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Mapping the Idiographic Dynamics of Emotion

Author
Bosley, Hannah Gail

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Mapping the Idiographic Dynamics of Emotion

By

Hannah Gail Bosley

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Committee in charge:

Professor Aaron J. Fisher, Chair
Professor Ann Kring
Professor Iris Mauss
Professor Babak Ayazifar

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Abstract

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Professor Aaron Fisher, Chair

Background. Emotions are both *idiographic* (i.e., idiosyncratic, experienced within the individual) and *dynamic* (i.e., they exhibit change over time). However, studies of emotion often utilize cross-sectional measurement and nomothetic (group-aggregated) analysis, inhibiting precise understanding of within-person emotion dynamics. Recently, ecological momentary assessment (EMA) has become a popular method to study emotion by measuring individuals at multiple points in time during daily life. While EMA time series data hold great potential for understanding emotions as idiographic, dynamic phenomena, a key barrier remains: *how* to model individual differences in emotional experience, while also obtaining generalizable information about the nature of emotions at the population level. To address this problem, we present an approach that is innovative in both data collection and statistical modeling.
Methods. We collected EMA data on six discrete emotions (*anxious, irritable, sad, joyful, content, excited*) from 115 undergraduates. These data represent the most intensively sampled emotion time series in the literature to date, with observations taken by smartphone surveys every 30 minutes (24 times per day) during a 14-day sampling window. Over 34,000 observations were obtained across the sample (M = 302 per person). This is vital for the precise detection of rapidly-varying emotion dynamics.
Results. We then applied finite mixture modeling (FMM; also known as latent profile analysis) to this data in a "nested" fashion. First, aggregating across time points within each individual, FMM was applied to each emotion time series to classify every individual's set of unique emotion profiles as blends of six discrete emotions. Next, a between-persons classification step was conducted by aggregating across the individual emotion profiles.
Conclusion. Individual-level models revealed 795 unique latent states of emotional experience across the sample, which we termed *affect profiles*. By then aggregating across the person-specific affect profiles, we identified 7 distinct types of affect profiles (in other words, meta-classes) across the sample. At this group level, we recovered three 'negative affect', two 'positive affect', and two 'mixed affect' profiles. Affect profiles are discussed with an eye toward their potential clinical implications and utility. Future analyses will examine the temporal dynamics of these categories and investigate their relation to psychopathology. Two supplementary sections present additional analyses that begin to address these future aims.
Impact. Crucially, the present approach offers a way to distill high-dimensional EMA time series into a manageable set of discrete affect states. In the two-stage modeling approach

discussed here, we first categorize moments of each person's life into their idiosyncratic, unique affect profiles. From the set of all idiosyncratic profiles, we can distill a set of common affect profiles across the group. Unlike most other analytic approaches to date, this allows us to consider affect at both the idiographic and nomothetic levels simultaneously. Comparison of the universality vs. idiosyncrasy of the identified affect profiles may shed light on our understanding of affect in general. Further, examining which individuals exhibit which types of affect profiles, and the temporal dynamics of these profiles as they occur, may be advantageous to both researchers and clinicians. By enabling momentary affect states to be dichotomized (i.e., occurring in a given moment or not), this approach facilitates the application of prediction modeling to determine *when* a person's affect states will occur. If affect profiles are reliably associated with relevant behavior patterns, as some preliminary evidence suggests, clinicians could utilize this information about affect states to inform behavior change.

Dedication Page

This dissertation is dedicated to many loved ones who supported me in my journey toward completing this project, and helped me navigate my own time-varying emotion dynamics along the way.

Special thanks to:

My parents, Shelly and Bruce Bosley, for encouraging me never to give up on pursuing my dreams.

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My sister, Caitlin Diamond, for being an emotional anchor throughout my life, and especially during the last few years.

My graduate school friends, who became like chosen family in this process.

Claire, for bearing witness to this journey from start to finish.

Thank you all for sparking countless positive mood states and helping me cope with negative ones!

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Introduction

The experience of emotion is a universal feature of being human. Emotions are one of the bedrocks of human phenomenology, shown to be common across culture, geography, and language (Ekman et al., 1987, Mandal, 1996; Matsumoto, 2001; Mesquita, 2003; Sauter et al., 2010). Thus, despite the vast diversity in intraindividual, interpersonal, and environmental influences, emotions constitute a shared reference for human lived experience. While the question of "what constitutes an emotion" remains a topic of academic discussion, nearly all affective scientists would agree that 1) emotions are subjectively experienced states that can occur at the level of the individual person (in other words, they are *intraindividual*) and 2) emotions arise and dissipate over a period of time (they are *dynamic*). It has been well-established that accurate representation of intraindividual processes requires idiographic methodologies—data collection and analysis carried out on person-by-person basis (Fisher, Medaglia, & Jeronimus, 2018; Hamaker, 2012). However, until recently, most academic studies of emotion were neither idiographic nor dynamic. Instead, extant work has typically measured emotion at one point in time and aggregated these cross-sectional data to obtain group-level (i.e., nomothetic) estimates.

While many such studies have been foundational in affective science, addressing important between-subjects questions—for example, the latent structure of affect across a large representative group of people (Watson, Clark & Tellegen, 1988; Watson, Clark, & Carey, 1988)—due to statistical limitations (Molenaar, 2004) these cross-sectional studies cannot be used to understand the nuances of a single individual's emotional experiences, or how these experiences vary and unfold over time (c.f. Borkenau & Ostendorf, 1998). To obtain a more granular understanding of how emotions change dynamically within an individual, it is necessary to conduct measurements of that individual's emotions at multiple time points, and employ idiographic, *within-person* analysis of the resulting time-series data.

To this end, there has been a recent surge in popularity of experience-sampling, or ecological momentary assessment (EMA) as a method of studying emotion. EMA methodology has been applied to studies of positive emotion (e.g., Kashdan & Steger, 2006), emotion differentiation and emotion regulation (e.g., Barrett, Gross, Christensen, & Benvenuto, 2001), emotion in relation to clinical assessment (e.g., Haedt-Matt & Keel, 2011; Moberly & Watkins, 2008; Trull & Ebner-Priemer, 2009), and many other domains. Within an EMA approach to data collection, participants are asked to provide in-the-moment ratings of their emotions (or other behaviors and experiences) at multiple points in time over some measurement period. Often, EMA studies of emotion require individuals to rate their daily emotional experiences using a daily diary, a smartphone app, or wearable device from their daily context or social environment. In recent years, engineers and psychologists have fostered collaboration around the goal of improving the methods available to conduct experience sampling studies of emotion efficiently and usefully (Picard, 2010).

It is likely that as the technology of smartphones and wearable devices becomes more advanced and accessible, EMA methods will become an even more widespread tool to study emotion, both in general and in the context of psychopathology (Shiffman, Stone, & Hufford, 2008; Trull & Ebner-Priemer, 2013). For example, the past decade has seen an exponential increase in the number of studies based on EMA and experience-sampling methodologies (Hamaker & Wichers, 2017). In addition to the obvious benefit of ecological validity, this is an exciting and important development in the clinical affective science literature because EMA studies of emotion offer the potential to capture the time-varying nature of emotions within an individual with more precision and nuance than cross-sectional or retrospective methods.

What is an Emotion?

Categorizing Emotional Experience

Since the beginning of Psychology as an academic discipline, scientists have asked the question "What is an Emotion" (James, 1884). Our field has a long history of attempting to characterize the nature of our subjective feeling states with the use of discrete emotion categories such as sadness, anger, or fear, often based on their links to specific physiology, facial expression, or behavior (Ekman & Keltner, 1970; Ekman & Friesen, 1971; Levenson, 1992; Levenson; 1999). Ekman (1999) identified at least 15 discrete emotion categories that can occur in humans from Western cultures, and some studies have found evidence for up to 27 (Cowen & Keltner, 2017). However, the boundaries between these emotion categories can often be blurred within real-world situations (Cowen & Keltner, 2017).

An ongoing debate in the field of Affective Science concerns whether extant emotion categories truly "carve nature at its joints" (for interpretation, see Barrett, 2012). There is not always a one-to-one mapping between a given emotion category (e.g., sadness, anxiety, joy) and accompanying physiological arousal or behavior output. For example, physiological responses like elevated heart rate may correspond to multiple categories of feeling states (e.g., anger and fear), and a behavioral response to some subjective feeling state is often context-dependent (Barrett, 2012). As a solution to this problem, emotion can also be conceptualized using dimensions rather than discrete categories. The core affect model describes subjective feeling states using a two-dimensional space given by orthogonal axes representing valence (i.e., pleasant to unpleasant) and arousal (i.e., high to low autonomic activation; Russell, 2003). Some experiences in this core affect space correspond to discrete emotions (e.g., anger is an unpleasant, high-activation state) but others (like *fatigue*) do not.

In the present study, mirroring the human experience in everyday life, we rely on discrete emotion category labels, such as *irritable, content,* and *sad,* to capture specific types of subjective emotional experience (Barrett, 2012)—whether these categories represent universal natural kinds (i.e., naturally-occurring ontological categories; Quine, 1969) or particular regions within a two-dimensional affective space. This decision also aligns with recent work by Cowen & Keltner (2017) who examined the discrete emotions evoked by over 2000 contextually diverse video clips; they identified 27 unique categories of emotional experience, and further concluded that a system of emotion categories (connected by smooth gradients, rather than rigid category boundaries) is the most accurate method of organizing dimensional emotion ratings. This suggests that emotion categories, rather than the two-dimensional valence and arousal system, provide a useful model for conceptualizing emotional experience—while also highlighting that the boundaries delimiting emotion categories can be quite blurry, individually-variable, and context-dependent (Cowen & Keltner, 2017).

Emotions Co-Occur as Dynamic Systems

Contributing to the fuzzy boundaries between emotion categories, discrete emotions do not always occur in isolation. Multiple emotions can co-occur at the same moment, or rapidly in succession (Trampe, Quoidbach, & Taquet, 2015), necessitating the use of multiple category labels to describe the experience. A recent study monitored individuals with ambulatory physiological sensors and prompted them to complete an assessment when a physiological shift indicated that an emotional episode had occurred; on average, individuals used approximately thirteen different emotion words to describe an emotion episode (Azari et al., 2021).

While the early emotion literature largely focused on discrete emotions, considered in isolation or represented orthogonally, more recent studies have begun to focus on mixed emotional states (cf. Kreibig & Gross, 2017). Real-world everyday stimuli are complex, and may elicit a range of discrete emotions simultaneously. For instance, graduating from college or moving homes can lead to simultaneous sadness and happiness (Larsen, McGraw, & Cacioppo, 2001). As another example, political crises such as the 2008 economic recession in the United States can lead to simultaneous fear (of losing one's job) and anger (at the contributing governmental factors; Rhodes-Purdy, Navarre, & Utych, 2020). Reviewing the literature in neuroscience and cognitive linguistic theories, Hoemann, Gendron, & Feldman-Barrett (2017) conclude that mixed emotions arise from our construal of a present situation in context of past emotion-linked experiences, which can span multiple emotion categories. We can experience multiple discrete emotions in response to the same stimulus.

The recruitment of multiple discrete emotions may confer an adaptive advantage, by increasing the number of motivational/behavioral options to address complex environmental demands (Izard, Ackerman, Schoff, & Fine, 2000). Many authors have discussed a dynamic systems framework of modeling emotion (Izard, Ackerman, Schoff, & Fine, 2000; Lewis, 2005; Scherer, 2009; Hamaker et al., 2015). In this framework, each discrete emotion is the product of multiple influences from biological to social and contextual. Groups of co-occurring emotions then constitute higher-level systems with emergent idiosyncratic patterns that provide preferred solutions to environmental challenges.

In this dynamic systems framework, environmental stimuli may elicit multiple discrete emotions; as elements of the dynamic system, these emotions interact reciprocally via positive and negative feedback cycles, leading to "the generation of unique and idiosyncratic emotion patterns" (Izard, Ackerman, Schoff, & Fine, 2000; p. 16). Over time, these idiosyncratic emotion patterns form *attractors*, or "unique organizations of simpler elements within a system that represent preferred solutions to organismic, environmental, and historical influences" (p.17), which become stronger over time. This framework suggests that different individuals likely have different patterns of co-occurrence of discrete emotions. These patterns become preferred solutions and consolidate over time, leading to the formation of idiosyncratic affect states.

From this framework, it follows that (1) these attractors should vary from person-to-person (that is, each individual may have a different set of emotional patterns); and (2) given constraints on the system and a finite number of attractors, some consistency in the emotional patterns should be identifiable at the population level when aggregating across idiosyncratic individual sets of emotion profiles. Quantifying and examining these person-specific affect states (i.e., clusters of discrete emotional experience) from an EMA time series provides a way to examine discrete emotions systems at a higher-order level. This may provide a more nuanced understanding of each individual's idiosyncratic internal processes that can influence motivation and behavior. As the field of clinical science becomes more idiographic, emphasizing a nuanced understanding of individual differences, the identification of unique affect states relevant to each individual (and understanding similarities in these affect states across a group) may deepen our understanding of psychopathology and methods of intervention.

Open Questions in the Literature

With the expansion of EMA methods comes greater ability to study dynamic intraindividual processes like emotion. However, many questions remain to be addressed to harness the full potential of EMA. For one, novel approaches to data analysis can be developed (or existing methods can be adapted in novel ways) to glean nuanced information from EMA data (Hamaker et al., 2015; Hamaker & Wichers, 2017). This is important to both the idiographic and nomothetic levels of analysis. Within-person analysis of time-series data holds the potential to provide a more precise understanding of how time-varying processes such as emotion unfold at the level of the individual, and the results of these analyses can later be aggregated at the nomothetic level to understand how such processes vary within and across groups.

The present study seeks to advance EMA research in Affective Science. We present an innovative method of classifying quantitatively a person's idiosyncratic affect states—unique blends of discrete emotions (see. Fisher & Bosley, 2020)—from an EMA time series, which enables the identification of a nomothetic set of possible emotion patterns. That is, the present work leverages person-level data-generating processes to delineate the composition of emotion-related states of being—emotional experiences in discrete moments of time. These states are then cluster-analyzed to determine the degree to which they represent common emotion profiles that are generalizable across the sample. This two-stage, person- and group-level analysis, is important because emotions are most often measured via self-report using discrete emotion categories (e.g., *sad* or *anxious*), and these categories are likely to co-occur in a given moment (Azari et al., 2021). On the one hand, understanding the idiosyncratic patterns of co-occurrence in discrete emotions will provide greater nuance and contextual detail about momentary experiences of mood and emotion. Conversely, it is important to understand the degree to which these experiences are genuinely idiosyncratic versus shared across individuals.

Identifying Idiosyncratic Affect Profiles

Ostensibly, EMA studies are *momentary assessments* within an individual's life. However, in addition to the tendency to aggregate across participants, EMA data are typically treated continuously as dimensions, rather than discretely as states. Moreover, it remains an empirical question whether singular emotion items can adequately capture momentary emotional experiences. Discrete emotions (like sadness, anxiety, and excitement) putatively co-occur, with person-specific blends or patterns of co-occurrence, rather than arising in isolation (Berrios, Totterdell, & Kellett, 2015; Izard, 2000; Kreibig & Gross, 2017). Thus, to describe and characterize a person's emotional experience in a given moment accurately would likely require multiple emotion-category labels. A recent study showed that for a given emotional episode (as indicated by a momentary physiological change) individuals utilized an average of thirteen unique emotion words to describe the episode (Azari et al., 2021).

While speakers of the same language use similar labels for emotion categories (e.g., *sadness* is commonly reflected by an unpleasant valence and low physiological arousal; Russell, 2003), the lived experience of sadness likely varies from person to person (and culture to culture; Barrett, 2012). This may be because sadness cannot be adequately understood in isolation from other emotions or people that may be present in context. Some discrete emotions theorists have argued that individual emotions co-occur as systems, forming consistent, idiosyncratic patterns of occurrence within a person (Izard, 2000). Therefore, different individuals exhibit idiosyncratic patterns of emotional co-occurrence. Care should be taken to account for and index such heterogeneity. For example, one person may regularly experience a dysphoric mood state characterized by marked elevations in sadness and slight elevations in anxiety. Another person's dysphoric mood may be better characterized by high anxiety and irritability, with sadness slightly below their intraindividual mean.

Here, we use the term *affect profiles* to refer to these idiosyncratic, person-specific blends of emotion levels occurring within the same moment. An affect profile represents a person's consistent momentary experience of specific combinations of each emotion's level as deviations from its intraindividual average; it is a specific type of affect state. Put another way, affect profiles are the discrete set of specific emotion blends that a person repeatedly, consistently experiences throughout their time series, regardless of their eliciting context. Each person's unique set of affect profiles represents the patterns of emotion co-occurrence that are observable in—and differentiable across—distinct moments of their life. Importantly, an individual's EMA time series can therefore be categorized according to which of their affect profiles was observed at each sampling instance.

For example, a person might have distinct episodes of an idiosyncratic affect profile characterized by high anxiety and excitement, and with below-average sadness. This individual could have moments where this affect state is present, and moments when it is not. A different individual might never experience this state at all.

Further, perhaps multiple people could have slightly different versions of the same affect profile. Although affect profiles are unique and person-specific, comparing similarities across the aggregate set of profiles may highlight important features of affect states that are shared in common across the group. As emotions and the affect states that they comprise likely emerge from shared human physiological data-generating processes, there is probable consistency in the person-specific affect states across the group, with each individual exhibiting their own idiosyncratic subset of possible affect states. Therefore, to obtain a generalizable understanding of these affect states requires a blend of idiographic and nomothetic analyses.

We present a method of quantifying these person-specific affect profiles, first identifying the discrete emotion patterns present for each individual, and subsequently using these to identify the higher-order set of common affect profiles. Classifying an individual's EMA time series according to their unique set of affect states may yield a more nuanced understanding of their specific emotional experience. Examining the relative universality vs. idiosyncrasy of the observed affect profiles may inform our understanding of emotion patterns more generally, enabling future investigation of the temporal dynamics of affect states and their links to clinical outcomes.

As affect is strongly linked to, and influenced by context (Aldao, 2013; Silk, 2019), it is likely that certain affect states may be consistently elicited in response to specific environments or situations. However, in the present study, we aim first to classify latent affect states *outside* of any information about what triggered the state. Putatively, affect profiles are states that arise repeatedly for an individual in response to a range of possible contextual stimuli. By sampling individuals across many repeated observations within their daily environment (i.e., 12-hour waking windows every day across two weeks), we will ostensibly sample from a wide enough range of possible contexts to enable a relatively comprehensive map of the individual's set possible affect states, which presumably were elicited across a two-week range of varying contexts. The specific mappings between eliciting contexts and particular affect states can then be explored as an avenue for future investigation in subsequent analyses, consistent with burgeoning directions in the literature (e.g., Silk, 2019).

Temporal Dynamics of Affect States

A rapidly-expanding body of literature uses EMA data to examine emotion and related processes within affective and clinical science (for reviews, see Russell & Gajos, 2020; Colombo et al., 2019; Santangelo et al., 2014; Singh & Björling, 2014; aan het Rot, Hogeneist, & Schoevers, 2012). Given the complex temporally-embedded nature of emotion and related constructs, EMA sampling frequency is an important area of investigation to ensure the continued validity of this work. EMA captures emotional phenomena *in situ,* which may allow researchers to gain crucial insights into the form and function of emotion and emotion-regulation processes in real life situations. However, crucially, the accuracy of such insights will be dependent on the degree to which the EMA sampling frequency corresponds to the time scales of the emotional processes under investigation. There is evidence that emotions have different durations, which can vary, from emotion to emotion, or from person to person (Verduyn et al., 2009; Verduyn et al., 2015).

To date, no empirically-established convention exists for determining how frequently these constructs should be sampled, because we simply do not know how fast, slowly, or continuously they are occurring. This forces researchers to rely on rules of thumb, precedents from other studies, heuristics, or informed guesses when determining how frequently to sample emotion. As measurement of emotion at the appropriate temporal scale is essential to understanding underlying dynamics of affect, myriad EMA papers discuss sampling frequency as a potential limitation of the work (e.g., Kubiak et al, 2013; for reviews, see Moskowitz & Young, 2006, Carpenter, Wycoff, & Trull, 2016, Shiffman, 2008, Cain, Depp, & Jeste, 2009). An empirical understanding of the temporal dynamics of affect states (e.g., how frequently they change) should be used to inform future studies' decisions about EMA sampling frequency.

Affect States' Link to Behavior and Clinical Outcomes

Identification of these person-specific affect states may present viable opportunities for clinical intervention and behavior change. Both adaptive and maladaptive behaviors are linked to emotion (Keltner & Gross, 1999). As such, tracking and regulating emotion is a foundational component of many behavioral interventions (e.g., Beck & Beck, 2011). If affect states are associated with differential patterns of behavior, and if certain maladaptive behaviors tend to occur more in one affect state than others, identifying and predicting affect states and their temporal patterns could be applied in clinical settings to predict when treatment-relevant target behaviors may occur. Consequently, affect states may come to represent person-specific risk or protective factors.

Our research group has found evidence that person-specific affect states are linked significantly to behavior in most participants—although the nature of the affect states themselves, and which behaviors are affected, are idiosyncratic (Bosley & Fisher, *in preparation*). To establish the potential clinical utility of these person-specific affect states, it may also be relevant to examine whether certain affect states are linked to greater levels of subjective stress or life satisfaction, and whether particular affect states are associated with psychopathology.

Aims of the Present Study

The present study aims to address these open questions with innovative approaches to data collection and analysis. Using an EMA smartphone app, we measured six discrete emotions, perceived stress, and life satisfaction 24 times a day for a period of 14 days. With very few exceptions (e.g., Koval & Kuppens, 2012) this intensity of sampling is among the highest reported in the current literature. Further, while a handful of other studies have sampled emotion at an exceptionally high frequency, this has only been done within a very short sampling duration—for example, Koval & Kuppens sampled participants' emotions 60 times per day, for a period of only one day. In

the present study, sampling 24 times per day across a 14-day period produces a relatively long and densely-sampled time series, allowing us to examine dynamics of emotion at both rapidly-changing and longer-range time scales. With these data, we aim to: (1) quantify person-specific affect states as mixtures of discrete emotions, (2) identify temporal patterns in the occurrence of these affect states, and (3) determine how these affect states correlate with self-reported stress and life satisfaction. The present manuscript addresses Aim (1) in detail. Supplementary Sections 1 and 2 address the second and third aims, respectively.

Methods of Data Collection and Preparation

Participants and Procedure

For two semesters (Spring and Fall 2019) participants were recruited from the undergraduate research participation pool (RPP) at the University of California, Berkeley. An advertisement for the study was posted on the RPP website, describing the present study in which Psychology undergraduates could participate for partial course credit.

Participant recruitment was conducted in four waves, so that participants within each wave all completed the procedures at approximately the same time. In each wave of the study, participation involved two parts: In Part 1, each participant received an email with a link to a baseline packet of questionnaires to be completed remotely via Qualtrics. Each person received the link to the packet on a Friday evening and was instructed to complete it by the following Monday morning. Part 2 of the study involved a two-week EMA sampling paradigm, beginning the Monday morning after the completion of the Part 1 packet and ending two weeks later.

Following administration of the baseline questionnaires, participants were presented with a five-minute instructional video that explained the EMA paradigm and instructed them on how to use the smartphone app for data collection. Participants received an email link to download a web-based EMA app for data collection (SEMA2, Harrison et al., 2017). Surveys were oriented to each participant's self-reported wake-up time, and were sent approximately every half hour during a 12-hour waking window, for a total of 24 pings per day. Surveys expired after approximately 30 minutes to prevent participants from completing multiple survey prompts at one time point. The EMA period lasted a total of 14 days, with a total of 336 possible survey prompts. To receive full credit for participation, the participants had to complete at least 75% of the observations. We checked survey compliance daily and sent periodic email reminders to participants whose compliance fell below the 75% threshold. To further incentivize survey compliance, participants who completed 90% or more of the surveys were entered into a drawing for a 1 in 10 chance to win a $100 gift card.

Across all four waves, 191 participants signed up for the study. Of these, 185 completed the Part 1 baseline packet and 176 completed at least some part of the EMA paradigm in Part 2. A total of 115 participants met the threshold of 75% compliance (at least 250 observations) required for inclusion in the present analyses. Of these 115 participants included in the present analyses, the average number of complete observations per person was 302.03 (SD = 30.72), representing M = 81.3% of surveys received. The number of completed observations in the final sample ranged from 250 to 382 observations per person. (Due to occasional technical difficulties in the app, some participants continued receiving surveys for a few days following the end of the study period and chose to complete them). The final 115 participants include *N* =49 from Wave 1 (April 2019), 27 from Wave 2 (September 2019), 35 from Wave 3 (October 2019) and 4 from Wave 4 (November 2019).

Measures

Part One: Baseline Packet.

The baseline packet measured demographic variables such as age, racial/ethnic background, linguistic background, as well as psychological variables including emotion regulation, personality traits, and psychopathology.

