also no significant differences between these subgroups on any symptom measures indicating that even sub-diagnostic clinical metrics were not definitive of

Figure 3

Data-Driven Subgroup Differences on Emotion Metrics

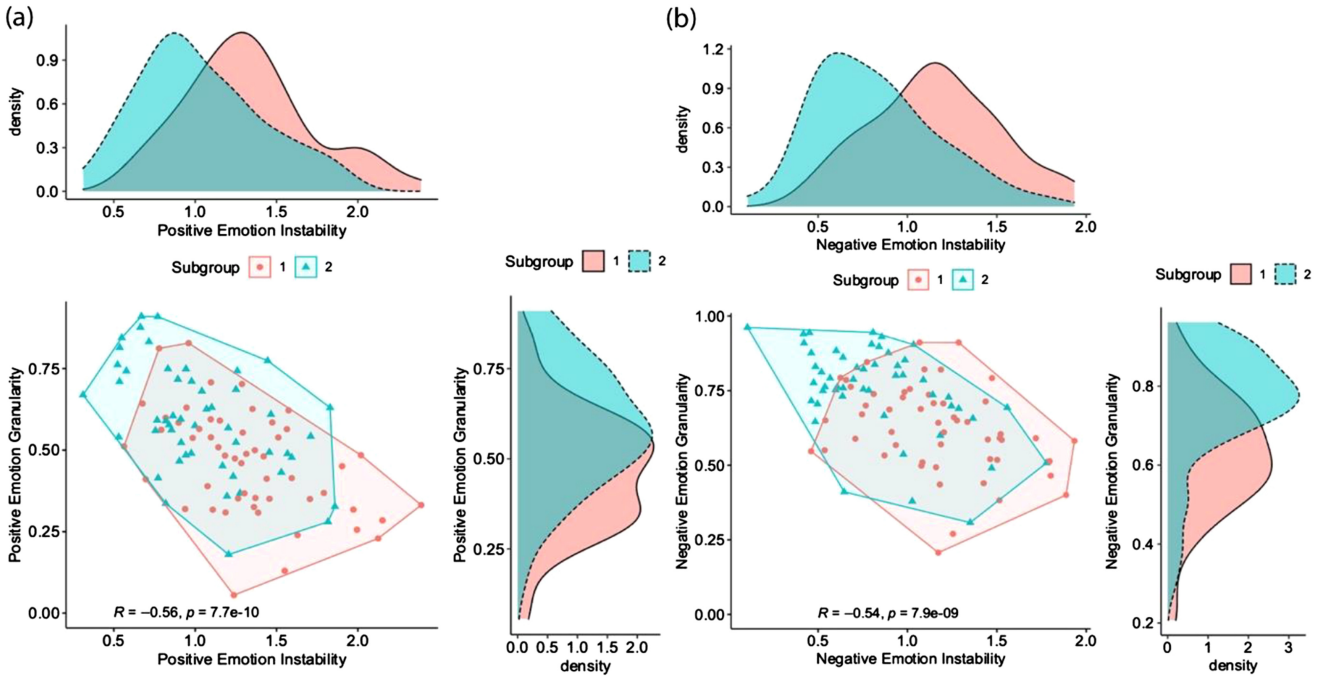


Note. (a) Aggregated positive and negative emotion intensity ratings across time in the diagnostic and data-driven subgroups with mean and standard error smoothed curves plotted per group. (b) Emotion metrics for the two data-driven subgroups in the form of boxplots for positive and negative emotion intensity, instability, and granularity (adjusted *p*-values as exact *p*-values in text) and multilevel modeling of subgroup interactions for positive and negative emotion inertia. See the online article for the color version of this figure.

** $p < .01$, *** $p < .001$, **** $p < .0001$.

Figure 4

The Inverse Relationships Between Emotion Instability and Granularity Across the Two Data-Driven Subgroups for Both (a) Positive and (b) Negative Emotions



Note. On the scatter plots, each individual score is plotted with granularity (*y*-axis) against instability (*x*-axis). Convex plots superimposed on the data scatter indicate the bounds of the data-driven partition for the two subgroups. Density plots of the subgroup scores are also shown above and to the right of the scatter plots, aligned with the axes, to illustrate group distributions for instability and granularity. See the online article for the color version of this figure.

subgroup status. Finally, demographics also did not delineate the two subgroups. This indicates that the within-person pattern of emotion dynamics that GIMME used to search for similarities across individuals provides information distinct from that provided by between-person clinical and demographic variables.

Importantly, despite their clinical and demographic similarity, the data did reveal strong and clear subgroup differences on our prespecified set of emotion metrics. Although there were no significant differences between the subgroups in mean levels of emotion intensity for either positive or negative emotions, the subgroups did differ in their emotion instability, granularity, and inertia. Notably, these differences were similar for both positive and negative emotions in that instability for both positive and negative emotions was significantly higher in Subgroup 1, while granularity and inertia for both positive and negative emotions were significantly higher in Subgroup 2.

