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Heterogeneity in Affective Complexity Among Men and Women

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Abstract

Background: Affective phenomena have noteworthy complexity and heterogeneity – shared experiences and emotions evoke distinct responses and risk for affective problems across individuals (e.g., higher rates in women than men). Yet, by averaging across individuals, affective science research traditionally treats affect as homogenous. Directly modeling person-specific heterogeneity in affective complexity (AC) – like the granularity and covariation of affective experiences – is paramount for identifying shared (i.e., common; nomothetic) and/or unshared (i.e., personal; idiographic) features of AC. The present study applied a person-specific technique to capture heterogeneity in daily affect and risk for affective problems in men and women and leveraged personalized results to improve general understanding of AC.

Methods: Young adults (n=56; 25 female) reported affect on each of 75-days of an intensive longitudinal study. AC was modeled using p-technique (i.e., person-specific factor analysis) and its utility over traditional, between-person models of affect (i.e., bivariate positive and negative affect) was compared for prediction of risk for affective problems in women compared to men. A community detection network algorithm was then applied to estimate person-specific AC to develop an idiographically-informed nomothetic model of AC.

Results: Person-specific analyses detected wide variation in AC across individuals (i.e., range of 2–8 factors). Relative to the traditional bivariate model, idiographic models had incremental utility for differentiating risk for affective problems by gender. Nomothetic review of idiographic results (via community detection) revealed distinct dynamics in positive and negative affect networks.

Conclusions: Person-specific science holds particular promise for mapping heterogeneity in AC and uncovering risk pathways for affective problems.

Keywords

affect; emotion; affective complexity; person-specific; gender; risk for affective problems

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Introduction

One of the most complex aspects of affective experience is its heterogeneity: individuals who experience the same situation or report feeling the same emotion exhibit different reactions and outcomes. Historically, the study of affective complexity (AC; e.g., emotional covariation or granularity) has aimed to establish what is emotionally universal across many people, often using bipolar group-level models of affect relationships, such as valence versus arousal or positive versus negative (Cacioppo et al., 1999; Green et al., 1999; J. Larsen et al., 2001; J. A. Russell & Carroll, 1999; Watson & Clark, 1997) with only mixed success in accounting for variation in the richness of emotional variation between individuals (Barrett, 2004; Kenny et al., 1998; Ong et al., 2017; Tennen & Affleck, 1996). Across individuals, AC appears to vary alongside factors like emotion regulation (Hay & Diehl, 2011) and psychopathology (Demiralp et al., 2012; Kashdan & Farmer, 2014; Tomko et al., 2015), suggesting that its person-to-person variation may provide insight into who is vulnerable to anxiety and depression, especially during late adolescence and young adulthood when risk for these problems is highest. Therefore, understanding person-specific variation in AC (Lindquist & Barrett, 2008; Reich et al., 2003; Wessman & Ricks, 1966) during emerging adulthood with models that are specifically informed by individual-level heterogeneity is a critical innovation in affective science with implications for understand early emergent risk for affective problems. By aggregating information across person-specific models of AC, more nuanced, accurate, and generalizable models of AC may be developed.

The present study applied person-specific models to 75 daily reports of affect to advance work in this area by: (1) testing for between-person heterogeneity in AC during young adulthood, when onset of affective problems is most prevalent, (2) comparing the utility of person-specific (i.e., idiographic) and group-level (i.e., traditional, nomothetic) approaches for differentiating known affective variation (e.g., by gender and risk for affective problems) and (3) identifying patterns in person-specific AC to develop a nomothetic model of AC that reflects the prevalence of effects across individuals rather than relying on averages (which obscure person-specific effects).

Heterogeneity in Affective Complexity

AC refers to the observed richness of emotional experiences – including phenomena like granularity (e.g., degree of differentiation between specific emotions) and covariation (e.g., co-occurring/mixed emotions and polarity/dialecticism). Prior studies of AC have linked complexity to numerous psychological phenomena that vary across individuals, including psychopathology (Demiralp et al., 2012; Kashdan & Farmer, 2014; Tomko et al., 2015), coping and adjustment (Tugade et al., 2004), and situational stress (e.g., dynamic model of affect; Reich et al., 2003; Zautra et al., 2001). Additionally, AC also appears to vary by gender, with women, on average, reporting a greater diversity and intensity of emotional experiences (Lutz, 1990) and some evidence that gender differences in AC track with psychological well-being (Larsen & Cutler, 1996). While these studies highlight effects of AC averaged across individuals, situations, and affective states, it remains unclear whether stable patterns in AC are unique to individuals or unique to subgroups of individuals or specific states of well-being (i.e., when experiencing persistent symptoms of affective problems like depression or anxiety). These are important knowledge gaps to fill because traditional, nomothetic models appear to have limited phenomenological or clinical predictive utility in predicting individual emotional experiences.