The Mini International Neuropsychiatric Interview (MINI; Sheehan et al., 1998). The MINI is a structured, standardized clinical interview that was designed as a brief, 15-minute measure to establish clinical diagnosis according to DSM-IV and ICD-10 criteria (Sheehan et al., 1998). The MINI has been shown to have good reliability and validity compared with diagnostic instruments such as the CIDI (Lecrubier et al., 1997) and the SCID (Sheehan et al., 1997). While the MINI was initially developed for administration by a clinical interviewer, we adapted the MINI items for self-report using a Qualtrics survey. For participant safety, as individuals were instructed to complete the self-report questionnaire at home, we removed the item assessing suicidality from the MINI Depression module. By scoring participant responses to assess DSM diagnostic criteria, we used this instrument to establish presence/absence of the following current diagnoses: major depression, dysthymia, generalized anxiety disorder, social anxiety disorder, obsessive-compulsive disorder, agoraphobia, PTSD, mania or hypomania, psychosis, and bipolar-spectrum disorders (bipolar I and II).

Part Two: EMA Surveys.

Discrete Emotions. EMA items measured six discrete emotions, including *irritable, anxious, sad, content, joyful,* and *excited.* These items were chosen in order represent both pleasant and unpleasant valence (with the first three and last three items, respectively) across both the high and low arousal quadrants of the affective circumplex (Russell, 2003). *Irritable, anxious, excited,* and *joyful* represent high-arousal states, while *sad* and *content* are low-arousal items. For each discrete emotion, the item read “how **____** are you?”; participants were instructed to rate their levels of each emotion at that moment using a visual analog sliding scale ranging from 0 (*not at all*) to 100 (*as much as possible*). This scale is advantageous over a traditional 5- or 7-point Likert scale as the present analysis requires sufficient variability in the emotion items. A 100-point scale therefore allows for a finer degree of granularity and precision in responding, and produces greater variability in the time series. Two additional emotions, *angry* and *afraid***,** were measured dichotomously with the stem “are you currently **____** ?”, and participants were instructed to select “yes” or “no”.

Stress and Life Satisfaction. Two additional EMA items assessed momentary subjective stress and self-reported life satisfaction. These items were *How stressful is your life at the moment?* and *Right now, I am satisfied with my life* (Diener, 1985*).* Similar to the first six discrete emotion items, these also utilized the visual analog sliding scale, ranging from 0 (*not at all*) to 100 (*as much as possible*).

Finite Mixture Modeling to Classify Affect states

Background

Identifying Affect States Within and Between Participants

Recently, our research group demonstrated a method for identifying person-specific discrete affect states from time-series data (Fisher and Bosley, 2020). In this paper, we applied Gaussian finite mixture modeling (FMM; Muthen & Muthen, 2014; Rosenberg, Beymer, Anderson, & Schmidt, 2018) one person at a time, to each individual's time series of emotion variables. Unlike the traditional approach to FMM, which uses cross-sectional data to cluster individuals, this approach uses time series data to cluster time points *within* an individual. The resultant latent classes represent discrete states of emotional experience, as within-person blends of emotion levels at each time point. In the present study, we refer to these person-specific classes as an individual's latent *affect profiles* or *affect states*.

In Fisher & Bosley (2020), we found that the average number of affect states per person was approximately three, with a range of two to four states. However, analyses were restricted to negative emotion items and intraindividual time series were relatively short (average series length = 113 observations). Either of these factors could have restricted the expression of latent affect states, and increasing either the dimensionality or the number of observations in the input data may result in a greater number of classes per person. Within the two to four affect states observed in Fisher and Bosley (2020), there was marked heterogeneity in the composition of affect states across individuals, reflecting differences in both kind and degree. In another sample (Bosley & Fisher, *in preparation*), we examined whether individuals' affect states, as identified by FMM, exhibited specific associations with behavioral outcomes such as avoidance or interpersonal conflict. We found that the nature of the affect states and their specific associations with behavior were idiosyncratic; however, *all* participants exhibited some significant association between the affect state they were experiencing at a given time and their behavior at the same observation. This association between affect states and behavior underscores the potential applied and clinical utility of these classes.

Importantly, both of the samples in which FMM has been previously tested were cohorts of individuals seeking treatment for mood and anxiety disorders. Examining the application of this method in a non-clinical sample represents an important extension of this work. Further, both Fisher & Bosley (2020) and Bosley & Fisher (*in preparation*) utilized time series with a sampling frequency of four times per day. A higher sampling frequency provides more densely sampled snapshots of emotional experience, which may enable us to detect a greater number of affect state kinds with a finer degree of temporal precision. For example, if a particular affect state occurs with a low frequency and does not last very long, it is more likely to be captured with measurement every 30 minutes as opposed to every four hours. Thus, the present study's use of a non-clinical sample with a more densely sampled time series allows for important extensions of this line of research.

A common concern raised by skeptics of idiographic science is that the models returned from person-level analyses are non-generalizable at best, and spurious products of modeling noise at worst (Piccirillo & Rodebaugh, 2021; Beck & Jackson, 2021). Thus, some care should be taken to assess the generality and generalizability of idiographic statistical results. The two-stage approach in the present study asks first whether there are recoverable patterns of emotion at the person level and then, whether there are types of emotion patterns that commonly co-exist across people.

As human emotions ostensibly arise from common physiological systems and mechanisms (e.g., sympathoadrenal activation, parasympathetic withdrawal), it stands to reason that there is some universal set of *possible* patterns in emotion co-occurrence (Izard, 2000)—even if each individual exhibits only a subset of these possible patterns. Examining the results of the idiographic classifications at the nomothetic level will, thus, allow us to examine the idiosyncrasy vs. commonality of these affect states. The idiographic step identifies how discrete emotions cluster together as idiosyncratic affect states for each person, and the nomothetic step reveals how the person-specific patterns are clustered at the group and, ostensibly, population level. Finally, employing inter-individual analyses of demographic, characterological, or clinical features may reveal whether certain types of people exhibit certain types of patterns, if any particular patterns typify psychopathology, or whether some patterns are more likely to be linked to maladaptive behavior.

When FMM is applied at the nomothetic level, the observations are no longer levels of emotion items at each time point within an individual, but instead the mean levels of emotion *within each affect state* for each individual across the sample. Aggregating intraindividual models at the inter-individual level estimates the potential generality of each affect state, including posterior probabilities for class membership for each person-level and group-level cluster assignment—that is, the degree of certainty with which we can assign a given person-level state to group-level clusters of states. With this approach, we can estimate the number and nature of common clusters. To the degree that each within-person affect state represents a generalizable organization of emotions, the affect states will cluster together with high certainty in the nomothetic model. Where within-person affect states are more genuinely idiosyncratic, these will be poorly associated within any single inter-individual cluster, and return a high uncertainty value. The nomothetic set of classes likely represents a broader range of affect states than are present in any single individual, given that individuals' unique affect states likely represent attractor states specific to each person. The set of nomothetic classes then represents the possible set of attractor states that could exist, given constraints on the system.

The Present Analyses

In this chapter we describe a two-stage approach to the classification of latent affect states. First, consistent with Fisher & Bosley (2020), we apply FMM to each individual's emotion time series to generate a set of affect profiles for each participant. Aggregating person-specific affect states, we next run a nomothetic FMM to identify potential generalizable clusters of affect states in the sample. We then discuss the nature of the resulting group-level clusters, their frequencies at the person level, and the statistical patterns observed. Our interpretation here mainly focuses on examining the affect states common across the group, rather than the nuances of the idiographic FMMs. In considering individual differences, we examine how the common set of affect states is expressed differently within the individual, with an eye toward how this information may be utilized clinically or in future studies.

Potential Impact. Quantifying affect states, mapping their temporal patterns, and determining their link to behavioral outcomes is important for a number of reasons. The two-stage FMM approach described in the present study contributes a possible solution to a number of important problems in the modeling of EMA emotion data. First, this approach has the capability of distilling high-dimensional EMA data—with many observations across variables, observations, and individuals—into a manageable set of latent emotion categories at both the individual and group level. By identifying categorical emotion states empirically, through the classification of person-specific emotion blends that are common at the group level, this approach may get around the aforementioned problem of blurry emotion category boundaries. Further, because emotions often co-occur in the real world, the idea of latent emotion categories more closely approximates real-world emotional experience than measuring discrete emotions singularly.

Another benefit of the present approach is its ability to deal with idiographic and nomothetic levels of analysis simultaneously. In doing so, we are able to model aspects of affect at the group level (e.g., the set of possible affect states across the sample) and also discern individual differences in the manifestations of these phenomena (e.g., which of these affect profiles a single individual may experience, and how they change over time).

Finally, an additional benefit of the present modeling approach is its ability to discretize affect as a dichotomous state that discretely is or is not occurring. This offers many advantages over traditional continuous measurement of discrete emotions, such as enabling prediction modeling and the precise localization of affect within certain moments (Fisher & Bosley, 2020).

Data Analytic Plan

Idiographic FMM

Each individual's time series of six emotion items was standardized (scaled relative to the person-specific mean of each item) by using the *scale*() function in R. This approach uses person-mean-centering, dividing by the standard deviation. Each standardized time series was then subjected to FMM, one person at a time, consistent with methods described in Fisher & Bosley (2020). The latent classes identified by each idiographic FMM represent states—consistently occurring clusters of intraindividual deviations in emotion-item scores—present throughout the individual's two-week sampling window.

Analyses were conducted using the mclust package in *R* (Scrucca, Fop, Murphy, & Raftery, 2016). The Mclust function was run for each time series; this function runs *k* competing models with up to *k* classes and outputs the best-fit solution according to two indicators of fit, the Bayesian information criterion (BIC; Schwarz, 1978) and the integrated completed likelihood (ICL; Biernacki, Celeux, & Govaert, 2000). Consistent with Fisher & Bosley (2020), model comparisons were limited to six parameterizations of within-class variance and covariance (Mclust calls these "EII", "EEI", "EVI", "VII", "VEI", and "VVI") to allow variation in the distribution, volume, and shape of the variance, while fixing correlations between class indicators to zero. For each individual, the best-fit model as selected by Mclust was retained.

Mclust also provides posterior probabilities for the likelihood that each row of the time series belongs to a given class, and Mclust will perform a forced-choice procedure for assigning each observation (row) to the class with the highest class-membership likelihood. Each person's time series was classified in this way, with each row dummy-coded for membership to a single affect state class, based on its maximum probability. The dummy-coded vectors representing each affect state's presence versus absence at each time point was appended to the original time series for further analysis.

Nomothetic FMM

After the set of 115 within-person time series was subjected to FMM, each unique affect state for each individual (that is, the average scaled score for the six indicator emotions within each class) was saved as a row in a new group-aggregated data frame. Next, a nomothetic FMM was conducted by applying Mclust to the resulting data frame in which each row represented a person-specific affect state (the total number of unique affect states identified across the 115 participants was 795, yielding a nomothetic data frame with 795 observations).

Final Model Selection

As noted above, the Mclust function runs *k* competing models with 1 to *k* classes. The *Mclust* model-selection procedure defaults to a maximum of nine components (i.e., classes). However, this can be overwritten to estimate as many components as desired. In the present analysis, *k* was estimated for one to 15 components to allow a more liberal estimation of the best-fit model. The optimal number of components for the nomothetic model was selected using the BIC and ICL, as well as the bootstrap likelihood ratio test (BLRT; Nylund, Asparouhov, & Muthén, 2007) and entropy plots (Baudry, Raftery, Celeux, Lo, & Gottardo, 2010).

The ICL is equivalent to the BIC, penalized by using an *entropy* term—an index of the extent to which the clusters overlap (i.e., the ICL penalizes models in which category boundaries are less distinct; Scrucca, Fop, Murphy, & Raftery, 2016). The BLRT successively tests whether each increase in the number of classes (two versus one, three versus two, etc) provides a significantly better fit to the data, to guard against overfitting. Finally, entropy plots visualize the model's entropy (i.e., category definition confidence and degree of separation) at each number of classes; higher entropy indicates less-distinct boundaries between classes. Entropy plots can be used for model selection by using visual inspection to identify inflection points, similar to the use of scree plots in factor analysis. If present, inflection points indicate the optimal number of components of the model (Baudry, Raftery, Celeux, Lo, & Gottardo, 2010); an inflection point at *k* classes can be used by indicating that after *k* components, adding more classes to the model leads to greater increases in entropy. In the present analysis, we aimed to identify discrete affect states as distinct categories of experience—therefore, clear category boundaries are paramount. For this reason, the ICL and entropy plots are particularly important indicators.

In the present data, these different metrics reflected preferences for slightly different models; thus, we compared the class solutions generated by each of the possible solutions to arrive at a final model. We examined the Mclust output according to these four indicators (BIC, ICL, BLRT, and entropy), alongside visual inspection of the identified components. The ultimate goal of model selection is to select a parsimonious model whose components will indicate meaningfully-differentiable sets of emotional experiences that our participants have in the real world. In the absence of clearly established precedent or convention in the literature, we prioritized the use of the ICL and entropy plots, alongside visual inspection, given our goal of identifying a parsimonious set of well-separated components.

Results

Of the 191 participants recruited for the study, a total *N* of 115 completed at least 75% of observations and were included in the present analyses. Table 1 presents the demographic characteristics of those included. Across the four waves of data collection, participants did not significantly differ on demographic variables of age (F [3,111] = 0.53; p = 0.66), gender (X^2 [4, N=115] = 1.86; p = 0.60) or ethnicity (X^2 [3, N=111) = 2.98; p = 0.81). Of note, in calculating group differences in ethnicity, statistics could not be computed for Wave 4 given that this group had only four participants with none who identified as Latinx or Multiracial. Further, it deserves mention that participants were able to describe themselves by selecting multiple ethnic categories, and no participants in the sample identified as their ethnicity only as Black (however, some participants selected Black alongside other ethnicities; these participants who selected multiple categories were classified as Multiracial).

Across the 115 participants, we collected a total of 34,733 complete EMA observations.

The average number of complete observations per participant was 302.03 (SD = 30.72, range = 242 to 379). At the idiographic level, the number of unique affect states per person ranged from 2 to 9 (M = 6.91, SD = 2.21). Aggregating across each participants' set of affect states, we identified 795 idiosyncratic affect states across the sample, yielding a set of 795 observations for nomothetic classification.

Nomothetic Model Selection

Initial model output suggested that the best nomothetic model, according to both BIC and ICL, was a 14-class model (a 13-class model provided the next best fit). The BIC and ICL plots are shown in Figures 1a and 1b. Visual examination of these plots revealed a clear inflection point at 7 classes. The difference in model fit between 7 and 14 classes was relatively flat, indicating that after 7 classes, additional classes added only incremental changes in BIC and ICL.

The BLRT indicated significant improvement in model fit for each class added up to 14. However, there is a possibility that while adding more classes improves model fit, it may not actually provide a more accurate real-world solution or interpretation of the data, potentially leading to results that are not generalizable. For this reason, entropy (as a measure of component overlap or classification uncertainty) can be considered alongside the BLRT to determine whether adding more classes to the model is justified. Mclust provides entropy plots that indicate the progressive change in entropy of models with each number of classes up to *k* (in this case, 14). Authors of the Mclust package suggest that a clear elbow in the entropy plot indicates the optimal number of classes (Baudry, Raftery, Celeux, Lo, & Gottardo, 2010). The entropy plot is shown in Figure 2. A clear elbow was once again observable at 7 classes, supporting the 7-class model as an optimal solution in terms of minimizing classification uncertainty.

Finally, we examined the class structures identified in the 7, 13, and 14 class models. Comparison of these classes is shown in Figures 3a, 3b, and 3c. All seven of the classes identified in the 7-class model were present in the 13 and 14 class structures, suggesting sub-structural stability of the nested models. That is, as the models became more complex and more components were added, the original classes identified by the simpler lower-dimensional model remained distinctly identifiable. Examining the seven additional classes added in the 14-class structure, we observed that two of the classes appeared to be duplicates, with only very small differences between them (see class 7 and 13 in Figure 3c). As this was an indicator of potential overfitting, we rejected the 14-class solution. In the 13-class solution, there were six additional classes, with no clear duplicates. While these may provide some additional nuance beyond the 7-class model, we decided to retain the 7-class instead of the 13-class model for the reasons described above.

Within-Person vs. Between-Person Class Frequencies

Once the seven group-level affect profiles were identified and coded within each individual time series, we then calculated the within-person frequencies of each identified profile. In other words, if a person exhibited a particular affect state in their time series, how much time did they spend in that state? An affect state's "frequency" could either refer to its between-person frequency (that is, how many people in our sample exhibited that state) or its within-person frequency (that is, how frequently the state occurs within a particular individual's time series). Thus, we use the term *proportion* to indicate an affect state's between-person frequency and *rate* to indicate an affect state's within-person frequency.

For each of the 7 nomothetic affect states that were identified, the proportion of the sample exhibiting each state was calculated by taking the number of individuals who exhibited each affect state as a proportion of our sample of N=115. To calculate the rate of occurrence of each affect state, if a given person exhibited affect state *x*, its frequency of occurrence in their time series (relative to their total number of observations) was computed. We then averaged these within-person frequencies across every participant who exhibited each affect state, yielding a nomothetic metric of how much time the average person spent in each affect state. Proportion and average rate for each affect state are shown in Table 2.

Shared Affect States Across the Group

Of the 7 affect states that were identified at the group level, the average number of these affect states that were observed within a single individual was 4.46, ranging from 2 to 7 (SD = 1.24). Figure 4 shows the composition of each of these 7 affect states ordered by their proportion in the sample, and Figure 6 provides a frequency distribution to illustrate the proportion of the sample exhibiting each class.

Mirroring what we have observed in idiographic affect profiles (Fisher & Bosley, 2020; Bosley & Fisher, in preparation) the nomothetic classes showed heterogeneity in their composition. Here, class composition can be most easily understood in terms of valence. That is, some classes were characterized by elevated negative affect (NA), some were characterized by elevated positive affect (PA), and others were mixed. Following from these conditions, an affect state was deemed to be an NA class if it featured elevated negative (and low/mean-level positive) items; conversely, a PA state was characterized by elevated positive relative to negative items. A mixed-valence state lacked this clear differentiation by valence (e.g., a state in which both negative and positive items are elevated simultaneously). Of the seven observed nomothetic affect states, three (42.9%) were NA classes, two (28.6%) were PA states, and two others (28.6%) were mixed-valence states.

Among the affect states of a similar valence, states were differentiated by relative level and kind of specific emotions, as well as the extent of polarization between positively- and negatively-valenced items. Figure 5a, 5b, and 5c present the compositions of the identified NA, PA, and mixed affect states, respectively.

NA Classes

Class Composition. Three NA states were identified in the present sample: class 2, 5, and 7 all featured negative emotions rated above the intraindividual mean level, whereas positive emotions were rated below the intraindividual mean level. The compositions of these classes are visualized in Figure 5a. These three affect states appeared to be distinguished primarily by which discrete negative emotion was the most elevated of the three items assessed. Class 2 featured the greatest elevations in *anxiety*; class 5 had the greatest elevation in *irritability*; and class 7 was defined by elevations in *sadness*. The three classes appeared to be differentiated also by the levels of positive emotions and the degree of separation between positive and negative affect.

Class 2 was a higher-anxiety affect state. In class 2, individuals rated anxiety at about 0.5 SD above their intraindividual mean level, with lower levels of elevation (about 0.25 SD) in irritability and sadness. Positive emotions during this state were slightly lower than their mean levels, but within -0.5 SD of the mean (*excitement* was rated slightly higher in this state than *content* or *joyful*). Class 2 occurred in 83 individuals in the present sample (72.17%). In the individuals who experienced class 2, it occurred on average 28.68% of the time (SD = 16.18, ranging from 5.52% to 79.77% of observations among the 83 participants with this class). Class 2 exhibited the second-highest rate of all the identified affect states. Individuals who experienced affect state 2 tended to spend over a quarter (28.9%) of their time in that state.

Class 5 appeared to be a high-irritability affect state. In this state *irritable* was rated 1 SD above its intraindividual mean level, followed by *sadness* and *anxiety*, between 0.5 and 1 SD above their intraindividual means. Of note, this state featured the most pronounced decreases in positive emotions: all positive emotion items were rated between -0.75 and -1.25 SD below their average levels. *Contentment* was the lowest-rated emotion in this state, rated even farther away from the mean than irritability. Thus, this state was characterized by a high degree of polarization (i.e., separation) between positive and negative emotion, with more irritability and less contentment than any other state. Class 5 was the most common by proportion of individuals in the sample, occurring in 90 individuals (78.26%). However, this state exhibited a lower rate of occurrence compared with class 2: those with class 5 spent an average of 15.23% of observations in that state (SD = 13.08; range 0.76-41.18%).

Class 7 was characterized by elevations in sadness. Here, sadness also exhibited a high degree of separation from the other two negative emotions. Sadness was rated almost 1 SD above its mean, while irritability and anxiety were elevated less than 0.5 SD above their mean levels. Thus, compared with *irritability* in class 5 and *anxiety* in class 2, class 7 was characterized by the greatest degree of differentiation among negative emotion items—indicating that sadness may be more phenomenologically discrete than irritability or anxiety in the current sample. Class 7 also stood out from the other classes by exhibiting the lowest frequency in terms of both proportion and rate. Only 30 individuals in the present sample exhibited class 7 (26.09%). Further, among these participants, class 7 occurred on average only 4.49% of the time (SD = 3.27, ranging from 0.3 – 12.94% of observations). This contrasted with the other two NA classes, as class 2 exhibited the second-highest rate of occurrence and class 5 occurred in the largest proportion of the sample.

NA Class Correlations. Figure 7 depicts the group-level correlations among the classes' presence or absence in each person, and Figure 8 depicts the group-level correlations among the classes' rate of occurrence. In terms of class presence/absence, class 2 and class 5 were significantly negatively correlated (r = -0.23, p = .012). The rates of class 2 and 5 were also significantly negatively correlated (r = -0.40, p < 0.001). The presence of class 7 was not significantly correlated with the presence of class 2 or 5 (rs = -0.12 and -0.17, respectively; ps > .05), again pointing to its potentially independent and discrete nature. In terms of rate, class 7 was negatively correlated with class 5 (r = -0.22, p = 0.03), but not with class 2 (r = -0.04, p = 0.48). Every individual in the sample experienced at least one of the NA classes: all but two participants (113 of 115) experienced either class 2 or class 5. The two participants who experienced neither class 2 or 5 both experienced class 7.

Class 2's presence was not significantly correlated with the presence of any PA or mixed-emotion classes. However, class 5's presence was significantly positively correlated with the presence of both PA classes, 3 and 6 (rs = 0.30 and 0.21, respectively; ps = 0.001 and 0.02). The presence of NA class 7 was significantly *negatively* correlated with PA class 6 (r = -0.21; p = 0.03).

PA Classes

Class Composition. Two of the identified affect profiles, class 3 and class 6, were characterized by higher levels of positive emotions and lower levels of negative emotions, relative to the intraindividual means. These are shown in Figure 5b. Unlike the NA classes, which appeared to be primarily differentiated by *type* of NA (i.e., we identified distinct anxiety, irritability, and sadness profiles) the two PA classes both featured *joyful* as the highest-rated item, with relatively little differentiation between the like-valenced positive items. In both classes, *joyful, excited,* and *content* were each separated by no more than 0.25 SD. Instead, the two classes appeared to be distinguished by the level of separation between positive and negatively valenced items. Class 3 exhibited high separation by valence and class 6 exhibited moderate separation.

In class 3, all positive emotions were elevated a whole standard deviation or more above their intraindividual mean levels. *Joyful* was the most elevated, followed by *excited* and then *content*. Class 3's positive emotion levels represent the greatest deviation from the mean relative to any other emotion in any other class. In other words, class 3 features the most extreme emotion ratings, with positive emotions rated markedly higher than their average levels. Class 3 occurred in 73 individuals (63.48%), and the individuals who experienced class 3 spent an average of 13.74% of observations in that state (SD = 7.14; ranging from 2.1 – 30.84% of observations).

In the other PA class, class 6, individuals experienced lower levels of both positive and negative emotions, with less polarization by valence. Here, *joyful* was also the highest-rated emotion followed by *content* and *excited*. The negative emotion items in this class were each rated about 0.5 SD below their intraindividual mean levels. This class occurred in the same proportion of the sample as class 3, in 73 individuals (63.48%). However, class 6 had approximately double the rate of class 3, as individuals spent an average of 27.42% of observations in this state (SD = 13.08; ranging from 3.73 – 63.18% of observations).

PA Class Correlations. Whereas class 3 and 6 occurred in the same number of individuals, it was not necessarily the *same* individuals who experienced both states. There were 44 participants who experienced both PA classes, 29 experienced only class 3, 29 experienced only class 6, and 13 individuals experienced neither PA class. The presence of class 3 was not significantly correlated with class 6 (r = -0.09; p = 0.35), suggesting that the presence of one PA class was unrelated to whether an individual would experience the other one. However, the rates of class 3 and class 6 were significantly negatively correlated (r = -0.46; $p < 0.001$) suggesting that the individuals who experience both states might exhibit tendencies toward one type of PA or the other.