The absence of support for any robust subgroups based on emotion-network dynamics within the sample that aligned to our a priori diagnostic groupings was counter to our expectations. This does not mean that extant body of nomothetic findings regarding affect dynamics and mood disorders needs to be discounted (Dejonckheere et al., 2019). Rather, it indicates that when the study of affective dynamics is extended to examine networks of emotions as they evolve across time, and to model patterns of change idiographically at a person-specific level that captures the heterogeneity across individual patterns, then there is no support for shared patterns across subgroups that are congruent with diagnostic categories.

Instead, our data seem to indicate distinct subgroups of individuals, with comparable compositions of individuals meeting diagnostic criteria, who not only evidence different idiographic patterns from one another (their "affective montage"), but also differ on the stability, granularity, and inertia of their emotional experience in aggregate nomothetic analyses. Notably, in contrast to the previous literature reporting these nomothetic metrics in diagnosed samples (Dejonckheere et al., 2019), here we found that these differences between subgroups pertained to both positive and negative affect. The presence of data-driven subgroupings that cut-across traditional diagnostic divisions in this manner is consistent with recent transdiagnostic approaches to understanding mental health and affect such as the RDoC (Insel et al., 2010).

Our results suggest that assessments of real-time emotion-network dynamics hold valuable information about individual differences in the unfolding experience of emotion that cut-across diagnostic boundaries and is thus adjunctive to traditional current diagnostic and symptom severity information (Wright & Zimmermann, 2019). We would argue that these data-driven insights emerge as a function of elucidating subgroups using the collective patterns of within-person pathways across our sample, in contrast to traditional nomothetic analytic approaches.

Constraints of Generality

There are some potential limitations of the present study that merit discussion. Although, based on the present data, it is hard to draw

firm conclusions regarding the clinical relevance of these data-driven subgroupings, it may be the case that other analyses might reveal such relevance in terms of vulnerability to later mental health problems or amenability to psychological interventions for those individuals who meet criteria for a diagnosis, and these questions remain for future research. For instance, we know from the nonclinical affective literature that the metrics of greater instability and lower granularity characterizing Subgroup 1 are associated with poorer emotion regulation and this group therefore might plausibly be more vulnerable to stressors or to a poorer prognostic course with respect to downstream mental health difficulties or to a more modest response to intervention in those meeting diagnosis (Kashdan et al., 2015; Tugade et al., 2004).

Future work could also consider measuring longer timelines of emotion changes beyond the 14-day period assess here. Longer-term prediction of changes in clinical or diagnostic status may help examine whether these two data-driven profiles will show differential longitudinal predictive relationships with mental health indices over longer time periods. Given that emotions can fluctuate and shift at faster rates than the 2-hr gap between experience sampling probes, future work could also consider more frequent ratings of emotions to model their micro time-course to possibly increase generality across timeframes.

It is also worth noting that although our assessments varied across time and, undoubtedly, situations, the models estimated here did not include potentially important intra- and inter-personal contextual factors, or life events that may also play a meaningful role in understanding the (dys)function of emotion dynamics. Emotions of course vary with context reflecting and facilitating interactions with our environment. Thus, by themselves emotion dynamics offer only part of the information relevant to their putative functions or dysfunctions (Wright & Hopwood, 2022). Future research could extend beyond the assessment of momentary emotion to include contextual features at the intra- (e.g., motivation, cognition) and inter-personal (e.g., interaction partner, social vs. nonsocial location) levels. Incorporating information that provides greater texture to the context of emotions would facilitate a move toward understanding individuals as complex dynamic systems, better approximating the full clinical picture with which practitioners are often presented. At the same time, due to issues of complexity and burden, acutely comprehensive assessments are unlikely to be viable, at least to the extent they rely on self-report (Wright & Woods, 2020; Wright & Zimmermann, 2019). An alternative is passive sensing of potentially relevant variables using Smartphone or wearable technology to allow automatic detection of some of these factors (e.g., whether a person is in a social environment, whether a person is indoors or outside) thus reducing reporting overheads, albeit at some cost in terms of privacy or anonymity (Doherty et al., 2014; Gruteser & Hoh, 2005). Finally, it is important to note that the sample size for the bipolar disorder subsample was modest.

In summary, the present ambulatory assessment study revealed that patterns of intra-individual emotion-network dynamics over a two-week period in participants with different diagnoses of mood disorders and healthy controls were best captured by two similarly-sized data-driven subgroups that were in fact comparable in terms of their diagnostic, clinical and demographic make-up. This contrasted with unacceptable model fit for any divisions of the data based on psychiatric diagnoses. The data-driven subgroups did however reliably differ on key emotion metrics comparably across both positive and negative emotions. These metrics indicated that individuals either belong to a subgroup with a relatively less stable and less granular emotion profile or to one with a relatively more stable, more granular profile, with higher inertia. The findings highlight the importance of both experience sampling and of data-driven approaches in understanding idiographic and nomothetic affective dynamics in daily life.

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