Figures 7 and 8 display the correlations of the two PA classes with the other classes in terms of presence/absence and rate, respectively. Of note, these correlations highlight similarities and differences between the two PA classes. Presence of class 3 and class 6 were both positively correlated with the presence of NA class 5. The rate of class 3 and class 6 were both negatively correlated the rate of mixed class 4. However, the two PA classes diverged with respect to their relationship with mixed class 1: the presence and rate of class 3 were *positively* related to class 1, while the rate frequency of class 6 was *negatively* related to class 1.

Mixed Classes

Class Composition. The final two affect state classes, 1 and 4, did not show a clear separation of positive and negatively valenced items. These mixed-valence classes are shown in Figure 5c. During both of these states, items were rated close to their intraindividual means (within 0.5 SD), with items of pleasant and unpleasant valence clustering together. The key factor differentiating the mixed classes was whether the items were rated slightly above, or below, their mean levels – in other words, whether affect was generally more intense, or less intense, compared to a person's intraindividual baseline.

In class 1, all items were rated at levels slightly below the intraindividual means. Here, *content* was rated highest, only slightly below its average level, while *joyful* was rated lowest, about 0.5 SD below its mean. As all items were rated below their mean levels, this could represent a *lower-intensity mixed affect* state. Class 1 occurred in 80 individuals in the present sample (69.57%). For the individuals with class 1, this state occurred on average 23.95% of the time (SD = 13.37, ranging from 2.95 – 67.06% of observations).

Class 4, by contrast, may be termed *higher-intensity mixed affect*. In this state, all items were rated slightly *above* their mean levels, but no item exceeded ratings of 0.5 SD above its mean. In this state, *excited* and *joyful* were rated very slightly higher than other items, followed by *irritated, anxious, content,* with *sad* rated closest to its mean. This state occurred in 84 participants (73.04%). Of note, this class exhibited the highest rate of all classes: for those who experienced class 4, they were in this state on average about one-third (32.17%) of the time (SD = 21.77, ranging from 2.9 – 95.8% of observations).

Mixed-State Class Correlations. The presence of class 1 was not significantly correlated with the presence of class 4 (r = 0.15, p = 0.11). However, the rate of class 1 was negatively correlated with the rate of class 4 (r = -0.24; p = 0.01). This is a similar pattern to the one we observed in the two PA classes: while the presence/absence of these two classes were unrelated, their rates of occurrence were negatively correlated.

The presence of class 1 was positively correlated with PA class 3 (r = 0.28, p = 0.002) while class 4 exhibited no significant correlations with other classes in terms of presence/absence. However, both class 1 and class 4 exhibited significant correlations with most other classes in terms of rate (see Figure 8 for r and p values). The rate of class 1 was significantly negatively associated with the rates of classes 2, 4, 5, and 6; and positively associated with the rate of class 3. The rate of class 4 was negatively correlated with the rates of classes 2, 3 and 6. Of note, the two mixed classes diverged with respect to their association with PA class 3: class 1 was positively correlated with class 3, while class 4 was negatively associated with this class.

Rates of Occurrence and State Duration

Averaging across the rates of occurrence by negative, positive, and mixed-valence states, we found that mixed-valence states exhibited the highest rates on average (M = 28.06% of observations), followed by PA (M = 20.58%) and NA (M = 16.1%). Thus, although mixed-valence states were not the most common across the sample, they were the most persistent within those who experienced them. That is, for those individuals who exhibited mixed affect states, they spent more time in these states on average compared to other affect states.

We found that the temporal patterns, including durations, of each affect state varied considerably from person to person. Figure 10 illustrates the time series of three participants as exemplars, showing a comparison between their levels of PA, NA, and affect profile occurrence across the sampling window. While these participants exhibited some of the same affect states, the states exhibited differential time-courses and patterns of co-occurrence within the different participants. Visually examining these plots may provide more nuanced information about how an individual’s affect shifts over time, in general or in response to specific contextual stimuli. This is discussed in more detail below.

Discussion

While EMA offers the opportunity to examine temporal dynamics and individual differences in emotion with a high degree of nuance, it remains a challenge to distill generalizable group-level information from these high-dimensional idiographic datasets. The two-stage analytic approach described here provides a way of bridging the gap between idiographic and nomothetic levels of analysis: mixture models were run at the first (idiographic) level in each time series to cluster and classify intraindividual emotion expression, and the second (nomothetic) level assessed idiographically-generated results to yield group-level information about generality and generalizability.

By applying this two-stage approach with FMM to the present data, we distilled a high-dimensional EMA dataset of over 34,000 observations across 115 individuals into a set of seven discrete categories of emotional experience at the group level. We were then able to retrofit these group-derived clusters to the individual data to summarize person-level (idiographic) experiences with generalizable, nomothetic classifications. In other words, we can now examine which of the shared affect profiles a person experiences, as well as when and how frequently they experience these states. Rather than interpreting the idiographic models, we focus our interpretation here on the shared, nomothetic affect states, and the individual differences in their expression.

With 115 densely-sampled time series comprising dimensional ratings of six emotions (*sadness, anxiety, irritability, joy, excitement, contentment*) we were able to (1) categorize each person's EMA time series into a discrete, person-specific set of affect states that they experienced over the two-week sampling window; and (2) use the 795 person-specific affect states to create a group-level set of *possible* affect states. We identified three NA states, two PA states, and two mixed states at the group level. Individuals were heterogeneous in which affect states they exhibited, and the rates at which they experienced each of them. Closer examination of these affect states may provide generalizable information about the nature of emotion at the between-persons level, with a higher degree of nuance than is available from traditional cross-sectional sampling.

Negative Affect Classes

The NA states were differentiated by which of the three negative emotions was most prominently elevated, with distinct *anxiety, irritability,* and *sadness* profiles. Class 2 appeared to be a heightened-anxiety state, class 5 was a high-irritability state, and class 7 was predominantly marked by sadness. Thus, a unique feature of the negative affect classes is their specificity. This aligns with the specific functional roles of negative emotions: negative emotions each serve to motivate particular behavioral responses to environmental demands (Keltner & Gross, 1999; Pratto & John, 1991). As examples, anxiety motivates reassurance seeking or other safety behaviors; irritability motivates one to distance from a bothersome stimulus; sadness motivates resting and conservation of resources. It stands to reason that correspondingly differentiated negative affect states would be important to motivate a context-appropriate behavioral response.

Class 2 and 5: anxious and irritable states. The importance of negative emotion, given its vital survival function, was highlighted by the high proportions of the two NA states most common in the sample, 2 and 5. Class 5 (irritability) was the most commonly occurring across participants, present in 90 individuals. Class 2 (anxiety) was the third most frequent state, occurring in 83 participants. Importantly, 113 of our 115 participants experienced at least one of these two states. We observed a significant negative correlation in the presence of class 2 and class 5, indicating that participants were more likely to experience *one* of the two states, rather than both. However, there were 60 participants who did experience both states. We also observed a significant negative correlation in the rates of these two classes, suggesting that among the 60 people who did experience both class 2 and class 5, they tended to spend more time in one of the two states. Interpreted broadly, this suggests a general picture of our sample with two predominant types of negative emotional experiences. Anxious states and irritable states seemed to fit discrete, differentiable profiles where people tend to spend more time in one or the other state. With individual differences in environmental context, baseline emotional vulnerability, and responses like emotion regulation (John & Gross 2007), it makes sense that individuals would exhibit different types of negative emotion profiles. Further, this specificity may be unique to negative emotion, as we did not find evidence of such differentiation by emotion items in the positive affect or mixed classes.

While classes 2 and 5 were among the most frequently occurring states *across* the sample, we observed substantial variability in the amount of time individuals spent in those states. For example, those with anxiety class 2 were in that state 28.7% of the time on average. However, among these individuals, the rate of occurrence for this class ranged from 5.5% to 79.7% of observations. This reflects that, while some people experienced anxious states on just a few occasions, others were in a high-anxiety state nearly 80% of the time across the two-week sampling window. Conversely, class 5 (irritability) exhibited an average rate of 15.2%, with a range from 0.8% to 41.2%. Thus, while some people were in the anxious state for a clear majority of the sampling window, no participants in the present study spent as much as half of their time in an irritable state. For some, class 5 only happened on a handful of occasions (i.e., less than 1%), while if a person experienced class 2, it occurred *at least* 5.5% of the time.

Of note, while class 5 was slightly more common *across* participants (78% experienced class 5 at any point, compared with 72% who experienced class 2), the rate of occurrence for class 2 was nearly double that of class 5. This could indicate either (a) generalizable features of these affect states themselves (i.e., anxiety might last longer or be harder to regulate than irritability), or (b) information about the nature of emotion in this particular sample. Perhaps UC Berkeley undergraduates have tendencies toward both irritability and anxiety; experiencing anxiety states occupied about twice as much of a student's time on average compared with irritability states.

It is also possible that these states may be elicited by different types of contextual variables, which could explain their differing rates of occurrence. For instance, anxiety is commonly evoked by evaluative situations (e.g., exams) or future-oriented problems (e.g., career planning)—both of which are common and frequent in the undergraduate college experience. Thus, anxiety has been shown to be a relatively stable state among undergraduates (Cassady, 2000). By contrast, irritability is typically triggered in response to blocked goal attainment (Vidal-Ribas et al., 2016). While this is a *common* human experience, it is not necessarily a *frequent* one. Within an undergraduate's typical life, perhaps anxiety-eliciting stimuli are chronic, whereas irritability-eliciting stimuli are more episodic or context-dependent.

Correlations among the classes may reveal more detail about the types of people who experience these irritable and anxious profiles. One notable feature is that the presence of class 5 was significantly positively correlated with the presence of PA class 3. These were the two most polarized affect states (in which there was a high degree of separation by valence, with emotions rated at the most extreme ends of the spectrum). In both of these states, opposite-valenced items were rated at least 1.5 standard deviations apart. Because these classes were significantly correlated, this could suggest a possible trait-level phenomenon in which some individuals experience emotions—both positive (class 3) and negative (class 5)—as more polarized, or in more extreme terms.

A debate has persisted in the literature for decades concerning whether positive and negative affect are two ends of a single, bipolar continuum (Green, Goldman, and Salovey, 1993) or whether they are separate, weakly-correlated dimensions (Watson, Clark, & Tellegen, 1988). There are likely individual differences in the structure of affect. For example, one study found that in anxious individuals, PA and NA are negatively correlated and unidimensional (i.e., part of one continuum from NA to PA), whereas in depressed individuals, NA and PA are not significantly correlated (Williams, Peeters, & Zautra, 2004). Later work by this group has led to a unified model of the structure of affect that relies on individual differences in affective structure (in other words, PA and NA can be both bipolar *and* orthogonal, depending on the individual and context; Ong et al 2017). It is possible that such individual differences in the structure of affect offer an explanation for our finding that some individuals exhibited polarized classes (in which positive and negative items appeared to be at opposite ends of one unipolar rating continuum) while others did not. Perhaps for these individuals, positive and negative affect are reciprocally antagonistic, such that the presence of PA inherently equals an absence of NA, and vice versa.

We also observed that the rate of class 2 (the anxious state) within persons was significantly negatively correlated with the respective rates of classes 1 and 4, the mixed states. Interestingly, the *presence* of class 2 was not correlated with the relative presence of the mixed states. This suggests simply having the experience of class 2 does not necessarily tell us anything about other states a person may experience, but the more time spent in this anxious state may preclude the experience of the mixed states.

Class 7: a sadness state. In addition to the anxious and irritable states, we also identified a third—and less frequent—NA profile in class 7. This class was characterized by the most pronounced elevations in sadness. Class 7 was present in only 30 individuals (26%), and among these individuals, it occurred quite infrequently, between 0.3% and 12.9% of the time. This suggests that, in the sample group of UC Berkeley undergraduates, states of predominant sadness are relatively atypical. Instead, negative emotional experience appears more likely to be characterized by high-arousal negative emotions, such as irritability and anxiety.

Perhaps those with class 7 experience sadness as an intense and highly-differentiated state. Individuals have been shown to vary in the extent to which they experience their negative emotion states as differentiated. For example, individuals high in emotion differentiation have been shown to use granular, precise category labels for their experienced affect such as *frustrated, nervous,* or *lonely,* whereas persons with low emotion differentiation are more likely to use broader terms like *feeling bad* (Barrett, Gross, Christensen, & Benvenuto, 2010, Smidt & Suvak, 2015). In class 7, sadness is clearly differentiated, so the presence of this state could point to individuals who are higher in emotion differentiation.

Another possibility is that this state is heavily context-dependent. Sadness is commonly elicited by events such as loss, rejection, or dwelling on the past (Verduyn et al., 2009). Compared with the types of events that elicit irritability and anxiety (such as immediate environmental stressors and future-oriented thinking; Verduyn et al., 2009), contexts that elicit sadness could be more clearly distinguishable and recognizable as *sad* events. This could explain why *sadness* in class 7 was markedly differentiated from the other emotions. Further, sadness-eliciting events may be more infrequent and episodic than anxiety- or irritability-eliciting events (Verduyn et al., 2009), consistent with class 7's low rate of occurrence.

While it seems at first that class 7 could indicate some sort of depression state, there are two reasons to believe that this class actually indicates adaptive rather than intrusive levels of sadness. First, those who experienced class 7 were typically not in this state for very long (in our sample, the person with the highest rate of occurrence of this state only experienced it roughly 12% of the time). Second, the rate of class 7 was unrelated to the rates of the positive affect states (classes 3 or 6). This suggests that experiencing class 7 did not preclude the experience of positive affect states, as we might expect if class 7 represented a clinical depression state. More information on each of the affect states' relationship to stress, life satisfaction, and psychopathology is provided in Supplementary Section 2.

Positive Affect Classes

The PA states, classes 3, and 6, each featured *joyful* as the highest-rated item with relatively little differentiation among the positive items. These states were distinguished by their level of separation between positive and negative emotions. Class 3 was a more polarized, higher-positive affect class, with high ratings for all positive emotions and low ratings for all negative emotions. Class 6 was a less-polarized, moderate positive affect class. Arguably, class 3 represents a high-arousal positive state, with *excited* rated higher than *content*, while class 6 may be a lower-arousal positive state, where *content* is rated higher than *excited*. Future work should validate these assumptions by cross-referencing explicit arousal items or physiological variables.

The fact that our sample exhibited less diversity and specificity in positive (relative to negative) affect states may be consonant with extant literature concerning the evolutionary function of emotion. While negative emotions signal the need to cope with a specific environmental stressor to avoid imminent harm (Quigley & Feldman Barrett, 1999), positive emotion is thought to motivate individuals to explore new pursuits and consolidate resources, in general, for the future (Frederickson, 2004). Thus, the function of positive affect states may be somewhat more diffuse and less specific than the motivating functions of negative emotions. In fact, scientific taxonomies of emotion (and the English language itself) exhibit a ratio of roughly one positive emotion word for every three or four negative emotion words (De Rivera et al 1989; Frederickson, 1998). This relative lack of differentiation among positive emotions may offer an explanation for the findings that (1) positive items appeared to cluster together in class 3 and 6; and (2) the two positive affect states were not delineated by discrete emotion type as we observed in the NA classes. Perhaps our participants experienced negative affect states as differentiable and specific (e.g., *anxiety* vs. *irritability* as discrete profiles), while their positive affect states were experienced as undifferentiated, generally pleasant states.

The rates of the two PA states were significantly negatively correlated, suggesting that if a person did experience both PA states, they tended to gravitate toward experiencing more of one or the other. To some extent, this may align with the literature on ideal affect (Tsai, 2007). While it is generally accepted that people value and want to experience pleasant emotional states, individuals vary in the type of positive emotion they prefer to feel. Some individuals prefer a lower-arousal positive state (e.g., *calm, content*, *serene*) such as class 6, while others value higher-arousal positive states (e.g., *excited, enthusiastic*) which may relate more to class 3. Affect valuation may be influenced by variables like culture (Tsai, Knutson, & Fung, 2006), and religion (Tsai, Miao, & Seppala, 2007). The type of affect that an individual values may shape their emotion-regulation tendencies (Mesquita & Albert, 2007), such that individuals would intentionally cultivate the type of positive affect state they prefer. Thus, whether a person values high or low arousal positive affect may predict their rates of class 3 vs. 6. The negative correlation in the rates of these two states may provide some preliminary support for this idea. Future analyses should explore whether and how affect valuation influences an individual's experience of particular affect states. For example, affect valuation can be measured using a scale such as the Affect Valuation Index (Tsai, Knutson, & Fung, 2006). It would be useful to examine whether, at the group level, affect valuation scores are correlated with either the presence vs. absence, or rates, of particular affect profiles.

Mixed Classes

The five affect states previously discussed were characterized by clear separation between positive and negative emotion, with same-valenced items clustering together. However, two additional affect states were mixed, with blends of positive and negative items. The presence of these two states (1 and 4) were quite common as a proportion of the sample, occurring in 80 (69.6%) and 84 (73.04%) individuals respectively. Further, for individuals who experienced these states, they exhibited a relatively high rate of occurrence; roughly a quarter of all observations were spent in mixed states 1 and 4 (M = 23.95% and 32.17%, respectively).

The relatively high proportion and rate of these states in the sample is consistent with the burgeoning literature concerning the advantages of mixed emotional episodes (see Kreibig & Gross, 2017; Hoemann et al, 2017). In the real world, emotional stimuli can be quite complex, eliciting multiple categories of emotions at the same time. The literature also suggests that such mixed emotional states confer an adaptive advantage, by mobilizing multiple behavioral responses through a variety of elicited emotions, potentially activating a diverse range of behavioral response options to cope with complex environmental demands. In this sense, it is unsurprising that mixed states had the highest rate of occurrence overall, if these mixed states can be elicited by the widest range of different contexts. This represents another area for potential future investigation.

There were key differences between classes 1 and 4, with the most prominent being whether the intensity of affect was lower than usual (class 1) or higher than usual (class 4). Class 1 appeared to be a lower-intensity affect state, in which all emotion items were rated below their intraindividual means (with *contentment* closest to the mean). On the other hand, in the higher-intensity affect state of class 4, all items were rated slightly above their intraindividual means with the greatest peaks for *excited, joyful* and *irritated*. Therefore, class 4 may represent an emotionally-activated state, with a blend of both pleasant (*excited*) and unpleasant (*irritable*) activation.

That the presence of these two mixed states was uncorrelated suggests they generally operated independently of each other. However, we did observe a significant negative correlation in the rates of occurrence of these two states, suggesting that individuals who experience both states likely tend toward experiencing one more than the other. Future research should investigate whether experiencing one mixed state over another is associated with differential clinical or behavioral outcomes.

Class 1 and 4 may each represent clinically meaningful phenomena. For example, the rate of class 1 was negatively correlated with the rates of four other classes (2, 4, 5, and 6), suggesting that individuals who spend more time in the lower-intensity affect state of class 1 may have less diversity in the types of other affect states they are able to experience. Conversely, class 4 represents a state of higher-intensity affect, which may indicate generalized emotional reactivity or activation. Further, those who experienced class 4 at any point spent an average of 32.2% of observations in this state. This was the highest rate of any affect state, with one participant spending over 95% of observations in this state.

Of note, it is also possible that these states are an artifact of measurement error and do represent meaningful constructs. An important possibility that should be examined further in future studies, is that some undergraduates were not paying careful attention to their emotions (i.e., indiscriminately rating emotions all-above or all-below the mean without thinking). Another possibility is that this state is clinically meaningful but not as a discrete type of affect – presumably, individuals low in emotion differentiation might also tend more toward the expression of such undifferentiated states in which all items cluster together above or below the mean. This could be examined in future studies by assessing whether higher presence or rate of class 1 or 4 (and lower presence or rate of other affect states) is significantly associated with low emotion differentiation scores.

More remains to be understood about whether these states are clinically meaningful, and if so, whether they are adaptive or maladaptive. One possibility is that the states represent different benign types of mixed affect, with all emotions are rated close to intraindividual average levels. Another possibility is that these mixed states represent pathological forms of lowered-reactivity (e.g., numbing), and activation, as would be observed in depression (Loas, 1994) or mania (Johnson, Edge, Holmes, & Carver, 2012) respectively. Future studies should continue to examine whether these states are linked to adaptive functioning or maladaptive behavior. It would be useful to examine whether these states are present, or more frequent, within a psychiatric sample, as opposed to a sample of typically-functioning undergraduates. Perhaps a goal of clinical treatment could be to increase the rate of occurrence of these affect states if they represent adaptive euthymic states (Fava & Guidi, 2020); if they are instead linked to maladaptive outcomes, clinicians could monitor and assess the presence of these states and aim to decrease them in treatment.

Heterogeneity

One of the most prominent patterns that we observed across both the idiographic and nomothetic analyses was heterogeneity in the set of affect states experienced by individuals across our sample. At the idiographic level, each individual exhibited an idiosyncratic set of affect states. Consistent with our earlier applications of idiographic FMM (Fisher & Bosley, 2020), the present sample varied widely in terms of the number and composition of latent affect states they experienced. When we subsequently applied a second-level, between-persons classification step (classifying the lower-order idiographic classes into latent group-level affect state categories), we again observed heterogeneity; individuals varied with respect to *which* group-level affect states they experienced, and *how frequently* they experienced each affect state. While we identified a set of seven possible affect states at the group level, only two individuals (1.7%) exhibited all of these possible affect states. Further, the rate of each affect state exhibited marked variability person-to-person.

This is unsurprising given substantial evidence for individual differences in emotion-generating processes (Verduyn et al., 2015) and responses such as emotion regulation (John & Gross, 2007). Our approach and the present findings also align with the rapidly-expanding literature in clinical psychology concerning the importance of idiographic analysis, given individual differences (Barlow & Nock, 2009; Piccirillo & Rodebaugh, 2019). A key goal of the two-stage FMM approach described in the present chapter is to yield generalizable, group-level information about emotion from idiographic time series data.

The heterogeneity in our results points to an important footnote: while our nomothetic results are useful to learn about the group tendencies and patterns in emotion experience in daily life generally (e.g., what sets of affect states are present in this group), it is still inaccurate to draw conclusions about any individual based on the group-level data (e.g., knowing the set of possible affect states in the sample does not tell you anything about the affect states of a particular individual). To illustrate this, consider the comparison of the three different exemplars in Figure 10. Of the seven possible affect states that we identified at the group level, no two individuals experienced them in exactly the same way. Each time series was unique. The three individuals in Figure 10 expressed different subsets of the affect profiles, and the affect profiles exhibited different time courses within each person. Thus, although the two-stage FMM provides more nuanced group-level information than was previously available (by aggregating across detailed idiographic models), this group-level information is limited in its generalizability to any individual. To achieve a nuanced understanding of any individual, it is still necessary to measure them directly. With burgeoning methods for the collection of long, intensively-sampled time series as smartphone and wearable technology expands (Hamaker, 2017), this person-specific data-driven approach may become more widespread in the near future.

Nonetheless, because the nomothetic results in this case are derived from aggregation across lower-order idiographic models, the present results may provide a more nuanced picture of group-level questions about emotion (e.g., the structure of affect or general patterns in time-varying emotion dynamics) than previously available. For example, by examining the group-level set of affect states, we observed that negative affect classes are differentiated by specific emotion type (i.e., different states for sadness, anxiety, and irritability), but we did not find this specificity for positive or mixed affect classes. This may align with a group-level conclusion about the specific motivating function of negative emotions (Keltner & Gross, 1999; Pratto & John, 1991), and is further underscored by the fact that the two most common classes across the sample (by proportion) were NA states. Conversely, in terms of individual differences, we found that mixed emotional states had the highest rates of occurrence among those who experienced them. This could point to important person-level differences (potentially explained by differences in emotional awareness or emotion differentiation); some people experience affect by having relatively-frequent moments where all emotions cluster together at either lower-intensity or higher-intensity levels and other people do not.

Further, our results may align with the idea that discrete emotions are organized within a person as a dynamic system (see Izard, 2000). It is hypothesized that certain combinations of emotions can become particularly frequent within an individual, if those emotions are repeatedly elicited together as a solution to environmental demands. In this sense, perhaps the affect states identified in the present study can be seen as a common set of attractors within this sample. Examining the rates of these states may then indicate the frequency or entrenchment of emotion attractor states within each individual. In other words, affect states with higher rates of occurrence may be attractor states that are stickier or more entrenched for a given person. For instance, class 2 (anxiety) occurred with relatively high proportion *and* rate in our sample. Perhaps this state represents a particularly common emotional pattern among and within UC Berkeley undergraduates. As researchers continue to build upon dynamic systems models of emotion (e.g., Wichers, Wigman, & Myin-Germeys, 2015), perhaps the present approach to identifying affect states can provide an additional method of identifying common attractor states either within an individual or within a particular group.

Limitations

There are a handful of ways in which the nature of our study sample and EMA sampling paradigm may impact the conclusions that can be drawn from the analyses in the present chapter. For example, our sample was drawn from the UC Berkeley undergraduate research participation pool, yielding a college-educated, young-adult, plurality-White American sample. Given evidence that emotional experiences vary as a function of age (Carstensen et al, 2011) and culture (Russell, 1991), a likely possibility is that if the present methods were repeated in other demographic groups, the group-level affect states identified could vary meaningfully. Future studies could endeavor to examine this question empirically. For example, perhaps certain affect states are unique to UC Berkeley undergraduates, while others are shared with the general population.

A related limitation is that, to minimize participant burden by using as few items as possible, the EMA sampling paradigm did not assess the environmental context in which emotion ratings were occurring. While demographic variables can provide one form of trait-level context for individuals' emotion ratings, information about the state-level (e.g., nuanced social dynamics or environmental variables that may have influenced momentary changes in emotion) would have enriched the present findings by providing a possible explanation for the onset of particular affect states. There may be types of experiences or contexts that are more likely to elicit particular states—and the mappings from context to affect state may or may not be idiosyncratic. Without more contextual information, the present study cannot identify the triggers for particular affect states; however, by providing a way to identify what the affect states are, the present methods may enable a future study to more thoroughly assess environmental factors via EMA, enabling the study of affect states as a function of context.

Relatedly, as mentioned above, it is possible that some participants were not paying careful attention or thoroughly considering the items. Thus, there is a chance that measurement error due to this possibility impacted the set of affect profiles that were identified. While steps were taken to minimize the likelihood of this occurring (e.g., the instructional video that participants watched beforehand, inspecting response variability throughout the sampling window and notifying participants with invariant responding), the possibility remains that such a process impacted results of the present study. Future iterations of the study could take steps such as adding an attention-check to certain EMA prompts, or explore other ways of discerning attention (e.g., by using wearable devices to provide additional measures of behavior and physiology; Bertz, Epstein, & Preston, 2018).

An additional limitation is that to obtain dense sampling within each day of sampling, the sampling duration was limited to a 14-day window. Consequently, while these time series can be used to establish the set of affect states that occurred within this window, we are presently unable to establish the stability vs. plasticity of the composition of the affect states over time. For instance, it is possible that an individual could exhibit different affect states during different phases of their life.

Future Directions

Future studies could address these limitations and build upon the present work in a number of ways. One of the highest priorities should be to replicate the present analyses in a larger and more diverse sample. As the present sample of UC Berkeley undergraduates is demographically quite limited, it is important to sample other demographic categories—particularly age and culture. This would enable between-groups comparison of the number or nature of affect states, which could augment the affective and clinical science literature. For example, there is evidence that as individuals age, they are more likely to experience positive emotion (Carstensen et al., 2011) and quicker to bounce back from negative emotion states (Larcom & Isaacowitz, 2009). Compared with our undergraduate sample, perhaps older individuals would exhibit a greater variety of positive-emotion profiles. Or, perhaps a similar set of affect states emerge, but older individuals spend more time in positive and less time in negative affect states.

Relatedly, there is evidence that language and culture play important roles in shaping subjective emotional experience, and the perception of emotion in others (Barrett, Lindquist, & Gendron, 2007; Lindquist, Barrett, Bliss-Moreau, & Russell, 2006; Russell, 1991). A person's cultural background has also been shown to shape their ideal affect and emotion regulation (Tsai, 2007, Mesquita & Albert, 2007). Therefore, despite our sample's cultural diversity in some respects, the fact that our sample were all English speakers (and the fact that the EMA surveys assessed emotion in English) likely influenced the mood categories that emerged in the present study. The extent to which language and culture influence the emergent affect states is an important area for further exploration. For example, if future studies could collect emotion data in multiple languages, across a range of cultural groups, and replicate the present analytic approach, it would be interesting to explore cross-cultural similarities, differences, and patterns in the affect states that emerge from group to group.

Because affect states are time-bound phenomena, it will also be important for future studies to examine temporal patterns in these states to determine when particular affect states are likely to occur. There is evidence that different emotions exhibit different duration patterns (Verduyn et al., 2009). Emotion duration also varies from person to person and situation to situation (Verduyn et al., 2015). Extending the work on emotion duration to map the duration (e.g., onset-offset) of affect states may be an important area of focus. Perhaps the duration patterns, rather than affect states themselves, are linked to psychopathology.

While detailed analysis of the duration of specific mood states is beyond the scope of the present study, a future study should endeavor to examine the average duration and onset-offset patterns of each of the mood states. Further, visual inspection of affect states over a time series—alongside a person's report of other events occurring during the sampling window—may provide a useful way to understand how that individual's affect shifts in response to context, by examining their within-person patterns of change.

In line with our previous work (Fisher & Bosley, 2020) future analyses should also examine linear and curvilinear trends in the expression of affect states, as well as their possible periodic oscillation (Golder & Macy, 2011). In Supplementary Section 1 we model the periodic oscillation of the 7 affect states and the 6 singular emotion items we measured. Future studies should build upon this by investigating the nuances of our affect states' temporal components (such as their links to time of day, day of the week, part of the year, and within-person linear/curvilinear trends).

Finally, a recent focus of clinical psychology has been the identification of transdiagnostic mechanisms—between-persons variables such as emotion dynamics (Sperry et al, 2020) or emotion regulation (Fernandez, Jazaeiri, & Gross, 2016)—that can explain covariance across multiple diagnostic categories of psychopathology. Heterogeneity in the affect states that we observed in the present study may represent fertile ground for future exploration of transdiagnostic mechanisms. Perhaps certain affect states relate to maladaptive personality traits, or confer a higher (or lower) likelihood of exhibiting psychopathology. Supplementary Section 2 provides additional analyses of the present data that begin to address this question by examining affect states' associations with momentary stress and life satisfaction, as well as current psychopathology.

Potential Clinical Utility. Regardless of their link to psychopathology, identification of these person-specific affect states may present viable opportunities for clinical intervention and behavior change. Both adaptive and maladaptive behaviors have been linked to emotion (Keltner & Gross, 1999). As such, tracking and regulating emotion is a foundational component of many behavioral interventions (e.g., Beck & Beck, 2011). If affect states are associated with differential patterns of behavior, and if certain maladaptive behaviors tend to occur more in one affect state than others, identifying and predicting affect states and their temporal patterns could be used to predict when treatment-relevant target behaviors may occur.

Our research group has found evidence that these person-specific affect states, as identified by the method in in the present study, are significantly linked to behavior in most participants—although the nature of the affect states themselves, and which behaviors are affected, are idiosyncratic (Bosley & Fisher, *in preparation*). To establish the potential clinical utility of these person-specific affect states, future studies should examine whether certain affect states are linked to greater levels of subjective stress or life satisfaction—or whether particular affect states are associated with psychopathology.

Finally, for the affect states to be clinically useful (for case formulation, treatment delivery, or progress monitoring) future studies should address the question of the affect states' stability vs. plasticity over time. For example, if affect states are generally stable over time, but can change in response to certain inputs, it may be the case that a person's individual set of affect states could represent a tool for tracking change in clinical treatment—that is, for some individuals, perhaps psychotherapeutic intervention could be operationalized as "successful" to the extent that it changes the structure of an individual's affect states.

Conclusion

We have applied a two-level finite mixture-model to a set of 115 densely-sampled EMA time series—first at the person-specific level and then the group level. The first step clustered time points in intraindividual data to identify idiosyncratic combinations of discrete emotions we termed *affect states*. The second step clustered the identified person-level affect states to return a set of seven group-level affect state categories. Taken together, examining the patterns in the identified affect states provides novel insight into the nature of experienced emotion in our sample.

Specifically, we categorized affect states into negative, positive, or mixed, with important differences by category. Negative affect states tended to be more greatly differentiated and specific, with unique classes identified for high anxiety, irritability, and sadness. By contrast, the positive affect states were largely undifferentiated by specific items, but instead exhibited differences in the degree of separation of the positive from negative items. Individuals generally spent the most time in mixed states of approximately-average emotional experience, including a blunted affect and a mildly activated state. Crucially, we observed marked heterogeneity with respect to the set of affect states each individual experienced, and the amount of time they spent in each affect state. Applying this method to densely-sampled EMA time series may improve future studies of emotion by distilling idiographic data into a format that can inform both basic research and clinical application.

Supplementary Section 1: Periodic Variation in Affect states

Background

Because emotions are processes that vary and unfold over time, a more complete understanding of emotion might include a more detailed consideration of their temporal patterns. A literature termed *affective chronometry* (Davidson, 1998; 2015) has established the importance of examining the time-varying nature of emotion. Work by several research groups has provided empirical support for the idea that different emotions have different time-courses (Frijda, 2007; Scherer & Wallbott, 1994; Verduyn et al., 2009). The duration of an emotional episode has been shown to vary from emotion to emotion and person to person. Single emotions typically last from a few seconds to a few hours (Verduyn et al., 2015) although this depends on factors such as the emotion-eliciting event (emotional events that are perceived as important lead to longer-lasting emotions; Verduyn & Lavrijsen, 2015), the emotion intensity, and trait-level factors of the person experiencing the emotion (e.g., regulation skills, Verduyn & Lavrijsen, 2015).

The nuanced temporal dynamics of single-emotion states still represents an open area of investigation that has become more compelling in recent years (Davidson, 2015)—particularly given the rise in methodology that enables the collection of densely-sampled emotion time-series (Hamaker & Wichers, 2017). The affect states discussed in the present document comprise momentary blends of single-emotion states that likely have their own temporal patterns. Understanding the temporal variation in these affect states is necessary to establish their utility within affective and clinical science. For example, understanding person- and group-level patterns in the duration, onset, and offset of these affect states could help researchers to measure them more effectively. Additionally, identifying particular times when affect states occur may aid in the prediction of behavior. Thus, mapping the temporal dynamics of affect states holds a great deal of potential for future research and clinical application.

In our earlier application of idiographic FMM (Fisher & Bosley, 2020), we used temporal components such as time of day, day of week, trends, and cycles to predict the occurrence of person-specific affect states. Using person-specific elastic net models with time variables as possible predictors of affect state, we achieved an average prediction accuracy of 83% across idiographic models, suggesting that these affect states can be localized in time reliably. While this opens many potential avenues for further exploration, the present section aims to examine in greater detail the cyclical or periodic variation in our seven identified affect states.

Periodicity in Emotion

Human emotion is associated with a range of periodic biological rhythms, at a variety of time-scales. For example, diurnal cortisol variation (Smyth et al., 1997) and the circadian sleep-wake cycle (Boivin et al., 1997) have been shown to affect emotion on a 24-hour cycle. Humans also exhibit an ultradian rest-activity cycle which repeats throughout the day, with associated emotional and motivational changes over a period of about 90 minutes (Kleitman, 1982). Other relevant biological cycles are infradian, such as the monthly menstrual cycle and its related hormonal shifts. Emotion itself has been shown to fluctuate according to diurnal, ultradian, and infradian rhythms. Similar patterns of periodic variation in emotion have been observed across cultures (Golder & Macy, 2011), in groups with and without psychopathology (Hall, Benedeck, & Chang, 1996), regardless of whether emotion is being measured via self-report or by objective measurement using behavioral indices (Hasler, Mehl, Bootzin, & Vazire, 2008).

One study (Golder & Macy, 2011) coded millions of Twitter messages by emotional valence to observe periodic variation in PA and NA over time. They found cross-cultural effects at both diurnal and infradian levels of analysis, showing that (1) individuals exhibit more PA in the morning that deteriorates throughout the day; and (2) seasonal change in baseline PA was associated with daylight duration. There is also evidence for more rapid periodic emotion cycles—for example, in studies measuring hourly change in depressed mood, ultradian cycles with a 3-4 hour period have been observed in both clinically-depressed and non-depressed control participants (Hall, Benedek, & Chang, 1996).

Information About Periodicity Can Inform EMA Sampling Frequency

Understanding the speed of cyclic variation in emotions is vital to our understanding of the emotion processes themselves, and therefore should inform how emotion is measured. As mentioned above, EMA studies of emotional phenomena have increased exponentially over the last decade (Hamaker & Wichers, 2017). However, to date, studies may not have sufficiently considered whether the EMA sampling frequency aligns with the underlying speed of temporal variation in emotion. Most EMA studies are interval based, meaning that researchers specify some sampling frequency—commonly once, twice, or four times per day—and participants are prompted to provide ratings of their emotions at those intervals (Moskowitz & Young, 2006). Among published studies using EMA methods to study emotion, the sampling frequency varies widely, from once per day as is the case with "daily diary" approaches (see Gunthert & Wenze, 2012) to as many as 60 times per day in one study (Koval & Kuppens, 2012). The selection of EMA sampling frequency and period is often based on convenience, precedent, and feasibility (e.g., considering participant burden) rather than empirical data about the nature of the underlying signal (e.g., the speed of variation in the emotion under investigation).

Trying to detect an emotion signal (i.e., capturing the level and variation in a specific emotion over time) with a suboptimal EMA sampling frequency—taking measurements either too frequently or too sparsely—greatly reduces researchers' ability to represent and model the actual change over time in that emotion. This could lead to inaccurate inferences about the nature of emotional processes themselves, or about how those emotions might influence, or be influenced by, other behaviors or experiences across time. For example, sampling a rapidly-changing emotion state at a frequency that is too slow may result in aliasing or masking the signal, making that emotion appear to change more slowly than it actually does in real life (Warner, 1998). Sampling too quickly, on the other hand, can lead to participant burden and may increase rates of dropout—obviously, this should be avoided if such a high sampling frequency is not needed (Carpenter, Wycoff, & Trull, 2016; Moskowitz & Young, 2006). It would therefore be useful for EMA studies of emotion to have an empirically-derived basis for selecting an optimal sampling frequency and duration of the sampling window, rather than the somewhat arbitrary process of using intuition or perceived participant burden to make decisions about this important part of the research design.

Aims of This Section

In this section we provide empirical data regarding the nature and speed of periodic oscillation in our seven identified affect states, to inform the optimal frequency at which to measure them via EMA. With this in mind, we applied spectral analysis to examine the presence of periodicity, and the cycle length, of each affect state within each individual. In doing so, we extend the *affective chronometry* literature in three ways.

First, the present data push the upper limit of the literature in terms of EMA sampling frequency and period, with measurements taken every 30 minutes for two weeks. Given this density of sampling, our data are uniquely suited to examine varying types of periodicity in the temporal variation of emotion because they enable the detection of faster emotion dynamics than are observable in previous data. There is evidence that emotions change on the order of minutes, so a sampling frequency of once, twice, or four times per day might be insufficient to capture rapidly-varying cycles. Whether rapidly-varying periodic cycles are detected in the present data can inform EMA sampling frequency in the future. If rapid cycling were detected in either discrete emotions or affect states with this density of sampling, it may indicate that EMA studies of emotion should sample more frequently so as to improve the accuracy of signal detection. Conversely, if we do not find evidence of rapid cycling, the current EMA *status quo* of a few observations per day may suffice.

Additionally, while the literature on emotion duration has generally examined how long emotions last from their incitement to dissipation (Scherer & Walbott, 1994; Verduyn, 2009; Verduyn et al., 2015), less is known about the patterns of periodic, cyclical variation in emotion. Emotion time series are complex, with many sources of both periodic and aperiodic variation. Identifying the nature and timing of periodic components may be helpful by providing insight into stable, predictable, reoccurring contexts or processes that give rise to affect states. Much of the literature on emotion dynamics focuses on the temporal dynamics of singular emotions or valenced composites (i.e., PA and NA). There is a need to extend the study of emotion dynamics to map the temporal dynamics of affect states identified in the present study.

Data Analytic Plan

After the seven group-level affect states were identified, each individual's time series was dummy-coded by appending a vector to represent the presence or absence of each affect state at each observation. Next, the timestamps associated with each observation were used to generate a vector representing the cumulative sum of elapsed time in hours since the start of the sampling window. For example, the second observation would occur at approximately 30 minutes after the first, the second one at 1 hour, and so forth in increments of 30 minutes until the end of the sampling window two weeks later at approximately 336 hours.

For each affect state within each individual, spectral analysis was applied to the vector of zeroes and ones representing presence or absence of the affect state across the time series, to test whether periodic rhythms are present in the occurrence of each affect state, and to determine their cycle length. The Lomb-Scargle periodogram (Lomb, 1976; Scargle, 1982) was developed by astrophysicists to detect weak periodic rhythms in data from astronomical observations (VanderPlas, 2018). This method was developed to overcome the problems of noisy, unevenly-sampled, or missing data—for example, due to planetary movements and weather conditions. Albeit for different reasons, human emotion observed via EMA yields data with similar problems. Uneven spacing is inherent to our sampling protocol given the 12-hour nighttime lag, sporadic missingness is expected as participants occasionally do not respond to surveys, and the data may be noisy due to a variety of contextual or environmental factors.

The *lomb* package in R (Ruf, 1999) enables the estimation of a Lomb-Scargle Periodogram from human biological time series. This package provides a function, *lsp()*, which estimates the variance in a vector (in this case, presence or absence of an affect state) that is explained by periodic components at varying cycle lengths. The range of cycle lengths that can be assessed is limited by the rate at which observations are collected, or the sampling period (λ), as well as the sampling duration (the window of time over which observations are collected). In the present study, our sampling period was 30 minutes over a sampling duration of 2 weeks. The fastest signal we can sample reliably has a frequency of $\frac{1}{2\lambda}$. Our sampling frequency is once every 30 minutes, or equivalently two samples per hour. Therefore, the signal we can assess cannot be faster than one cycle per hour. Conversely, the slowest detectable cycle has a sampling period equal to half of the duration of the sampling window (in this case, 336 hours or two weeks.

The resulting periodogram for each affect state shows the possible cycle lengths (periods ranging from 1-hour to 336-hour cycles) on its horizontal axis, vs. normalized spectral power (i.e., variance explained by cycles with each possible period) on its vertical axis. A peak on the periodogram suggests that the variable (either affect state or emotion) oscillates with the corresponding cycle length at which the peak occurs. P-values are also provided for each spectral peak to delineate whether periodic variation at that cycle length is statistically significant (i.e., that periodic component at the peak's cycle length explains significantly more variation in the vector than noise). If no significant peaks emerge in the power spectrum, this suggests that variation in that vector is aperiodic (at least, within the range of periods assessed).

For each affect state, we first assessed the number of individuals who exhibited significant periodicity in that class based on whether or not they had a significant peak in their power spectrum at any period. Next, for each affect state we calculated summary statistics (M, SD, range) for periodic cycle length, among those who did exhibit significant periodicity. Importantly, as mentioned above, given our sampling frequency and period we are unable to detect cycles faster than 1 hour or slower than two weeks. Finally, we repeated the procedure described above with each of the six individual emotion vectors (*sad, anxious, irritable, joyful, content, excited)*.

Results

For all affect states except class 7, a significant spectral peak was present in about half of the people who experienced each affect state. This ranged from 34 of the 84 individuals with class 4 (40.48%) to 45 of the 83 individuals with class 2 (54.22%). Class 7 was a notable outlier, with only 1 person out of 33 exhibiting significant periodicity in the occurrence of this state.

Supplementary Table 1 presents summary statistics for the periodicity and cycle length observed across the individuals who experienced each of the seven affect states. For each state, the number and proportion of individuals with significant periodic variation is listed in the *N Significant Peak* column. Across the individuals with a significant spectral peak, the mean, SD, and range of the cycle length are shown in hours—for example, a peak at 24 indicates circadian/daily cycling; a peak at 336 indicates slower two-week cycles.

Supplementary Figures 1-6 show, for each affect state, the distributions of cycle length across participants with significant periodicity (excluding the single case for Class 7). The distributions each appear to be centered around 5-7 days with similar shape. The average cycle length was similar across the affect states, with a median average cycle length of 138.23 hours (5.76 days; class 4). Average cycle length ranged from a 117.1 hour (4.86 day) average period for class 2, to a 159.77 hour (6.66 day) average period for class 1. While an average cycle length for class 7 could not be calculated as only one participant exhibited periodicity in that class, the cycle length for this participant was 182.7 hours/7.61 days, consistent with the other states' average cycle lengths. Thus, our results indicate that for the participants with periodic variation in their affect states, the affect states completed an oscillatory cycle about once every five to seven days on average, with minimal differences between the affect states.

The states were also similar in the range of cycle lengths that were observed across participants within each state. Each affect state had at least one participant with periodicity at slower, two-week cycle lengths, as the upper end of the range reached nearly 336 for each state.

Notably, no participant exhibited rapid cycling for any affect state: at the faster end of the range, the shortest cycle length observed for any affect state for any participant was 8.58 hours (class 5). For other affect states, the shortest observed cycle length ranged from 8.58 hours (class 5) to 22.76 hours (class 3).

Finally, we repeated this procedure with the six individual emotions (*irritable, anxious, sad, joyful, excited,* and *content*). Again, we first determined the individuals in the sample who exhibited significant periodic variation in each of the six emotions, and then computed summary statistics on the cycle length among those who exhibited significant periodicity in each emotion variable. These data are presented in Supplementary Table 2.

Overall, the results for the individual emotions mirrored what we observed in the affect states. Significant periodic variation was observed in a plurality of participants for each emotion, ranging from 55/115 participants (47.8%) showing periodic variation in *sadness*, to 84/115 participants (73%) showing periodicity in *joyful.* As observed in the affect states, the six discrete emotions each displayed an average cycle length of roughly 5 days. This ranged from an average cycle length of 113.48 hours (4.73 days) for *anxious,* to 136.43 hours (5.68 days) for *sad*. In terms of the ranges in the cycle lengths for each discrete emotion, we observed that the longest periodic cycle length for all single emotions was roughly 2 weeks (336 hours). The shortest cycle lengths were roughly 8 to 16 hours (ranging from 8.07 hours for *excited* to 16.4 hours for *joyful*). As with the affect states, none of the single emotions exhibited periodic variation with a rapid cycle length of *less* than 8 hours.

Discussion

In the present section, we applied spectral analysis to examine periodicity in each participants' experience of affect states and individual emotions. We were interested in (1) whether or not affect states and single emotions exhibited periodic variation; and (2) the cycle length among the individuals who did experience significant periodic oscillation in their affect states. To begin to address these questions, we estimated a Lomb-Scargle periodogram for each affect state and emotion for each individual. We then calculated the number of individuals with significant periodic variation, and computed summary statistics across these individuals to examine the cycle length for each affect state and emotion.

With one exception (class 7), the affect states exhibited periodicity in roughly half of the individuals who experienced them. Similarly, the six discrete emotions showed periodicity in 48% to 73% of individuals. This likely points to individual differences in the sources of variation in emotion. For some, this variation is periodic. For those without a significant periodic component in their affect states or emotions, perhaps other sources of aperiodic variation are a stronger influence on experienced emotion (e.g., aperiodic contextual or interpersonal factors).

Among those whose affect states demonstrated significant periodicity, there was a wide range in cycle length: some individuals experienced ultradian rhythms (such as 8-hour or 12-hour cycles), some experienced diurnal, roughly-24-hour cycles, and some exhibited infradian (i.e., weekly or biweekly) cycles. These varying cycle lengths point to a range of possible biological influences on emotion, such as circadian rhythms or diurnal cortisol variation (for those with 12- or 24-hour cycles), or hormonal shifts due to longer-range processes, such as the monthly menstrual cycle (for those with 336-hour cycles).

The presence of periodic variation in affect states may also point to emotion-eliciting contexts or environments that recur on a periodic basis in an individual's life. For example, particular events (classes, group meetings, and social events) that recur on a weekly basis may frequently elicit similar emotional patterns. Some support for this possibility is drawn from the fact that, across the individuals who exhibited periodic variation in affect states, the average cycle length for each affect state was roughly 5 to 7 days (with similar findings observed in discrete emotions). Given that our sample were undergraduates, who as full-time students were likely engaged in routine weekly classes and events that repeat on a 5-7 day basis, it is plausible that these events impacted emotional responding on a correspondingly periodic cycle. Put another way, our data point to the possibility that some undergraduates exhibit periodicity in their affect states, and that *on average* this periodicity tends to align with the routine schedule of the five-day workweek and seven-day calendar week. This makes sense given that emotional experience is linked strongly to occupational challenges and pursuits (Haase, Heckhausen, & Silbereisen, 2012). Whether other populations, outside of that represented by our undergraduate sample, would experience similar average cycle lengths in affect state or emotion remains an open area of investigation, to be addressed in future research.

Importantly, contrary to our expectation, no participants exhibited rapid periodic oscillation in any affect state or emotion. Instead, the fastest periodic cycles that emerged were approximately 8-hour cycles. Given the literature that suggests a shorter duration of emotion (e.g., that emotions change on the order of minutes; Verduyn et al, 2009; Verduyn et al., 2015), we expected that some participants would exhibit much faster oscillatory cycling. If this were true, it would suggest that EMA studies should conduct more frequent sampling to capture faster-moving emotion dynamics. However, our data did not support this possibility. Because the fastest cycles we observed were 8-hour cycles (and many participants exhibited much slower oscillation), the current EMA *status quo* of sampling every 4, 8, or 12 hours is likely sufficient to capture underlying periodic variation in affect states and emotion. Crucially, this does not mean that affect states are not changing more rapidly—just that the rapid intra-daily changes in affect state, at least as assessed every 30 minutes via self-report, are not periodic. Future analyses of this densely-sampled EMA data will directly model the nuances of emotions' aperiodic time courses, in terms of their onset, offset, and duration, to continue investigating the utility of such dense sampling of emotion via EMA.

We also observed that, for some participants, both affect states and emotions exhibited relatively slow oscillations. For each affect state and emotion assessed, there were some participants with significant spectral peaks at the slowest possible end of the range for cycle length, at 336 hours. For these participants, this could indicate the presence of a linear trend (Warner, 1998). Because our ability to assess slow cycles was constrained by our two-week sampling duration, we were unable to assess whether longer (e.g., monthly) periodic cycles are present. However, the preponderance of participants with spectral peaks at the two-week cut-point suggests the possibility that longer periodic cycles may be present in these participants. Future studies could undertake a modified sampling protocol with a similar number of observations over a longer period of time to assess this. For example, sampling every one or two hours for a one month period would yield a time series of similar length, which could be used to detect cycles with a longer period.

Crucially, across participants, we observed heterogeneity in the presence of periodic fluctuations in mood and in the specific oscillatory cycles among those with significant periodic variation. However, across the *affect states*, we found relative homogeneity in the number of individuals for whom the states exhibited periodicity with similar distributions of cycle lengths. There is a suggestion in the affective chronometry literature that different emotions can be distinguished from one another by their time courses (e.g., sadness might last longer than disgust). However, while we found heterogeneity across people in terms of whether affect states varied periodically, and in the speed of this variation, we did not find support for this heterogeneity across affect states. Instead, all affect states (and discrete emotions) were similar in terms of their group-aggregated spectral analysis results. All affect states and emotions were similarly periodic in roughly one-half to three-quarters of participants, with an average cycle length of 5-7 days. This suggests that, in terms of future investigation of affect states' and emotions' temporal dynamics, it might be more relevant to examine person-to-person differences instead of differences based on affect state or emotion type.

Limitations

As mentioned above, some design features of the present sample and measurement protocol limit the extent of the conclusions that can be drawn from these data. Specifically, our undergraduate sample may entail certain temporal artifacts unique to that population, such as the 5-day Monday-to-Friday class schedule and particular class/university events. This is likely to be particularly influential in studies of the temporal dynamics of emotion, and may offer an explanation for our finding that affect states and emotions followed an average 5-7 day oscillatory cycle. Future studies could apply similar sampling and analyses within a more diverse group of participants to determine generalizability of the present findings to other populations.

Although we conducted more frequent sampling than most EMA paradigms in the literature to date, with sampling every 30 minutes, it is possible that even this frequency of sampling would not be sufficient to capture rapid change in emotion. With some suggestion in the literature of emotions that arise and dissipate in only a few seconds (Ekman & Rosenberg, 2005); it is possible that a rapidly-changing affect profile would not be detectable without continuous sampling. While continuous sampling is not feasible with EMA, perhaps future studies could leverage technology for passive measurement (e.g., wearable devices with physiological sensors). Through future studies that could link passively-measured physiology to affect, it might ultimately be possible to achieve an even finer degree of nuance with continuous sampling to detect the most quickly changing of affect states.

The present study is also limited by its two-week sampling window. Our results suggested the possibility that many participants with periodic variation in affect states experience *slower* cycles, or oscillations that occur over a longer period of time. Future studies could assess the influence of infradian rhythms (such as the monthly menstrual cycle, or seasonal changes in day-length) on affect states by conducting sparser sampling over a longer period of time to enable detection of slower-moving oscillations.

Additionally, while the present analyses were specifically aimed at examining periodicity in emotion, it should be noted that many important sources of temporal variation in emotion are aperiodic, which would not be detected by the present analyses. More remains to be understood about the temporal dynamics of affect states, such as whether states can be localized by time of day, weekday, or season (Golder & Macy, 2011; Stone, Schneider, & Harter, 2012), how long they last in terms of onset/offset (Verduyn et al., 2015; Davidson et al., 2015), or other metrics of emotion dynamics in the recent affective chronometry literature, such as *variability*, *instability*, and *inertia* (Houben, Van Den Noortgate, & Kuppens, 2015).

Future Directions

This section highlights several important areas for future investigation. Replicating the present study in a more diverse, representative sample would help to determine whether the patterns observed in the present sample are generalizable beyond an undergraduate population. Further, if future studies utilized a longer sampling window, this would enable the detection of potential periodic variation at longer intervals. Therefore, future studies may endeavor to collect time series of similar length, with sparser frequency and a longer period.

Beyond modifications to study design, additional questions emerged from our findings of heterogeneity in the presence and nature of affect states' periodic variation. Future studies could aim to understand this person-to-person heterogeneity by assessing whether person-level variables such as age, biological sex, or psychopathology predict the presence of periodic variation in, or the cycle length of, particular affect states. For example, perhaps different clinical groups (e.g., individuals with depression, or individuals with borderline personality disorder; Trull et al., 2008) would exhibit different cycle lengths in emotion. This is potentially relevant to clinical research, as it could indicate these populations have different optimal sampling frequencies. This could be addressed by replicating the present methods in clinical samples. It would also be helpful to examine, in a longitudinal framework, whether temporal patterning in affect states can shift over time.

Understanding whether certain types of affect states are characteristic of certain clinical populations, whether affect states' periodicity or cycle length is associated with maladaptive outcomes, and whether the periodicity of these states changes over time may have important clinical implications. For example, there is evidence that in patients with generalized anxiety disorder, anxious distress that follows a rigid diurnal rhythm is associated with greater overall symptom severity—and that the degree to which this distress becomes less entrained to diurnal patterns is associated with better treatment outcomes in cognitive behavioral therapy (Fisher & Newman, 2016). Applying this to affect states, perhaps certain types of temporal patterns can be identified as potential treatment targets for intervention.

Finally, the present findings have implications for the future of EMA measurement of affect states within clinical and affective science. Specifically, the heterogeneity we observed in cycle lengths among those with periodic variation suggests the possibility that personalizing the EMA sampling frequency could be helpful. For example, a "pilot" sampling window could be used to tailor EMA sampling to an appropriate frequency for each individual, given the presence or nature of their periodic variation in emotion.

Summary and Conclusion

We applied spectral analysis to 115 densely-sampled emotion time series to assess the presence and nature of periodic variation in affect states and discrete emotions. We found that affect states and discrete emotions showed periodic variation in a plurality of participants. Among those who experienced periodic variation in affect states and emotions, their oscillatory cycle lengths ranged from roughly 8 to 336 hours. The average cycle length observed across the affect states was approximately 5-7 days. Despite person-to-person heterogeneity, similar patterns and distributions of periodic variation were observed across the affect states—the affect states did not exhibit state-specific time courses. Instead, person-to-person heterogeneity suggests that a personalized EMA sampling frequency may be more helpful in future studies.

Supplementary Section 2: Relationships Between Affect Profiles and Momentary Stress, Life Satisfaction, and Current Psychopathology

Background

Folk wisdom suggests that positive emotions are good for us, promoting health and wellness (Tugade et al., 2004), while negative emotions are often viewed as subjectively distressing and unwanted (Solomon & Stone 2002). Individuals lead richly emotional lives—one study that measured emotion continuously found that people generally report experiencing at least one emotion about 90% of the time—but these experiences are not always simply "positive" or "negative" (Trampe, Quoidbach, & Taquet, 2015). In fact, positive and negative emotions frequently co-occur (Trampe et al., 2015) and these mixed-valence emotional states may even offer benefits to physical health (Hershfield, Scheibe, Sims, & Carstensen, 2013).

Affect profiles, as identified in the present study, indicate momentary blends of emotion that likely arise in response to a variety of contexts. It remains unclear whether the occurrence of certain profiles is associated with momentary levels of perceived stress, or perceived wellbeing at the person (or group) level. Further, an open question remains as to whether the presence or rate of occurrence of our seven affect states can be predicted by current psychopathology.

Emotions and Momentary Stress

Stress and emotion are tightly intertwined. Lazarus once argued that stress should be considered as a sub-type of negative emotion (Lazarus, 1993). However, in later work, he drew an important distinction between these constructs (Lazarus, 2006). He pointed out that while stress is a unidimensional construct (that is, stress is perceived as low to high in intensity), emotional responses to stress are more varied and complex, with multiple associated behavioral drives (Lazarus, 2006; pp. 32-37). Many different emotions can arise in response to stressors, and individuals likely exhibit person-specific patterns in the emotions that are associated with their experience of stress. Thus, examining the correlation between stress and affect states within a particular individual may provide a contextual map of that individual's emotional response tendencies during stress. This may eventually aid in understanding behavioral patterns or clinical syndromes that arise in connection with stressful periods.

Both negative and positive emotions are linked to the stress response. Increases in momentary negative emotions are linked to increases in biological markers of stress, such as higher cortisol and inflammation (for recent reviews, see Joseph, Jiang, and Zilioli, 2021; Szabo, Slavish, & Graham-Engeland, 2020). Psychological factors such as rumination and trait pessimism have also been shown to affect the strength of the association between negative emotions and stress (Jones et al., 2017). This aligns with the notion that negative emotions can motivate adaptive behaviors (e.g., seeking reassurance, removing oneself from danger) to cope with environmental challenges (Keltner & Gross, 1999).

Positive emotions are also linked to the stress response, offering both a potential buffer against the effects of stress and a pathway toward increasing coping. Positive emotions have been shown to reduce occupational stress in the workplace (Galanakis, Galanopoulou, & Stalikas, 2011), and are associated with lower levels of biological markers of inflammation such as inflammatory cytokines (Stellar et al., 2015). Positive emotions may aid longer-term recovery following stressful situations by predicting lower levels of inflammation and other stress biomarkers. Relatedly, happiness is inversely correlated with perceived stress—the happier a person is, the less perceived stress they generally have (Schiffrin & Nelson, 2010). There is also evidence that individuals who experience greater diversity of positive (but not negative) emotions tend to exhibit fewer biomarkers of stress and inflammation (Ong, Benson, Zautra, & Ram, 2018).

Positive emotions and negative emotions have been shown to co-occur within stressful situations. It has been suggested that positive emotions may provide an adaptive function within the stress response by motivating creative problem-solving to generate a range of response options, and enhancing behavioral activation toward pursuit of these behavioral goals (Folkman, 2008). Thus, while negative emotions "feel bad" and positive emotions "feel good," *both* negative and positive emotions provide a helpful set of motivational functions within the stress response.

The affect profiles identified in the present study reflect blends of emotions occurring in the same moment, so it is plausible that particular profiles would exhibit correlations with momentary stress. Likely, these relationships operate on a person-specific basis, so we might expect the correlations between momentary stress and affect state to be idiosyncratic. While the presence and direction of these relationships probably varies from person to person, it would also be useful to understand group-level patterns in the tendency for affect states to correlate with stress. For example, if a profile exhibits significant positive correlations with stress in most participants, it could be concluded that that affect state represents a "stressed" state, or tends to be associated with a stress response, across people in general. Some affect states may conversely be associated with lowered stress in the majority of people, which could indicate that the affect state may buffer against—or tends to arise in the absence of—a stress response.

Understanding the pattern of relationships between affect states and momentary stress at the group level could enhance foundational knowledge about the relationship between stress and emotion as it unfolds in daily life. While stress does not necessarily equate to psychopathology, understanding how affect states are linked to perceived stress may also increase the clinical applicability of affect states by providing insight into the affect states' tendencies to occur with high-stress or low-stress contexts—whether as a cause, or an effect, of stress.

Emotions and Momentary Life Satisfaction

An individual's *subjective wellbeing* is generally considered in two domains: their emotional experiences, and their sense of satisfaction with their life (Diener, 1985). These domains are psychometrically distinct (Diener, Suh, Lucas, & Smith, 1999), but correlated. For example, a large cross-cultural study of the link between emotions and life satisfaction showed that life satisfaction is more strongly related to the presence of positive emotions than the absence of negative emotions (Kuppens, Realo, & Diener, 2008). However, these authors also found an important effect of culture (or, values) on the strength of these relationships. In nations with individualistic values, negative emotions had a stronger negative impact on life satisfaction, whereas nations with collectivistic values showed a stronger direct relationship between positive emotions and life satisfaction.

Recent work has shown that not only cultures, but individual people, vary in the extent to which emotions affect life satisfaction (Willroth, John, Biesanz, and Mauss, 2019). Measuring individuals' emotions and life satisfaction across multiple daily observations using EMA, it was shown that the within-person correlation between emotion and life satisfaction varied considerably across individuals. This correlation between emotion and life satisfaction, termed *emotion globalizing* (Willroth et al., 2019) is stable within an individual over time. For individuals high in emotion globalizing, their report of life satisfaction in a given moment is strongly associated with their emotions in that moment. For these individuals, the experience of positive emotions is consistently linked with greater life satisfaction (positive globalizing), while a negative emotional state consistently leads to their perception of lowered life satisfaction (negative globalizing). Importantly, emotion globalizing is related to greater neuroticism and worse psychological health (i.e., tendencies toward depression and anxiety).

Given the well-established link between emotions and life satisfaction, it may be useful to consider whether, and how, our seven affect states relate to life satisfaction. This may offer important extensions to the literature on subjective life satisfaction. For example, the literature to date has commonly examined the relation of life satisfaction to valence composites (i.e., aggregated NA and PA measures). While this is useful to determine how unpleasant vs. pleasant states *in general* are linked to life satisfaction, individuals often do not experience *only* negative or *only* positive emotions in isolation. Pleasant and unpleasant emotions have been shown to co-occur relatively frequently in large population-based studies (Trampe, Quoidbach, & Taquet, 2015). It is plausible that different types of emotional blends, occurring in different moments of an individual's life, would exhibit differential effects on life satisfaction. Considering the relationship between affect states and life satisfaction will allow us to determine whether and how specific emotional *moments* within an individual's life are related to their intra-daily changes in life satisfaction. As with our models examining the links between affect states and stress, we are interested in determining the universality vs. idiosyncrasy of these relationships within our sample. It would bolster our knowledge of the meaning of these affect states to establish how they affect perceived quality of life in the moments during which they occur.

Emotions and Psychopathology

It has long been established that people with psychopathology exhibit differences in their emotional experience compared to the general population, whether this is due to emotional reactivity, emotion regulation, or other mechanisms (Gross & Jazaeri, 2014). Different forms of psychopathology are commonly characterized by differential emotional patterns (DSM; APA, 2013). As a few examples, the familiar tripartite model established decades ago that high levels of negative affect are common to both depressive and anxiety pathology, while low positive affect is characteristic only of depression (Clark & Watson, 1991). Later work has shown that low positive affect is also problematic in social anxiety disorder (Kashdan & Steger, 2006). For individuals with bipolar disorders, manic and hypomanic episodes are characterized by elevated positive affect and irritability (APA, 2013)—however, there is evidence that individuals with Bipolar 1 diagnoses, when assessed during a euthymic period, experience greater negative emotion (but no difference in positive emotion) compared with controls (Johnson, Tharp, Peckham, & McMaster, 2017). Psychosis is associated with blunted, flat, or diminished affect (APA, 2013), but this may reflect differences in emotional *expression* rather than experience (Kring & Moran, 2008). Finally, considering substance use disorders, there is evidence that both negative and positive emotions influence individuals' experience of cravings to use substances (Schlauch et al., 2013), and that substance users may experience greater levels of negative emotions, such as anxiety, compared to non-users (Prosek et al., 2018).

It has been argued that the future of emotion research in clinical science lies in moving beyond considering one component of emotion (e.g., sadness) toward a comprehensive understanding of emotional processes in psychopathology (Kring, 2010). The literature on emotion in psychopathology to date has commonly considered emotional *valence*, such as measures of negative or positive affect, often examining the relation of valenced emotion composites (PA and NA) to various clinical syndromes. Our affect states provide an avenue to expand our understanding of emotion in psychopathology, as they indicate momentary blends of specific emotions that individuals experience in discrete moments of their life. Perhaps individuals with psychopathology experience a different set of affect states than individuals without psychopathology. Or, perhaps psychopathology affects the rate of occurrence but not the presence of particular affect states. If affect states exhibit specific links to certain syndromes or disorder categories, this could offer clinical utility, because information about the presence or frequency of certain affect states could eventually be implemented to aid in diagnosis, treatment planning, or progress monitoring. For this reason, it is worth examining whether affect states exhibit particular patterns of association with different diagnostic profiles.

Aims of This Section

In this section we endeavor to achieve a better understanding of the qualia associated with affect states by examining their relationships to momentary stress, momentary life satisfaction, and current psychopathology. Within this goal we have two exploratory aims: (1) to examine how the momentary presence of affect states influences momentary ratings of perceived stress and life satisfaction; and (2) to understand how current psychopathology influences the presence and rate of occurrence of affect states.

Data Analytic Plan

For each individual, each observation was dummy-coded to reflect the presence or absence of their respective affect states. Measures of momentary perceived stress and life satisfaction were collected at each time-point, via the items "*How stressful is your life at the moment?"* and "*Right now, I am satisfied with my life"* (Diener, 1985*)*, respectively, with the same 0-100 scale that was used for emotion items. The presence of psychopathology was assessed as an individual difference variable at the beginning of the EMA sampling window by administering the MINI (Sheehan et al., 1998) as a self-report online questionnaire.

Affect States and Momentary Stress/Life Satisfaction

To assess the relationship between momentary affect states and momentary experiences of stress and life satisfaction, person-specific bivariate linear models were run for each person and each affect state by aggregating across each person's individual time series and saving summary results for each model (beta coefficients and p-values) in a new data frame. First, person-specific models were run for each participant with each affect state's presence (relative to its absence) as a predictor of stress ratings in the same moment. A similar set of within-person models was then run for each participant to assess affect state as a predictor of momentary life satisfaction. Summary statistics across these person-specific models were calculated to assess the number of participants with significant relationships between affect state and stress/life satisfaction, as well as whether these were positive or negative correlations. This enabled us to gain a general group-aggregated picture of whether each affect state was commonly associated with stress or life satisfaction, and to understand whether an affect state tended to increase or to decrease perceptions of momentary stress or life satisfaction across the sample.

Affect States and Psychopathology

Current symptoms of psychopathology at the threshold of probable clinical diagnosis were assessed at the beginning of the EMA period, via the MINI adapted for presentation as a self-report online questionnaire. Diagnostic categories assessed via the MINI included mood disorders (major depressive disorder [MDD], dysthymia, mania, and hypomania), anxiety disorders (generalized anxiety disorder [GAD], social anxiety disorder [SAD], panic disorder, agoraphobia, obsessive-compulsive disorder [OCD], post-traumatic stress disorder [PTSD]), substance use disorders, and psychosis. Due to small cell sizes within certain diagnostic categories, we also generated three composite variables to represent anxiety spectrum psychopathology (i.e., the presence of GAD, SAD, panic, agoraphobia, OCD, or PTSD diagnosis), bipolar-spectrum psychopathology (e.g., presence of current mania, current hypomania, or meeting Bipolar 1 or 2 criteria with evidence of past manic or hypomanic episodes), and any substance use disorder symptomatology (individuals meeting criteria for alcohol abuse, alcohol dependence, or abuse/dependence with any other substance).

We first tested generalized linear models with current psychopathology modeled as a predictor of the presence versus absence of each affect state. This was done separately for each affect state. We first assessed whether the presence of *any* diagnosis predicted the presence/absence of affect states; we then repeated the model again for each specific diagnostic category to assess the effect of each type of psychopathology on affect state separately. However, due to small cell sizes, some of these disorder-specific models may be limited in their generalizability.

Next, we repeated a similar procedure using affect states' rates of occurrence, rather than their presence/absence, as the outcome variable. This enabled us to assess whether current psychopathology was associated with how frequently each affect state occurred. Similarly, we modeled any psychopathology—and then each diagnosis separately—as a predictor of the rates of each affect state. Model statistics such as beta and p values were retained for each model and utilized to compare effects across affect states and types of psychopathology.

Results

Affect States and Momentary Stress

Supplementary Table 3 shows, for each affect state, the number of participants with significant relationships between that affect state and momentary stress. This is broken down by the direction of these relationships, such that the *positive relationships* column represents the number of people for whom an affect state's occurrence predicted significantly *greater* stress, and the *negative relationships* column represents the number for whom an affect state predicted significantly *less* momentary stress.

In general, we observed heterogeneity in whether individuals' affect states were associated with momentary stress. Across the affect states, the presence of significant associations with momentary stress (as a proportion of those who experienced each state) ranged from 40.48% of participants (class 4) to 84.44% of participants (class 5). For the participants who did experience significant associations between affect states and momentary stress, we also observed pronounced heterogeneity in R^2, or the extent of the variance in momentary stress that is attributable to an affect state's occurrence. While the average R^2 across the models ranged from 0.06 (class 1) to 0.12 (class 5), there were some participants at the upper end of the R^2 range for whom a large proportion of the variance in stress was accounted for by affect state. For example, the R^2 values observed across the significant models for class 3 ranged from 0.01 to 0.47—suggesting that for the participant at the upper end of the range, nearly half of the variance in their experience of momentary stress can be attributed to whether or not they were experiencing the affect state of class 3.

We observed person-to-person heterogeneity in whether the affect states' relationships with stress were positive or negative—no affect state exhibited only positive, or only negative, relationships with stress across participants. However, some clear patterns in the associations did emerge at the group level. These are depicted in Supplementary Table 3. In terms of the direction of these relationships, states with elevated negative and low positive emotion (classes 2, 5, and 7) were more commonly associated with greater momentary stress. Positive affect states (classes 3 and 6), as well as mixed-affect class 1, were more frequently associated with less momentary stress. However, some people within each affect state (ranging from 1 in class 6 to 8 in class 1) exhibited the opposite pattern. For those who exhibited mixed-activated class 4, exactly the same number of participants (n=17) exhibited positive and negative relationships with stress.

Affect States and Momentary Life Satisfaction

Supplementary Table 4 shows the number and direction of significant relationships between each affect state and momentary life satisfaction. Similar to Supplementary Table 3, these relationships are further broken down into the number of people with positive relationships (that is, an affect state was associated with significantly greater life satisfaction when it occurs) versus negative relationships (an affect state's occurrence was associated with significantly lower life satisfaction).

Mirroring our findings with momentary stress, we observed heterogeneity in whether participants exhibited significant relationships between affect states and momentary life satisfaction. This ranged from 40% of participants exhibiting associations between life satisfaction and class 1, to 88.9% of participants with associations between life satisfaction and class 5. We also observed heterogeneity in the R^2 across the significant models, suggesting that some individuals experienced only small effects of affect states on life satisfaction. However, the upper end of the R^2 range across the significant models for life satisfaction was somewhat higher than we observed in the stress models. For example, for some participants who experienced classes 3, 4, 5, or 7, over half of the variance in their momentary life satisfaction was attributable to whether or not these affect states were occurring (R^2 values over 0.50).

For certain affect states (class 1, 4, and 7) we observed person-to-person heterogeneity in whether the affect state's relationships with life satisfaction were positive or negative. The mixed states—classes 1 and 4 – showed a more heterogeneous pattern with a blend of some negative, and some positive, relationships with life satisfaction, depending on the individual. Class 1 was more commonly associated with lower life satisfaction (for 22 participants this state was negatively related to life satisfaction, whereas10 showed positive relationships); class 4 was more commonly associated with greater life satisfaction (for 6 participants this state showed negative relationships, compared to 28 with positive relationships).

However, three states (3, 5, and 6) did not show this heterogeneity, instead exhibiting a clear pattern at the group level. For all participants with significant effects for these affect states, class 3 and 6 only exhibited positive associations with life satisfaction, whereas class 5 demonstrated only negative relationships. No individual with PA class 3 or 6 ever experienced *lower* life satisfaction in these states; conversely, NA class 5 was never observed to associate with greater life satisfaction. Similar to class 5, NA class 2 exhibited *almost* exclusively inverse relationships with life satisfaction (with the exception of one person).

Affect States and Psychopathology

The number of individuals coded for presence of each diagnosis is listed in the first column of Supplementary Table 5. In the present sample, 54 of 115 participants (46.9%) met symptom criteria for presence of at least one psychiatric diagnosis. The most common diagnoses in the present sample were MDD (n=27; 23.5%) and GAD (n=24; 20.9%).

With one exception—namely that current agoraphobia was negatively associated with the presence of class 1—current diagnosis was not related to the presence or absence of any affect states. However, we observed several effects of psychopathology on the rates of occurrence of the affect states. Put another way, psychopathology did not necessarily affect whether certain affect states *occurred*, but it did have an effect on *how much time* was spent in particular states.

The effects differed by affect state, and by type of psychopathology. Supplementary Table 5 shows the effects of current psychopathology on the rates of occurrence for each of the seven affect states, with effect sizes and p values.

We first examined the effects of *any* psychopathology on the rates of occurrence of affect states, by modeling presence of any current diagnosis as the independent variable that predicts the rates of each affect state. We found that people who met the criteria for *any* current diagnosis tended to experience more frequent class 3 (PA), class 4 (mixed-valence emotional activation) and class 5 (NA with predominant irritability). Conversely, participants with psychopathology experienced *less* of class 1 (blunted affect), class 6 (PA) and class 7 (NA with pronounced elevations in sadness). Class 2, an NA state with high anxiety, was not related to psychopathology in these aggregated-diagnosis models. While these results are useful to glean a general picture of how psychopathology affects affect states, examining the effects within each individual subtype of psychopathology reveals heterogeneity by specific diagnosis that could be obscured by examining psychopathology as an aggregate category. Across the specific diagnostic categories, several general patterns were identified in their relationship to positive affect, negative affect, and mixed states.

PA and psychopathology. First, it appears that most diagnostic categories involve a change in the type of positive affect that is experienced, as evidenced by the fact that several categories of psychopathology involved either an increase in class 3 and a decrease in class 6 (MDD, GAD, SAD, Agoraphobia) or the opposite, with a decrease in class 3 and an increase in class 6 (bipolar spectrum, current hypomania, and mood disorder with psychotic features). Some forms of psychopathology involved only one of the PA states: current mania was associated with an increase in class 6, panic was associated with a decrease in class 6, and PTSD was associated with an increase in class 3.

NA and psychopathology. While psychopathology exhibited specific, and often opposite, effects on frequencies of the two PA states, the NA states showed three divergent patterns of association with psychopathology. Class 5, a heightened-irritability state, modally exhibited positive relationships with psychopathology. Many disorder categories (MDD, GAD, OCD, PTSD, current mania, and substance abuse or dependence) were associated with increased frequency of class 5. Only individuals with panic disorder showed significant decreases in the frequency of this class.

By contrast, psychopathology commonly predicted decreases in the frequency of Class 7 (a state of differentiated sadness). Individuals with MDD, GAD, agoraphobia, and bipolar-spectrum psychopathology all tended to exhibit less-frequent experiences of class 7. Only individuals with current psychosis tended to experience more of this state.

Finally, class 2—an NA state characterized by heightened anxiety—showed differential effects; some forms of psychopathology led to increases in this state (MDD, GAD, Panic, and Agoraphobia) while other forms of psychopathology were associated with significantly *lower* frequency of this state (OCD, PTSD, hypomania, substance abuse/dependence, mood disorders with psychotic features). The heterogeneity in the direction of these effects could be an explanation for why the models with aggregated psychopathology showed no effect for class 2.

Mixed states and psychopathology. The mixed states, classes 1 and 4, similarly showed specificity in their relationships with psychopathology. Modally, across diagnostic categories, the presence of current psychopathology was associated with less frequent experiences of the blunted-affect state of class 1, but more frequent experiences of the activated state of class 4. There were a few notable exceptions: individuals with psychosis were the only group who experienced increases in the blunted affect state of class 1. Individuals with GAD, agoraphobia, and PTSD were the only groups who showed decreases in class 4 while most other forms of psychopathology were associated with increases in this activated state.

Discussion

In the present section, we aimed to examine whether and how the momentary occurrence of affect states is associated with momentary ratings of stress and life satisfaction. We also aimed to determine whether current psychopathology predicted changes in whether and how frequently each of the affect states occurred. To examine the connection between affect states and momentary ratings of stress and life satisfaction, we ran person-specific bivariate models on each participant's time series to assess the presence and direction of significant relationships between affect state occurrence and momentary stress and life satisfaction throughout the sampling window. Summary statistics across these models were used to examine group-level patterns in how affect states affect stress and life satisfaction. Next, we ran a set of group-aggregated generalized linear models to examine the association between the presence of current psychopathology and the frequencies with which affect states occurred. The presence and direction of these effects were compared across affect states and diagnostic categories to yield a group-level understanding of how psychopathology uniquely and specifically effects an individual's affect states.

Affect States and Stress

Participants exhibited idiosyncratic patterns of association between each of their affect states and momentary stress. Across the affect states, we similarly observed heterogeneity, as affect states varied in terms of how frequently they were associated with stress (as a proportion of the sample who exhibited significant relationships between stress and each state). Affect states also varied in the direction of their relationship to stress.

Overall, we observed that positive and blunted affect were generally associated with times of significantly lower stress. Conversely, negative affect was generally associated with times of significantly higher stress. A majority of participants exhibited negative relationships between stress and classes 1, 3, and 6, while a majority exhibited positive relationships with classes 2, 5, and 7. However, there were a handful of participants within each affect state who exhibited an opposite pattern. Mixed activation class 4 was differentiated from this pattern by exhibiting relationships with both higher *and* lower stress. While it is unsurprising that negative affect would relate to higher stress and positive affect would relate to lower stress, this alignment with expectation adds a bit of credibility—akin to convergent validity—to the affect states as representations of "real", meaningful experiences rather than noise.

Examining patterns within and across the affect states in terms of their relationships with perceived stress may aid in better understanding the subjective experience or function of these affect states. For example, class 4 was related to stress in fewer than half of the participants who experienced that state. Conversely, a clear majority (over 80%) of those who experienced class 5 exhibited significant relationships between that state and stress. Typically perceived stress was rated higher during class 5, which aligns with putative expectations given that class 5 is marked by high irritability and anxiety. We might conclude that that this irritable state seems generally to be characteristic of stressful periods for undergraduates in our sample.

Class 4's pattern appears much less clear, as this mixed state of generalized emotional activation coincided with either heightened *or* lower perceived stress. A handful of participants exhibited class 4, alongside elevations in self-reported perceived stress. But an equal number of participants showed the opposite, experiencing class 4 in times of lower levels of perceived stress. The remaining majority did not experience significant relationships between class 4 and stress (which likely suggests, for these participants, class 4 occurred in times of both low and high perceived stress). Therefore, we can conclude that class 4 is not specific to a stress response in most of our sample.

Among the significant relationships between affect states and stress, we also observed heterogeneity in R^2, which indicates the extent to which variation in a person's momentary stress is accounted for by the co-occurrence of a particular affect state. The range in R^2 values was similar across the affect states, but the width of these ranges suggested that the strength of relationships between affect state and stress varies considerably from person to person. While R^2 values were small enough to be inconsequential in some participants, the upper end of the range in R^2 values showed that for some participants, affect states accounted for a relatively large share of their variation in perceived stress. For example, for one participant, experiencing class 5 accounted for 45% of the variance in perceived stress.

Importantly, as we examine these within-person correlations between affect states and stress across time, a key limitation is that we cannot draw conclusions about causal relations between stress and mood. Based on the present data, we cannot say whether (a) the affect state arises first, affecting perceptions of stress; (b) perceived stress triggers the onset of a particular affect state; or (c) contextual or environmental events elicit both the affect state and stress simultaneously.

Instead, the present study aimed simply to identify patterns in the co-occurrence of affect states with stress, considering stress to be a context in which an affect state can occur, or not. At the individual level, this may elucidate a person's emotional tendencies within a stress response, distinct from times of *low* stress. Group-level data can also inform which affect states generally coincide with perceived stress, versus which are generally associated with low-stress periods. Future studies may be able to unpack this distinction further by looking at time-lagged relationships between stress and mood, and by measuring relevant context variables to identify types of stressors that are present at each observation. Perhaps among the "stressful" states, different affect states would be associated with specific types of stressors (e.g., interpersonal conflict vs. academic obligations). This is worth exploring in future studies to inform clinical application.

The present approach may have potential clinical utility by delineating which emotional experiences co-occur with increases (or decreases) in perceived stress. Whether an affect state is associated with stress does not inherently signal that the state is maladaptive. However, to inform case conceptualization, a clinician (or, future researcher) could potentially examine the function of affect states within a stress-eliciting context. There is evidence from our research group that affect states are significantly correlated with behavior in a clinical sample (Bosley & Fisher, *in preparation*). If these behaviors are found to be maladaptive, the identification of affect states may aid in diagnosis, treatment planning, and progress monitoring by providing a map for the context in which maladaptive behavior occurs. Further, it is possible that within times of heightened stress, affect states would be more strongly linked to behavior. To further explore the clinical utility of the current approach, future research should examine the relationships between affect states and behavior.

Affect States and Life Satisfaction

Similar to our observations of affect states and stress, while individuals varied in their patterns of association between affect states and life satisfaction, some potentially important patterns emerged across the affect states. Valenced positive and negative affect states were significantly related to momentary life satisfaction in a clear majority of individuals. By contrast, mixed-valence states (1 and 4) were associated with life satisfaction in fewer than half of individuals who experienced them.

Of the significant relationships between affect states and life satisfaction, positive states (3 and 6) *only* exhibited positive relationships, suggesting that positive states generally co-occurred with self-reported increases in an individual's momentary report of life satisfaction. There were no participants for whom positive states were associated with *decreased* life satisfaction in the moment. Two of the three negative affect states showed a similarly homogeneous pattern, in the opposite direction. Irritability class 5 was associated with significantly lower momentary life satisfaction across almost 89% of those who experienced it.

Consistent with the directional homogeneity of class 3 and 6, no participant exhibited *greater* life satisfaction within this state. Anxiety class 2 showed nearly the same pattern, with the exception of one participant for whom class 2 exhibited a direct relationship with life satisfaction. Because the direction of the relationships between these four states and life satisfaction were nearly universal across participants, we can conclude that positive affect states (3 and 6) are associated with greater life satisfaction, while irritability (5) and anxiety (2) are associated with lower life satisfaction.

However, class 7—a state of prominently-differentiated sadness—demonstrated a pattern that was more similar to the mixed states than to the other negative affect states. As a proportion of those who experienced each affect state, class 7 was less frequently associated with life satisfaction compared with class 2 or 5. Further, while classes 2 and 5 exhibited a nearly-universal negative relationship with momentary life satisfaction, class 7 was related to greater life satisfaction in some participants and lower life satisfaction in others. The mixed classes (1 and 4) also exhibited this pattern, with some participants showing negative and some showing positive relationships between these states and life satisfaction. Sadness and blunted affect (class 1) are more commonly associated with lower life satisfaction, while mixed-activation class 4 is more commonly associated with greater momentary life satisfaction.

Examining R^2 ranges across the models, we observed that for some people up to half of the variance in their momentary life satisfaction was attributable to what affect state they were experiencing at that observation. This was true for classes 3, 4, 5 and 7. This may align with recent work (Willroth, John, Biesanz, & Mauss, 2019) on *emotion globalizing*, which is the tendency for a person's life satisfaction/life satisfaction to be tightly coupled with their emotional state. Perhaps the individuals in our sample with high R^2 values across these models are high in emotion globalizing.

Future research in this area may offer an important extension of the literature on this construct by examining whether individuals high in globalizing also show robust relationships between *affect state* (rather than valence composites) and life satisfaction. It has also been shown that high globalizing is associated with maladaptive outcomes such as neuroticism, depression, and anxiety (Willroth et al., 2019). Thus, in future studies it may be worth examining whether the individuals with high R^2 values for the relationships between affect state and life satisfaction (i.e., those whose momentary mood strongly influences their sense of life satisfaction) exhibit greater tendencies toward psychopathology. Given the literature, future analyses should also aim to include other potential moderating variables, such as culture (Miyamoto, 2013; Kuppens, Realo, & Diener, 2008), personality traits (Jones, 2017), or affect valuation (Tsai, 2007), in evaluating between-persons differences in the relationship between affect states and life satisfaction.

Affect States and Psychopathology

Current psychopathology was not significantly associated with the presence or absence of affect states. However, across diagnostic categories, psychopathology was significantly associated with the *rates* of affect states. These findings suggest that psychopathology is unrelated to whether a person experiences particular affect states. Instead, psychopathology may be related to the *frequency* with which certain affect states occur within a person's daily life. Participants with and without psychopathology in our sample experienced roughly the same set of seven possible affect states, supporting the idea that psychopathology arises from shared normative experiences that occur along a continuum of intensity. Our results indicate that the rates of occurrence for each affect state represent important continua to consider in relation to psychopathology, as we demonstrated that different forms of psychopathology exhibited specific patterns of association with the rates of each affect state.

Each disorder category showed specific patterns of association with affect states—no two diagnostic groups showed exactly the same pattern. Many of the patterns observed in the rates within each diagnostic category aligned with the extant diagnostic taxonomy and symptom profiles outlined in the DSM (APA, 2013) and the HiTOP (Kotov et al., 2017). However, it should be noted as a key limitation that in the present sample, the cell sizes for the individual diagnostic categories are too small to warrant generalizable conclusions. Future studies could address this by recruiting a clinical sample large enough to represent varying clinical populations, and observing affect states in those samples. This could provide some initial validation that the affect states serve to model "real," clinically-meaningful momentary experiences.

PA and psychopathology. As noted above, almost all diagnostic categories were associated with changes to positive affect. Further, the two positive affect classes appeared to be linked, in the sense that diagnostic categories commonly involved an increase in one, alongside a decrease in the other. For example, depression and anxiety disorders were associated with increased frequency of class 3 and fewer experiences of class 6; and bipolar-spectrum disorders were associated with the opposite pattern, more frequent experiences of class 6 with less of class 3. Given the nature of these disorders' typical symptom presentation, it is possible these two forms of positive emotion differ in the extent to which they drive motivation and behavior. Low motivation and behavioral avoidance is associated with depression and anxiety (Grant et al., 2013), whereas motivation, activation and goal pursuit are heightened during mania and hypomania (Johnson, 2005). Thus, perhaps the type of PA that is experienced within these different forms of psychopathology reflects these differences in motivation. If this were true, perhaps class 3 represents a low-arousal positive state while class 6 is a high-arousal state. Future studies should examine the behaviors that occur within each of these two positive affect categories to investigate this possibility further.

NA and psychopathology. Across the three negative affect affect states, we observed heterogeneity in relationships with psychopathology. Irritability class 5 appeared to occur more frequently in individuals with current psychopathology, with increased rates across a range of diagnostic categories. Sadness class 7 showed the opposite pattern—this state generally occurred *less* frequently within most diagnostic categories. Anxiety class 2 showed a mixed pattern, occurring more frequently within some diagnostic groups and less frequently in others.

Class 5 is a state of high irritability and negative affect, which was also commonly associated with higher perceived stress and lower ratings of life satisfaction during the moments in which it occurred. This state was relatively common across our participants, and its occurrence alone was not associated with psychopathology. However, across many diagnostic categories, class 5 occurred with a significantly higher frequency relative to those with no diagnosis. This suggests that class 5 may represent an important symptom domain, and a possible treatment target for individuals seeking to decrease stress, increase life satisfaction, and ameliorate psychological problems. While our data show that class 5 occurred ubiquitously across participants without psychopathology, perhaps in individuals with psychopathology this state is more entrenched as an attractor state, is more difficult to regulate, or is associated with maladaptive behavior patterns. These questions concerning *why* class 5 is more frequent in those with clinical disorders should be explored in more detail in future studies.

Class 7 is a state of elevated negative affect with prominently differentiated sadness. This state was the least frequent by proportion of the sample, and by rate among those who experienced it. Based on the composition of class 7, *prima facie* we might expect this state to indicate some sort of depressive process. Instead, our data support that this state may actually be adaptive rather than maladaptive.

Unlike the two other negative affect states, class 7 was differentially associated with stress and life satisfaction across participants (experiencing this state led to *less* stress and *greater* life satisfaction in the moment for some, and showed the opposite pattern in others). Interestingly, this class occurred less frequently among those with any diagnosis, and was negatively correlated with several specific diagnostic categories (one exception was that participants with psychosis experienced increases in class 7). This could suggest that class 7 represents some sort of protective factor among those who experience this state. Again, the precise reasons for this association remain a mystery, but could be explored further in future research. If this state is associated with adaptive coping, and occurs less frequently within psychopathology, perhaps treatment could aim to increase the frequency of this state.

Class 2, a high-anxiety state, showed differential patterns of relationships with psychopathology. Predictably, class 2 occurs with a significantly higher frequency in anxiety and mood disorders. However, in other diagnostic categories (OCD, substance use, current hypomania, and PTSD) individuals experienced *less* of this anxiety state. This may align with the cognitive-behavioral symptoms that characterize each of these syndromes: for example, OCD and substance use are both associated with engaging in compulsive behaviors, which may temporarily reduce anxiety (Mancebo et al., 2009). Perhaps individuals with these disorder categories experience lower frequencies of anxiety as a result of their engagement with compulsive behaviors. Further, a key element of PTSD symptoms involves numbing of emotions (APA, 2013), which may also explain lower rates of class 2. Again, exploring affect states' link to behavior in future studies would enable these associations to be clarified and more explicitly linked to treatment goals.

Mixed states and psychopathology. The two mixed-valence states, class 1 and class 4, showed opposite relationships with psychopathology. In general, individuals with psychopathology experienced class 1 *less* frequently, and class 4 *more* frequently, compared to those with no diagnosis. Given that both of these states exhibited heterogeneous patterns of relation with momentary stress and life satisfaction, their association with psychopathology may further shed light on these states as potential adaptive vs. maladaptive factors.

Class 4 is a state of mixed-valence emotional activation with all emotions rated slightly above their mean levels. Nearly all diagnostic categories assessed were associated with increased frequency of this activated state. Notably, those with current PTSD and dysthymia were associated with significantly less of this affect state, possibly due to the associated symptoms of numbing and fatigue, respectively. However, this state's increased frequency across most other categories of psychopathology indicates the possibility that, if this state occurs with too high a frequency, individuals could be at risk for emotional and behavioral problems. Future research is needed to determine whether and how this state can be effectively regulated, and the exact behavioral problems with which it may be associated.

On the other hand, class 1 showed the opposite pattern. In this mixed-affect state, all emotions were rated slightly below their mean levels. This state occurred less frequently within individuals experiencing current psychopathology. Thus, perhaps experiencing class 1 is helpful, or represents a protective factor in terms of psychological health. For example, this state may indicate momentary disengagement from emotional activation. To further understand whether class 1 is a protective factor or buffers against psychopathology in some way, future studies could also examine momentary links between this state and behavior.

While the present analyses begin to lay initial groundwork for understanding affect states' relationship to psychopathology, a few limitations must be considered and future research must be done to establish the clinical utility of affect states. For example, due to using an undergraduate sample, we were limited by small cell sizes within most diagnostic categories. Therefore, in the present data, it may be less useful to consider the nuances of specific mood patterns within diagnostic categories. At this stage, we are only able to draw general conclusions about the affect states' pattern of association with psychopathology in aggregate, by stating that certain classes seem to be more vs. less frequent among individuals with any diagnosis, compared to healthy control participants. We are also limited in the scope of affect states' relationships with actionable clinical targets such as behavior, as we did not assess behaviors (or cognitions, or environmental contexts) within the present study.

Future research should endeavor to examine these questions using a diverse clinical sample, alongside measuring contexts, thoughts, and behaviors, to obtain a fuller picture of the events that occur within a moment, alongside each affect state, within a person's life—and how this may be altered in psychopathology. This line of work may yield important advances to the person-specific assessment and treatment of emotional disorders.

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Table 1. Participant Demographics by Wave

	Full Sample	Wave 1	Wave 2	Wave 3	Wave 4
Total N	*115*	*49*	*27*	*35*	*4*
Age M (SD)	19.79 (2.2)	19.92 (1.64)	19.89 (1.48)	19.58 (1.48)	19.25 (1.5)
Gender					
Cisgender Man	17 (14.8%)	9 (18.4%)	2 (7.4%)	5 (14.3%)	1 (25%)
Cisgender Woman	97 (84.3%)	40 (81.6%)	24 (88.9%)	30	3 (75%)
Other	1 (0.9%)	0	1 (3.7%)	0	0
Ethnicity					
Asian	60 (52.2%)	26 (53.1%)	13 (48.1%)	18 (51.4%)	3 (75%)
Latinx	11 (9.6%)	5 (10.2%)	2 (7.4%)	4 (11.4%)	0
White	28 (24.3%)	13 (26.5%)	5 (18.5%)	10 (28.6%)	0
Multiracial	12 (10.4%)	4 (8.2%)	5 (18.5%)	3 (8.6%)	0
Other	4 (3.5%)	1 (2%)	2 (7.4%)	0	1 (25%)

Table 2. Between vs. Within Person Frequencies of Affect states

CLASS	**N**	**PROPORTION** *between-person frequency, % of sample with class presence*	**RATE** *average within-person frequency for those with class presence*	**RATE SD (%)**	**RATE RANGE (%)**
1	80	69.57%	23.95%	13.37	2.95—67.06
2	83	72.17%	28.68%	16.18	5.52 -79.77
3	73	63.48%	13.74%	7.14	2.10-30.84
4	84	73.04%	32.17%	21.77	2.90-95.80
5	90	78.26%	15.13%	8.45	0.76-41.18
6	73	63.48%	27.42%	13.08	3.73-63.18
7	30	26.09%	4.49%	3.27	0.30-12.94

Supplementary Table 1: Summary Statistics of Normalized Spectral Power for Classes

Class	N with Class	N Significant Peak (% of those with class present)	M Period at Peak (Hours)	SD Period at Peak (Hours)	Range of Peak Period (Hours)
1	80	33 (41.25%)	159.77	126.64	18.61—335.98
2	83	45 (54.22%)	117.09	104.02	14.00—335.52
3	73	39 (53.42%)	154.73	87.35	22.76—335.60
4	84	34 (40.48%)	138.23	121.69	22.44—335.52
5	90	46 (51.11%)	129.85	111.52	8.58—335.60
6	73	36 (49.32%)	114.29	94.81	15.05—335.19
7	30	1 (3.33%)	182.43*	NA	NA

* = this is the individual value given N=1 with significant periodicity for this class

Supplementary Table 2: Summary Statistics of Normalized Spectral Power for Discrete Emotions

Emotion	N with significant periodicity	M Peak Period (Hours)	SD Peak Period (Hours)	Range (Hours)
Excited	78	122.66	99.65	8.07—335.60
Content	82	120.54	100.59	8.11—335.60
Joyful	84	118.04	96.67	16.4—335.99
Sad	55	136.43	100.21	14.5—335.99
Irritated	63	121.71	111.17	12.16—335.6
Anxious	81	113.48	91.61	15.25—335.60

Supplementary Table 3: Affect states Presence/Absence Predicting Momentary Stress Ratings

Class	N with class	N for whom class significantly predicted stress (% of those with class presence)	positive relationships (more stress in this state)	negative relationships (less stress in this state)	average R^2	R^2 range across models with significant relationship
1	80	44 (55%)	8	36	0.06	0.011—0.392
2	83	64 (77.11%)	59	5	0.09	0.011—0.321
3	73	57 (78.08%)	7	50	0.10	0.011—0.466
4	84	34 (40.48%)	17	17	0.07	0.01—0.321
5	90	76 (84.44%)	72	4	0.12	0.012—0.447
6	73	57 (78.08%)	1	56	0.09	0.011—0.292
7	30	17 (56.67%)	10	7	0.07	0.01—0.16

Supplementary Table 4: Affect states Presence/Absence Predicting Momentary Life satisfaction

Class	N with class	N for whom class significantly predicted life satisfaction (% of those with class presence)	positive relationships (greater life satisfaction in this state)	negative relationships (lower life satisfaction in this state	average R^2	R^2 range across models with significant relationship
1	80	32 (40%)	10	22	0.04	0.01—0.10
2	83	61 (73.49%)	1	60	0.07	0.01—0.33
3	73	64 (87.67%)	64	0	0.15	0.01—0.56
4	84	34 (40.48%)	28	6	0.06	0.01—0.59
5	90	80 (88.89%)	0	80	0.16	0.01—0.53
6	73	62 (84.93%)	62	0	0.11	0.01—0.40
7	30	21 (70%)	7	14	0.01	0.01—0.65

Supplementary Table 5: Affect States' Relationship to Psychopathology

Current Diagnosis	**Class 1** *Mixed: Blunted*	**Class 2** *NA: Anxiety*	**Class 3** *PA: Low-Activation*	**Class 4** *Mixed: Activated*	**Class 5** *NA: Irritability*	**Class 6** *PA: High-Activation*	**Class 7** *NA: Sadness*
Any Diagnosis n = 54	β = -0.19 z = -7.11 p <0.001		β = 0.08 z = 2.24 p = 0.03	β = 0.08 z = 3.47 p <0.001	β = 0.10 z = 3.17 p = 0.002	β = -0.11 z = -4.33 p <0.001	β = -0.51 z = -4.83 p <0.001
MDD n = 27		β = 0.10 z = 4.08 p <0.001	β = 0.17 z = 4.01 p <0.001		β = 0.13 z = 3.65 p <0.001	β = -0.15 z = -4.67 p <0.001	β = -1.05 z = -6.32 p <0.001
Dysthymia n = 7				β = -0.39 z = -7.04 p <0.001	β = 0.19 z = 3.19 p = 0.001		β = -1.18 z = -3.33 p <0.001
Anxiety Spectrum n =31	β = -0.18 z = -5.76 p <0.001	β = 0.22 z = 8.77 p <0.001	β = 0.28 z = 7.09 p <0.001		β = 0.15 z = 4.49 p <0.001	β = -0.26 z = -8.61 p <0.001	β = -0.45 z =-3.65 p <0.001
GAD n = 24	β = -0.11 z = -3.46 p <0.001	β = 0.19 z = 7.18 p <0.001	β = 0.18 z = 4.31 p <0.001	β = -0.10 z = -3.59 p <0.001	β = 0.16 z = 4.02 p <0.001	β = -0.18 z = -5.41 p <0.001	β = -0.33 z = -2.43 p =0.015
Social Anxiety n = 8			β = 0.40 z = 6.57 p <0.001	β = 0.21 z = 5.28 p <0.001		β = -0.43 z = -7.06 p <0.001	
Panic Disorder n = 4	β = -0.74 z = -7.23 p <0.001	β = 0.23 z = 4.09 p <0.001		β = 0.31 z = 5.78 p <0.001	β = -0.39 z = -3.88 p <0.001	β = -0.40 z = -4.77 p <0.001	
OCD n = 7	β = -0.45 z = -6.71 p <0.001	β = -0.14 z = -3.60 p <0.001	β = 0.37 z = 5.73 p <0.001	β = 0.26 z = 6.28 p <0.001	β = 0.22 z = 3.70 p <0.001	β = -0.41 z = -6.36 p <0.001	
Agoraphobia n = 4	β = -1.04 z = -9.82 p <0.001	β = 0.50 z = 10.93 p <0.001	β = 0.47 z = 6.57 p <0.001	β = -0.31 z = -4.94 p <0.001		β = -0.20 z = -2.89 p = 0.004	β = -0.97 z = -2.54 p = 0.011
PTSD n = 2		β = -0.26 z = -2.57 p = 0.01	β = 1.08 z = 12.88 p <0.001	β = -0.22 z = -2.33 p = 0.02	β = 0.78 z = 9.59 p <0.001		
Bipolar Spectrum n = 11	β = -0.34 z = -6.57		β = -0.65 z = -7.98	β = 0.47 z = 14.8		β = 0.10 z = 2.29	β = -0.68 z = -3.04

	p <0.001		p <0.001	p <0.001		p = 0.022	p = 0.002
Current Hypomania n = 5	β = -0.28 z = -3.85 p <0.001	β = -0.64 z = -8.30 p <0.001	β = -1.15 z = -7.47 p <0.001	β = 0.37 z = 7.89 p <0.001		β = 0.52 z = 10.35 p <0.001	
Current Mania n = 2				β = 0.63 z = 9.94 p <0.001	β = 0.40 z = 4.11 p <0.001	β = 0.67 z = 9.35 p <0.001	
Substance Abuse/Dependence n = 9	β = -0.26 z = -4.75 p <0.001	β = -0.46 z = -8.71 p <0.001	β = -0.29 z = -3.84 p <0.001	β = 0.39 z = 10.89 p <0.001	β = 0.25 z = 4.89 p <0.001	β = -0.24 z = -4.47 p <0.001	
Current Psychosis n = 2	β = 0.42 z = 5.03 p <0.001			β = 0.45 z = 6.54 p <0.001			β = 1.06 z = 4.61 p <0.001
Mood Disorder with Psychotic Features n = 5	β = -0.33 z = -4.43 p <0.001	β = -0.14 z = -2.37 p = 0.02	β = -0.84 z = -6.37 p <0.001	β = 0.48 z = 10.95 p <0.001		β = 0.27 z = 4.84 p <0.001	

Anxiety Spectrum = GAD, SAD, Panic, OCD, Agoraphobia, or PTSD.
Bipolar Spectrum = Current mania, current hypomania, or met criteria for Bipolar I or II.
Substance Abuse/Dependence = Alcohol abuse, alcohol dependence, substance abuse, or substance dependence.

Figure 1a. BIC Plot for Nomothetic FMM

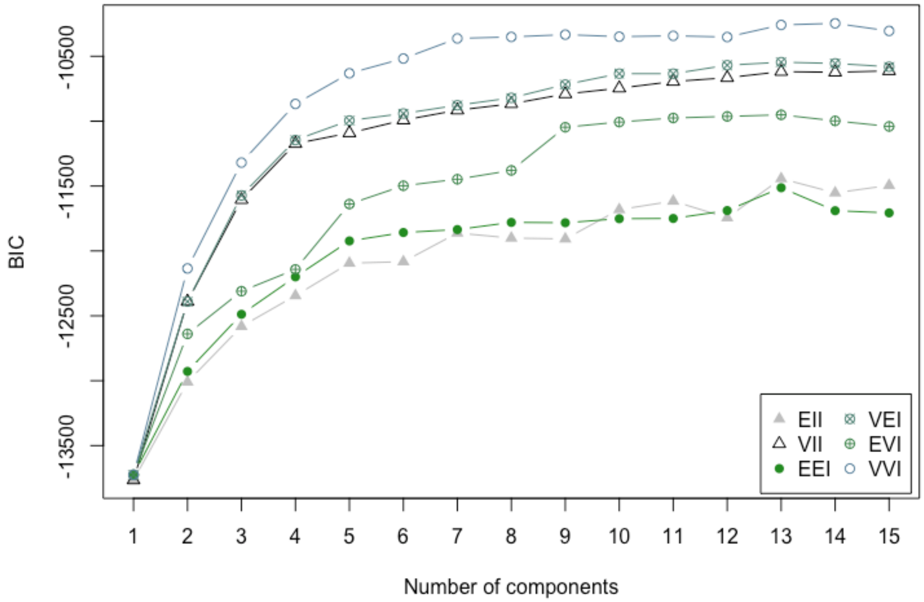
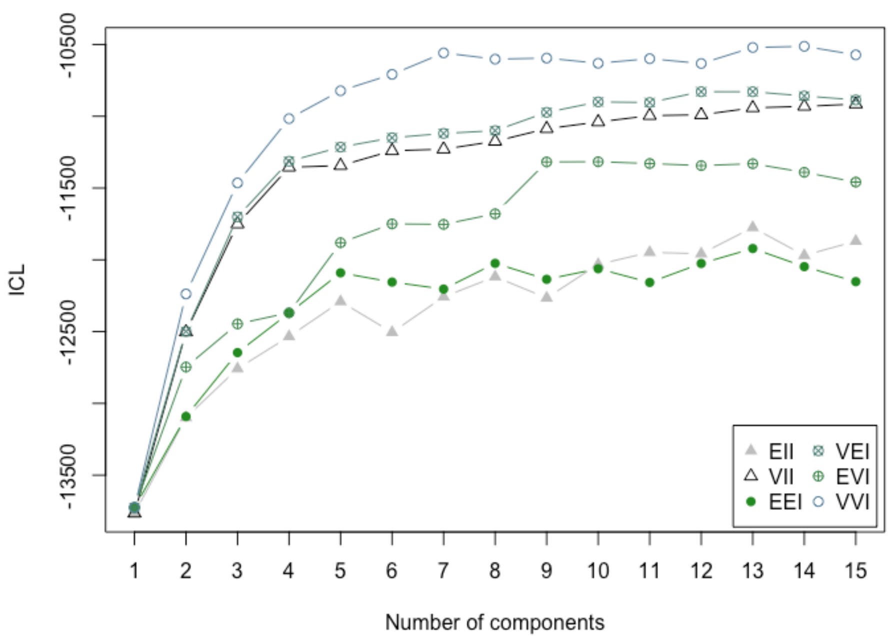
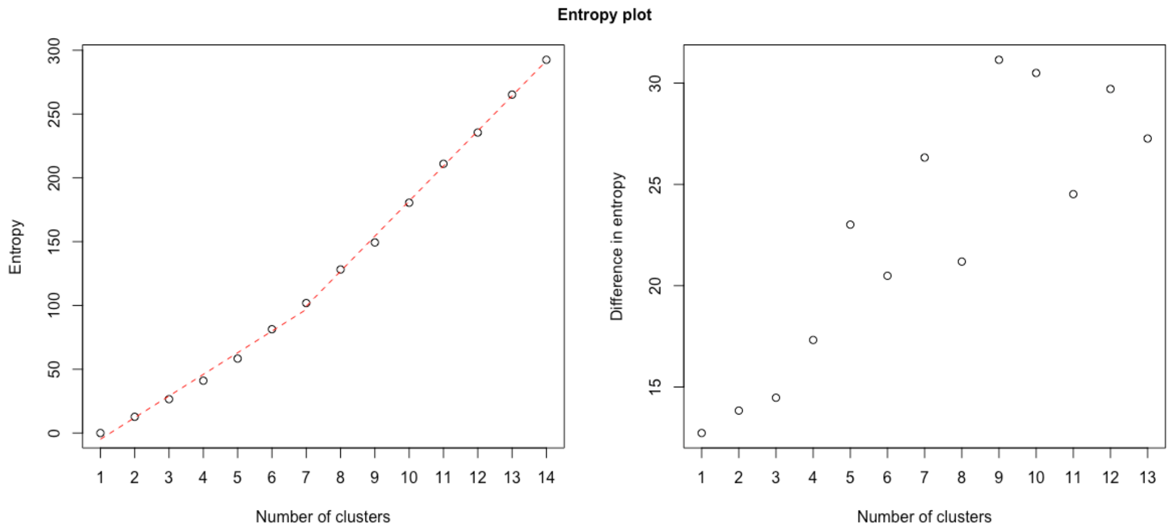


Figure 1b. ICL Plot for Nomothetic FMM



Note: BIC = Bayesian Information Criterion; ICL = Integrated Completed Likelihood

Figure 2. Entropy Plot for Nomothetic FMM.



Note: BIC = Bayesian Information Criterion; ICL = Integrated Completed Likelihood

Figure 3a. 7 Class Structure

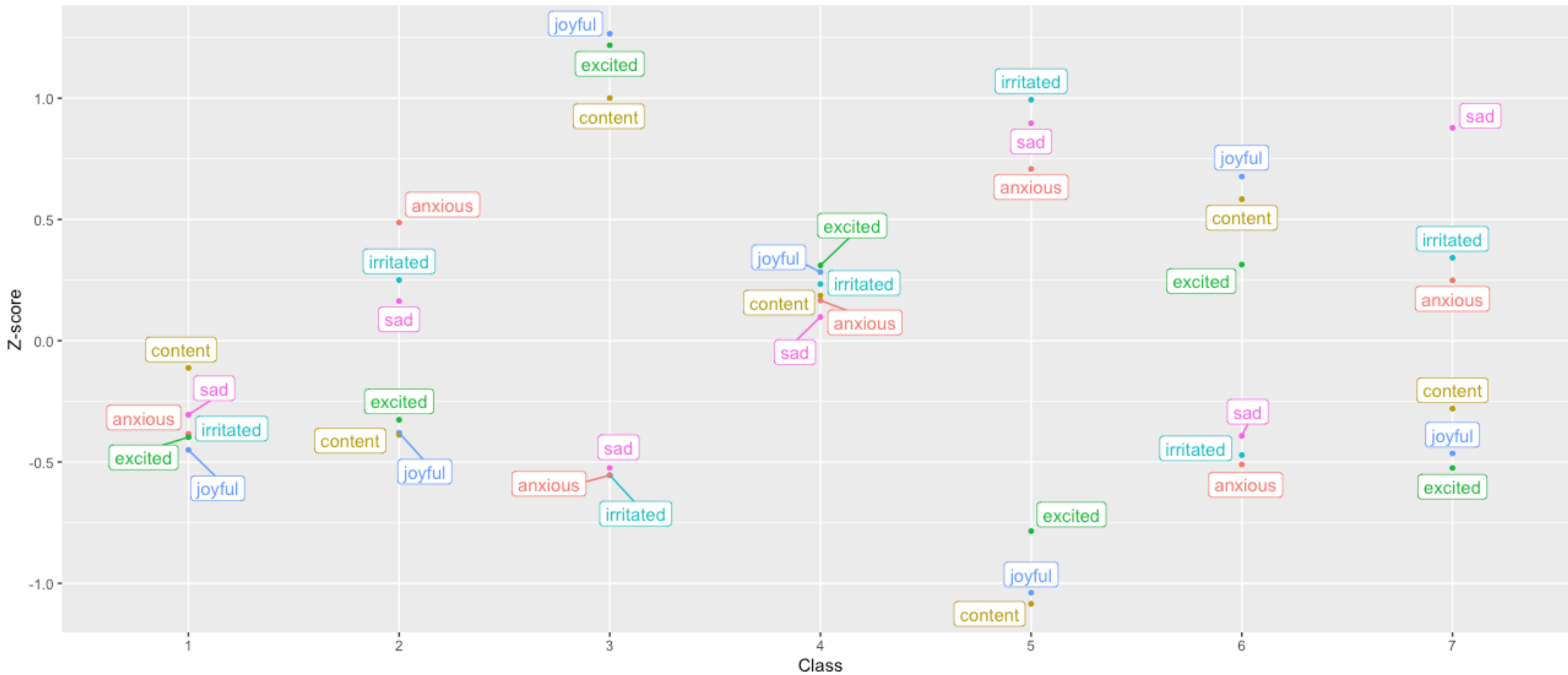


Figure 3b: 13 Class Structure

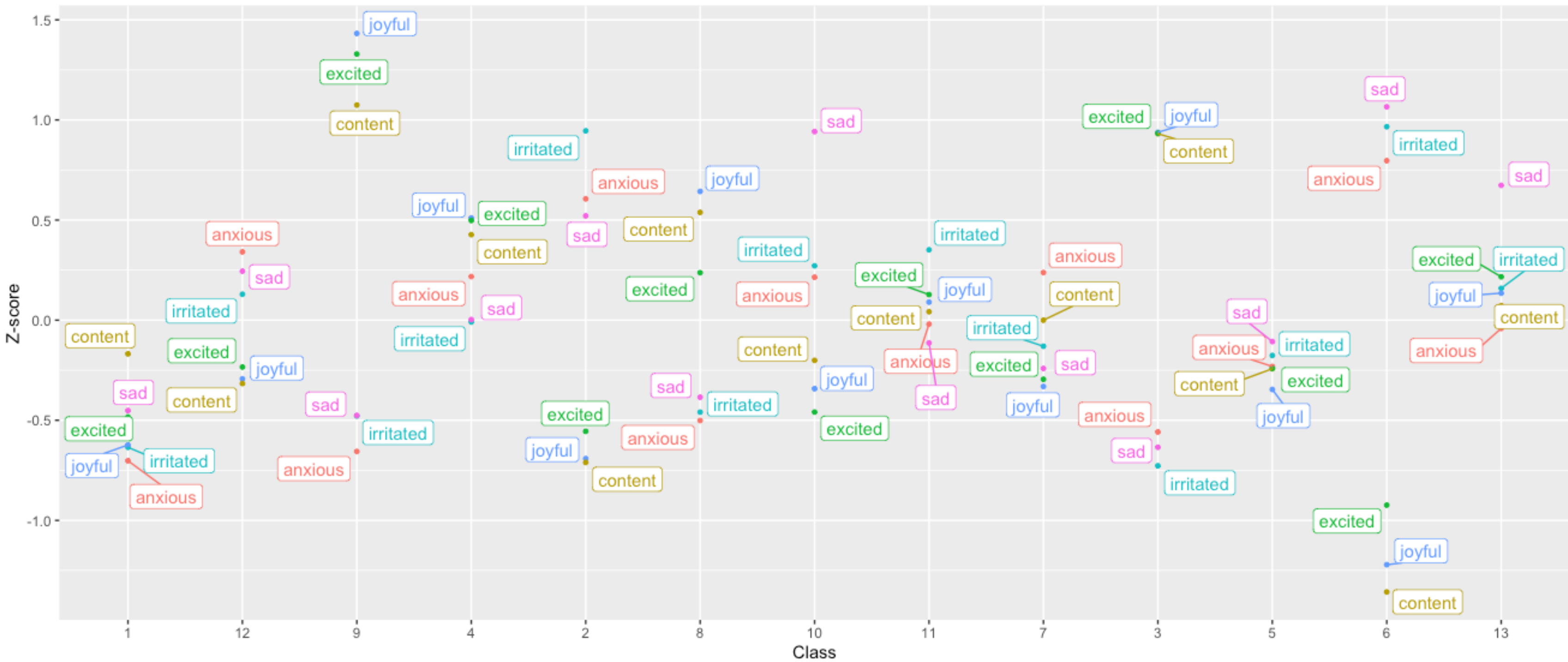


Figure 3c: 14 Class Structure

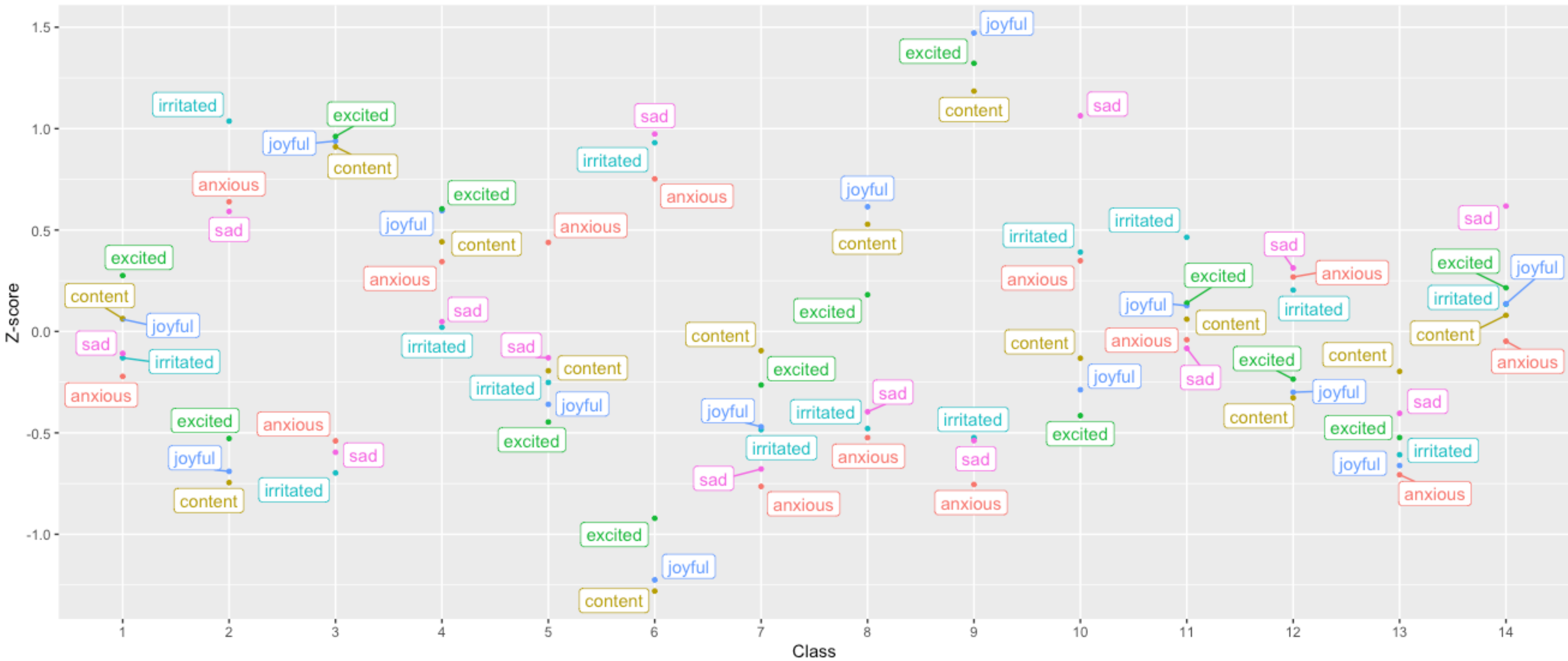


Figure 4: Final Nomothetic Model with 7 Classes Ordered by Frequency

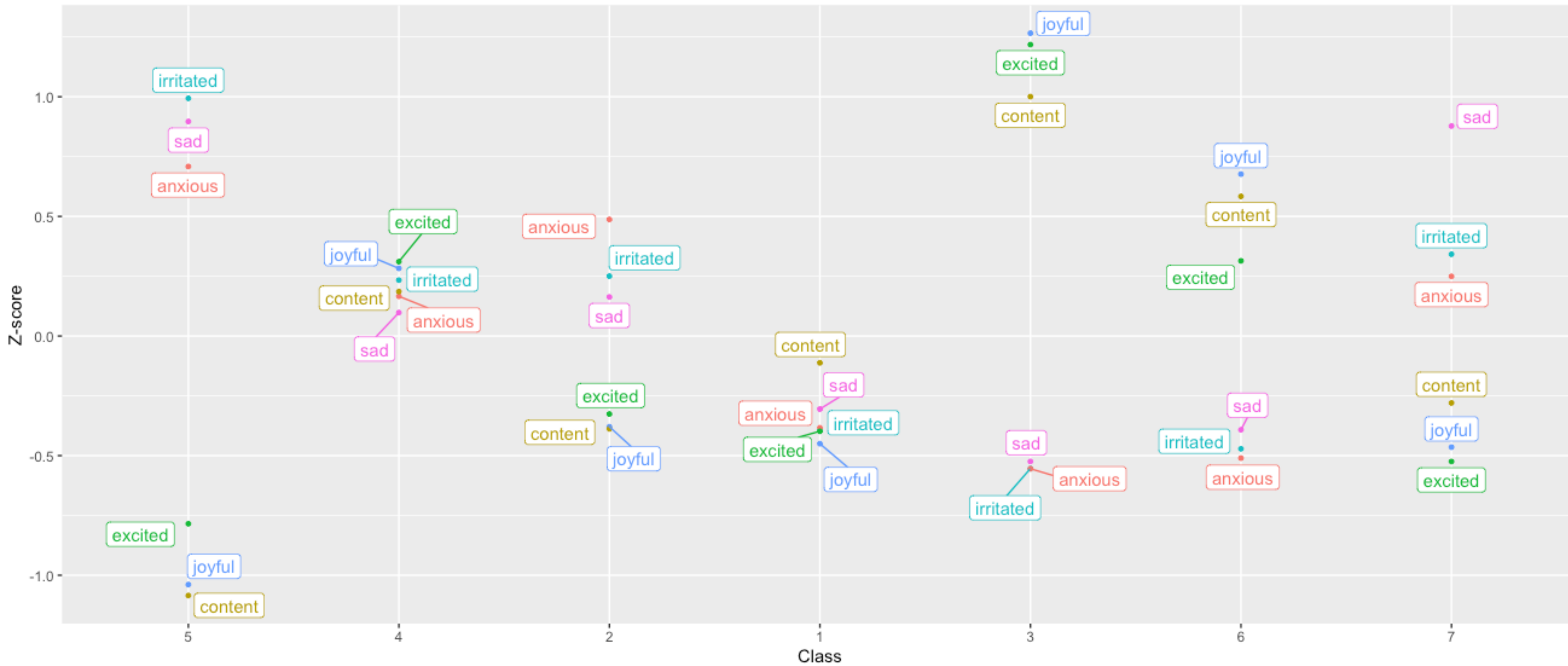
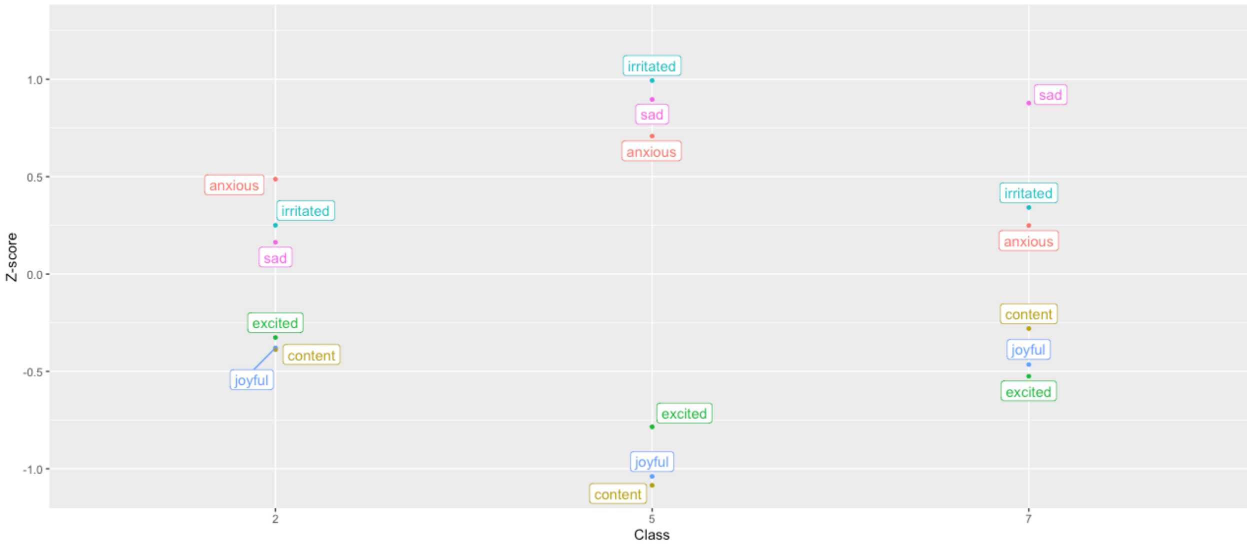
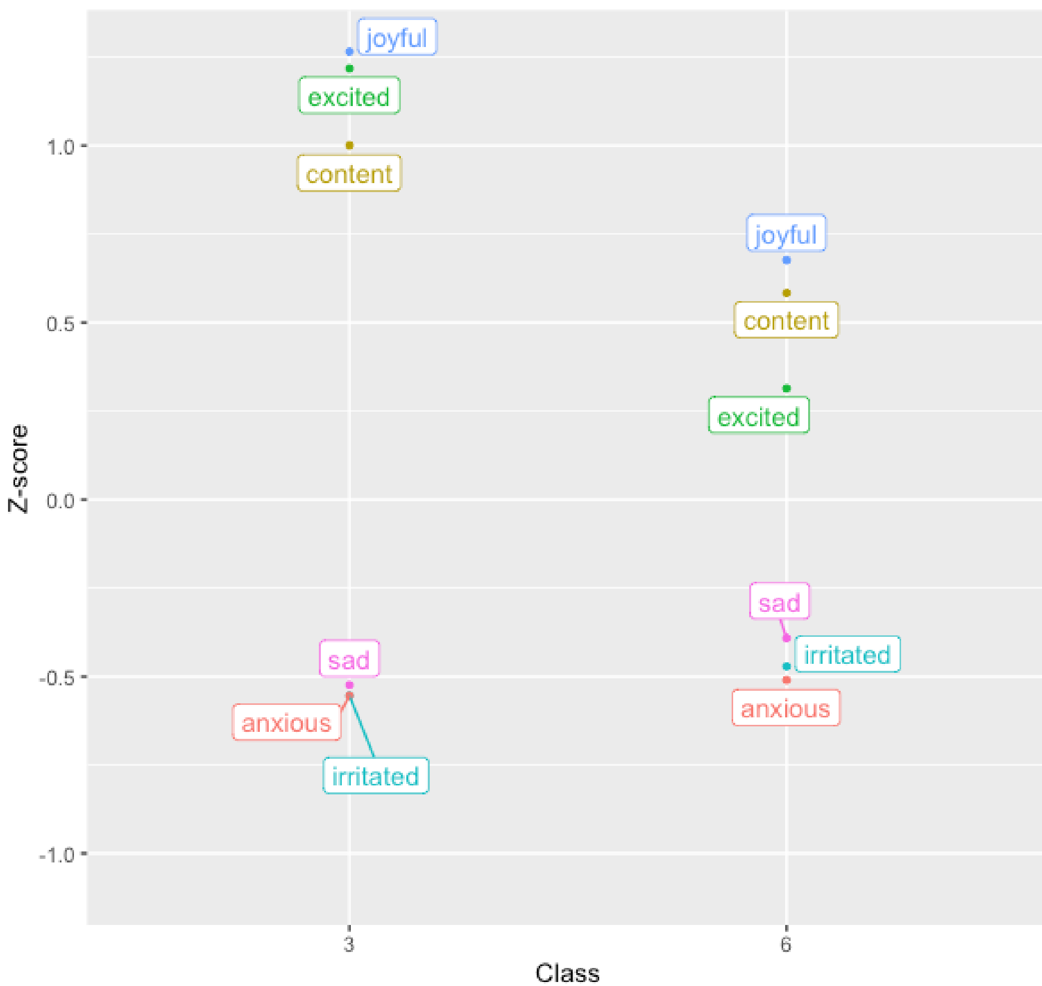


Figure 5: NA, PA, and Mixed Classes

5a: NA Classes



5b: PA Classes



5c: Mixed Classes

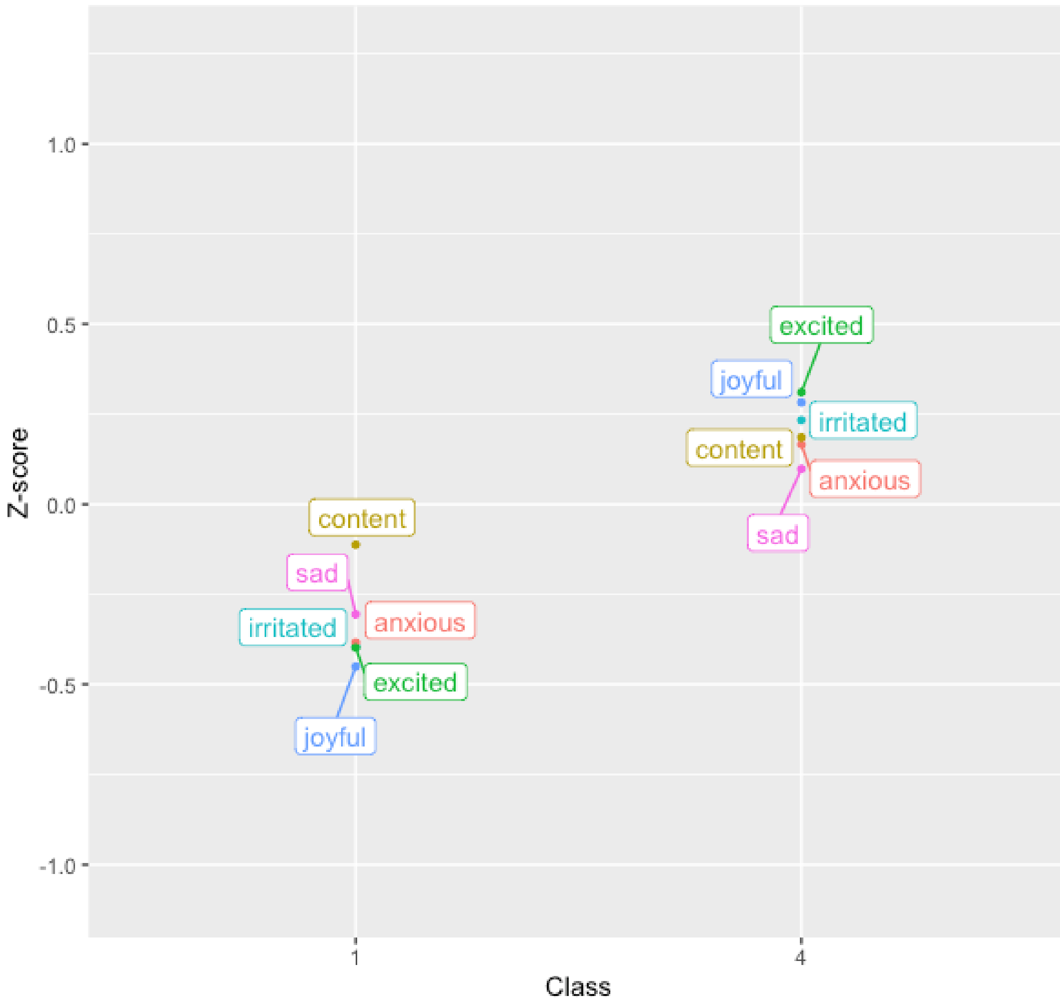


Figure 6. Between-Persons Frequency Distribution of Classes

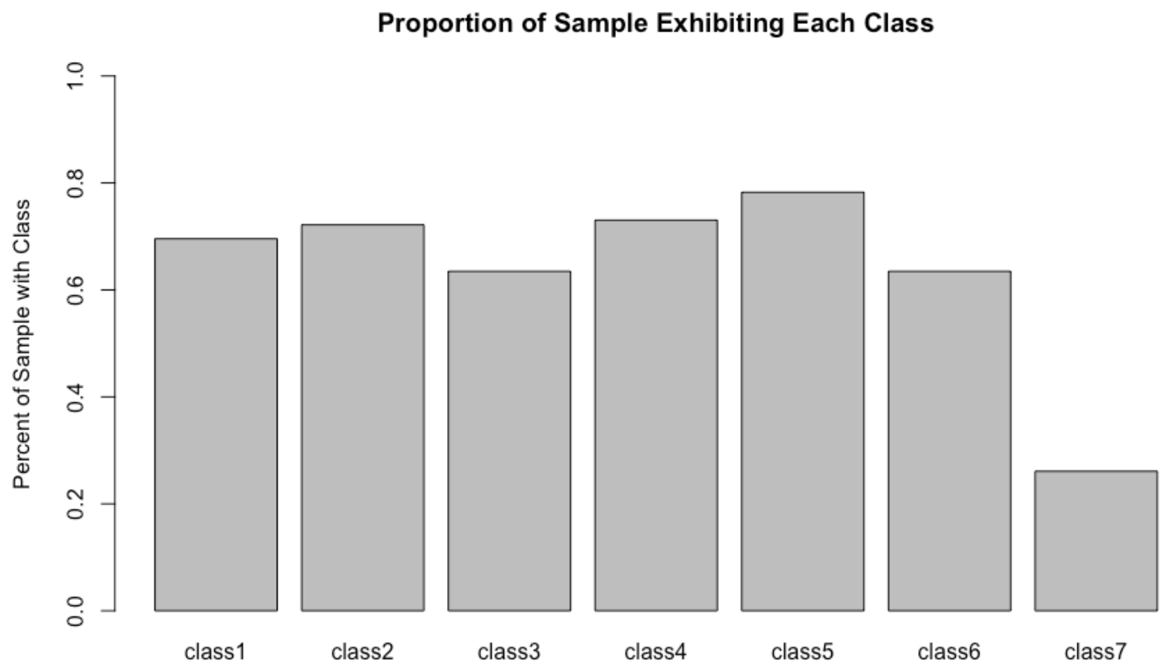
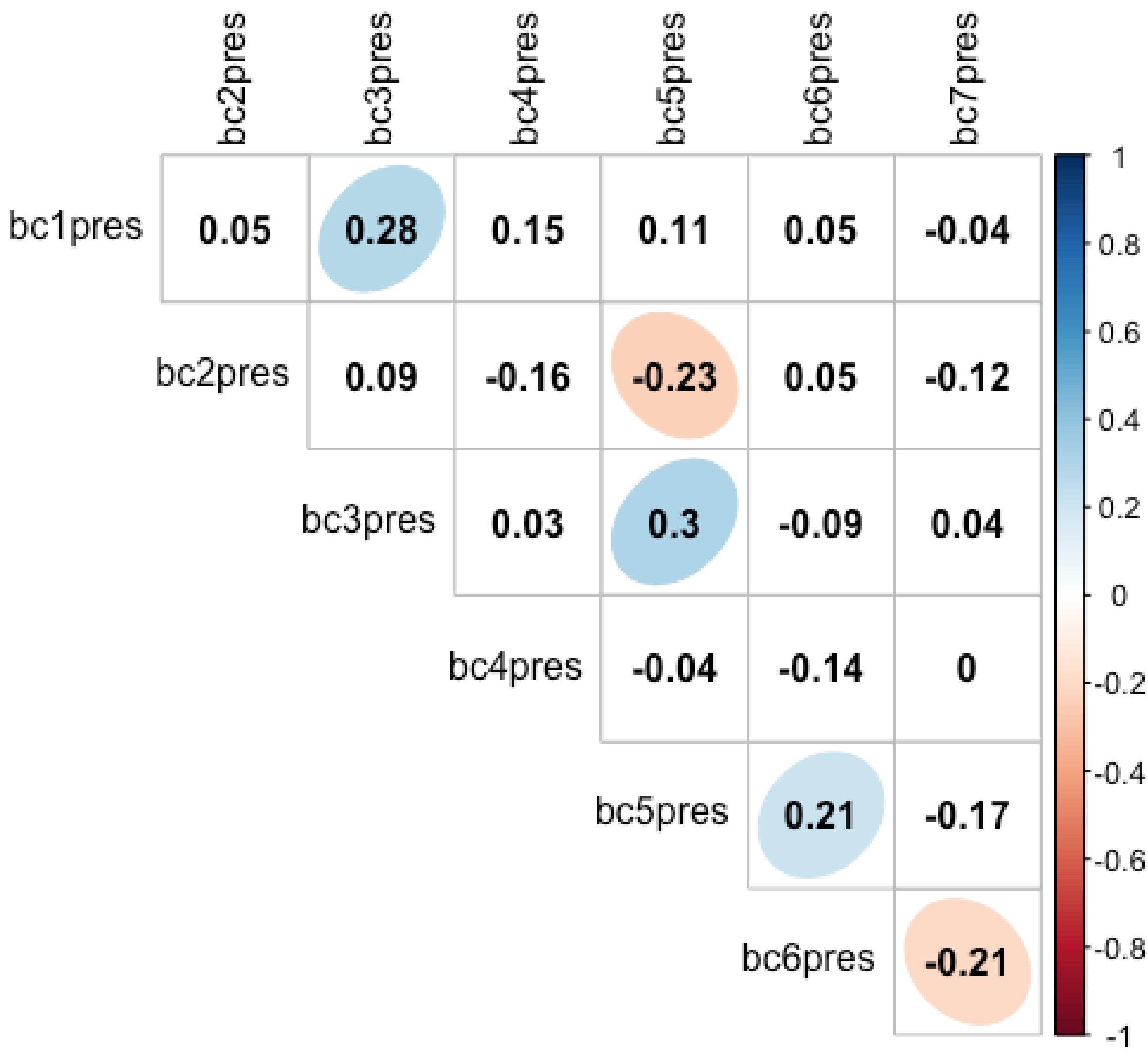
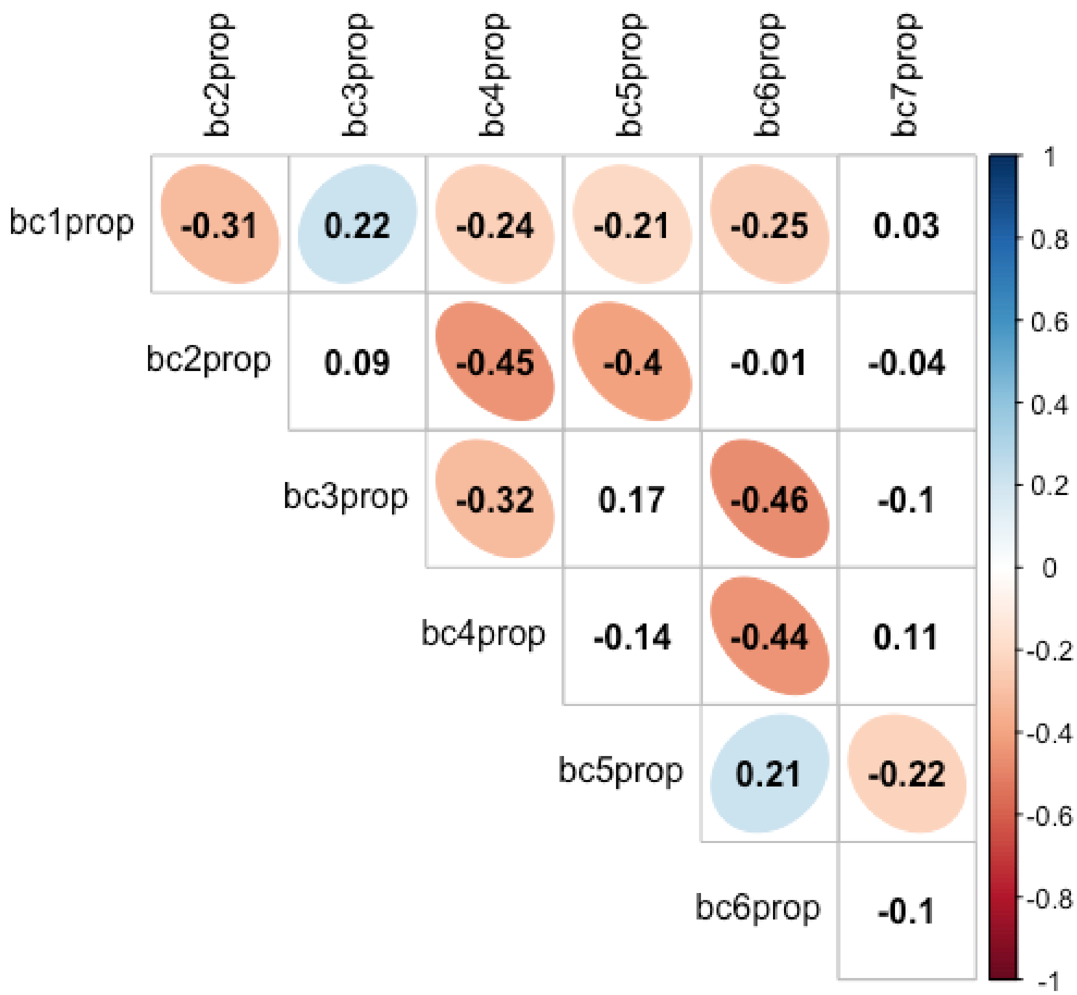


Figure 7: Correlations among Classes by Presence/Absence.



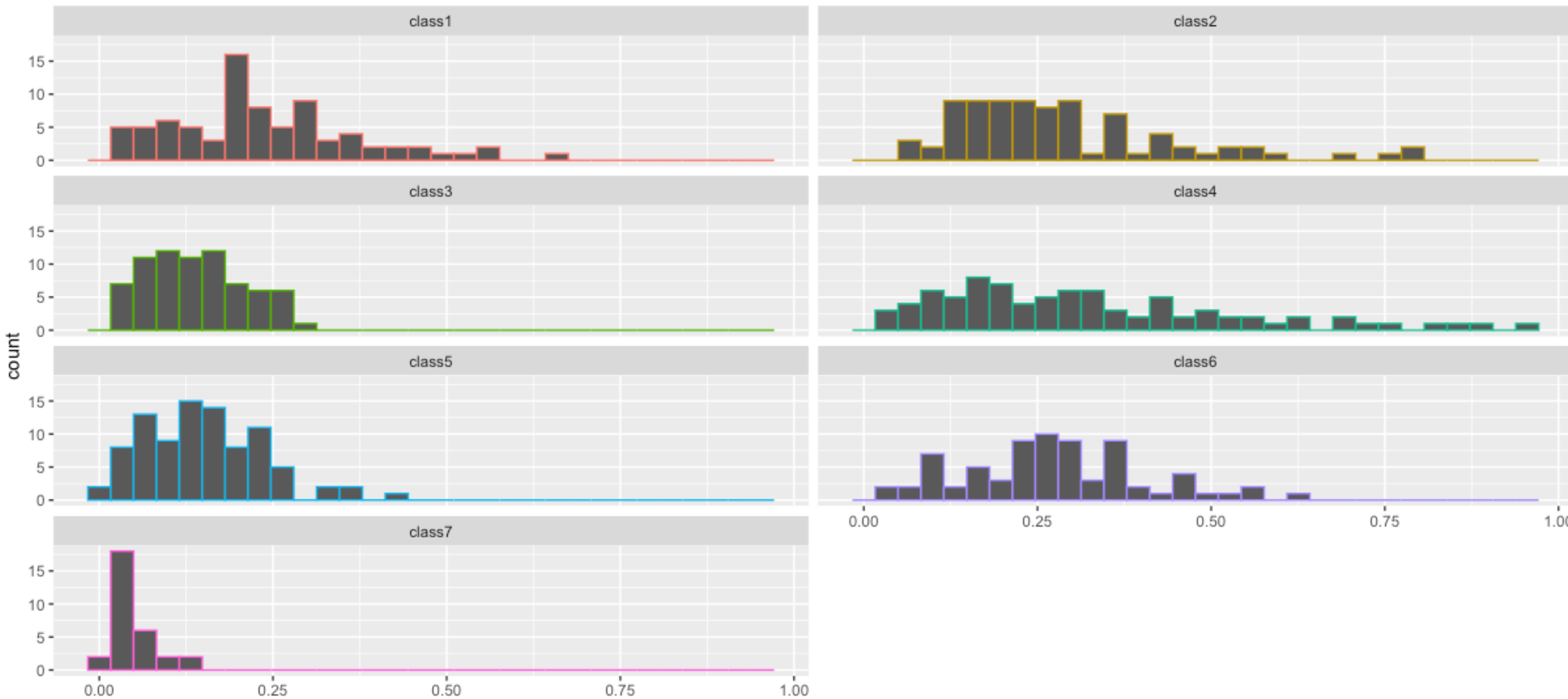
Correlations between classes' presence/absence. Correlations that are statistically significant at the $p<0.05$ level are indicated by a colored circle. Red indicates negative correlations while blue indicates positive correlations.
Variable names "bcXpres" indicate the variable representing the presence/absence of each class, 1-7.

Figure 8: Correlations among Classes by Within-Person Frequency



Correlations between classes' within-person frequencies, or rates of occurrence. Correlations that are statistically significant at the p<0.05 level are indicated by a colored circle. Red indicates negative correlations while blue indicates positive correlations.
Variable names "bcXprop" represent the variable that indicates the within-person rate of each class, 1-7.

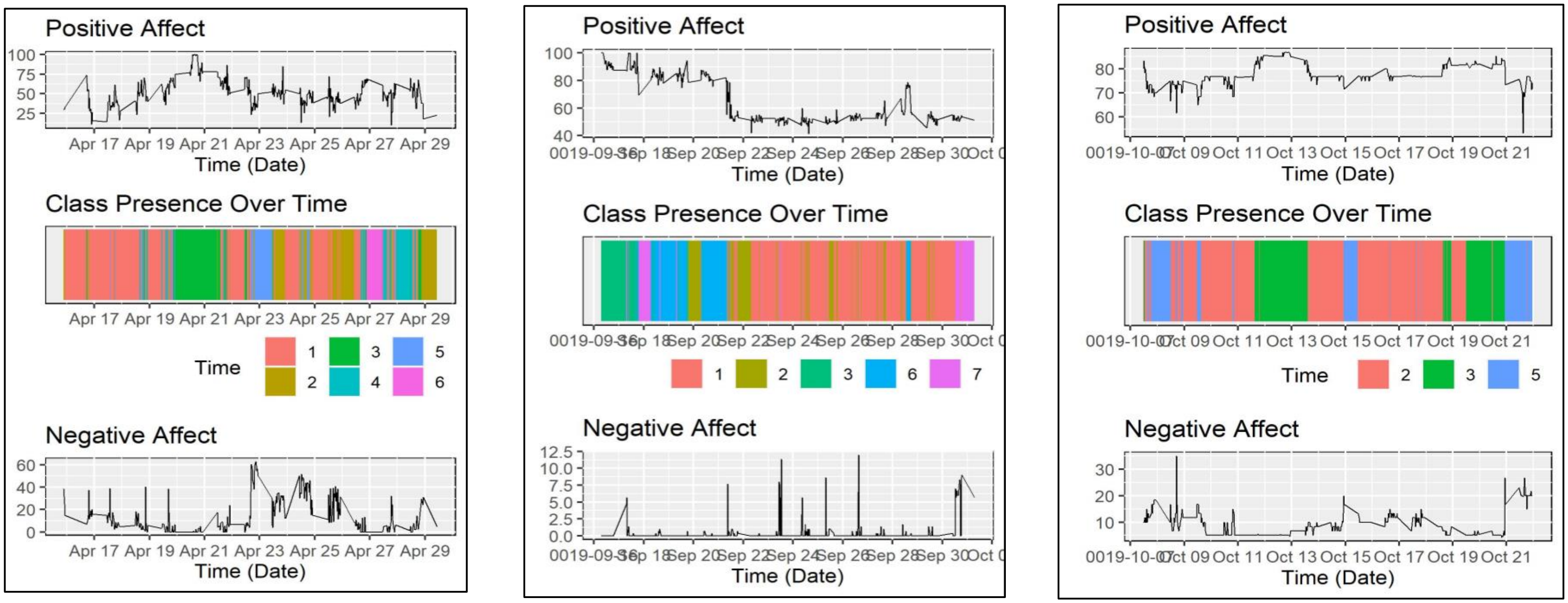
Figure 9: Within-Person Frequency Distribution of Classes.



The panel for each class shows the within-person frequency distribution for that class, among those who exhibited each class. As each class has a different N, the total number of individuals represented by each facet differs.

Units*: X axis (on each facet) represents the proportion of a time series spent in each of the affect states. Y axis represents the number of participants.*

Figure 10: Positive Affect, Negative Affect, and Affect State Duration in Selected Individual Examplars



Panel C: Participant 067 *Panel B: Participant 129* *Panel C: Participant 222*

Each panel shows the participant's composite positive and negative affect time series (top and bottom, respectively), alongside their affect profiles and their durations (middle). Positive affect composite scores are the average of positive items joyful, excited, *and* content. *Negative affect composite scores are the average of negative items* sad, anxious, *and* irritable. *Note that the color of the affect states is idiosyncratic.*

Supplementary Figure 1: Distribution of Peak Period for Each Affect State

Units: *on the X axis, peak period is listed in hours. The Y axis depicts the number of participants. The red line indicates the mean peak period (i.e., average cycle length) for that affect state. (only for participants with significant periodicity, those w/ no significant peak/only noise were removed)*