Though dynamics of affective experience appear highly individualized, study of AC rarely applies methods capturing variation at the individual-level. Early theories posited universality and alignment between the expression and physiological underpinnings of affect (e.g., Darwin and Ekman). By extension, approaches to the study of affect have historically aimed to define what is systematic or mechanistic across individuals (i.e., general scientific laws that uniformly explain affective phenomena in the population). Using this approach, inferences about AC are drawn by averaging across individuals and similar situations in a given sample to create a “mean case” expected to uniformly account for aspects of AC across the population.

A fundamental problem with this approach is that, in the presence of any real-world heterogeneity in AC across individuals, the “mean case” could not only be a poor representation of what is common across individuals but may actually be unmatched with any individual in the population (Molenaar, 2004). For example, in a study of the Five Factor Model (FFM) of personality, Borkenau and Ostendorf (1998) applied a person-specific factor analytic technique (i.e., p-technique; Cattell & Luborsky, 1950; Molenaar & Nesselroade, 2009) to intensive longitudinal data (i.e., more than 90 days of daily measurements for each person) to identify the structure of personality for each individual. Though the FFM is well replicated across people, not one participant exhibited five factors within their person-specific model and many had fewer than five (Borkenau & Ostendorf, 1998). When taken together, these results illustrate that sample “averages” of psychological phenomena may not reliably generalize to individuals. Nomothetic (i.e., group-level) approaches are especially problematic to the extent that they obscure heterogeneity at the individual level and, in so doing, omit critical information in determining whether an effect is actually universal (i.e., prevalent across individuals, not combined).

Individual affective experiences are increasingly characterized as heterogeneous, such that individuals are thought to have relatively unique affective lives (Barrett, 2009). Most recently, affective experience is characterized as “constructed” such that modes of affective expression (e.g., facial, vocal, and behavioral), physiological activation (e.g., heart rate, cutaneous blood flow, and sweating), and subjective affective experience are highly nuanced at the individual-level, but may also have some overlap across individuals and affect episodes (Barrett, 2006b, 2006a; Barrett & Russell, 1999; Cacioppo et al., 2012; Larsen et al., 2001; Pfeifer & Allen, 2012). Despite acknowledgement of heterogeneity and a vast set of determinants for emotional experience, nomothetic, mean-level methodologies that assume similarities instead of differences across individuals (e.g., within-emotion or within-gender; Bekker & van Mens-Verhulst, 2007) prevail, limiting understanding of what is common across individuals and what is not.

Overlap in the dynamics of emotional experiences may indicate that patterns in person-specific heterogeneity may, at some level, exhibit homogeneity (i.e., some patterns may be consistent across people while others may not). The traditional approach of averaging across people to draw a nomothetic conclusion may then obscure how emotional experience operates at the individual-level. By necessity, individual-level models may be ideal for developing more nuanced and accurate models of group-level similarity. This conclusion is supported by ergodic theory and largescale simulations in the neuroimaging literature (Gates & Molenaar, 2012), but has not been widely employed in behavioral science likely because person-specific modeling requires time series data (i.e., many observations per person as in intensive longitudinal data). Implementation of methods specifically aimed at understanding if and how AC is person-specific will yield important advances in affective science by determining whether traditional averaging across individuals supports sufficiently accurate and comprehensive inferences about AC, or whether a “bottom-up” approach that first models at the individual-level is required.

Study of between-person AC variation is ubiquitous and often predicated on testing mediating or moderating effects of other factors like gender, personality, and even affective problems (i.e., presence/absence of disorder diagnosis or count of problems along a dimensional continuum). Avenues of research using this approach have been somewhat successful in accounting for variation in affective experiences. For example, documented gender differences in not only affect (Arendell & Brody, 2001; Chaplin & Aldao, 2013; Koch et al., 2007; Simon & Nath, 2004) and its complexity (Larsen & Cutler, 1996) but also affective disorder prevalence (Nolen-Hoeksema, 1990; Schuch et al., 2014) and symptom-specific phenomenology (Gressier et al., 2016; Kornstein et al., 2000; Nolen-Hoeksema, 1990) provide evidence that heterogeneity tracks with aspects of gender. Despite the focus on AC variation, most of this work still assumes homogeneity in affective experiences within each gender. Yet, this may be a faulty assumption, as the long-held gender similarities hypothesis posits there is as much psychological variation within men and women as between them (Hyde, 2005, 2007, 2014). It is therefore critical to identify the degree of person-specific heterogeneity within well-documented gender differences in affective experience.

Understanding heterogeneity in AC in men and women separately is especially important as women appear to develop affective disorders at twice the rate of men, and are three times more likely to experience severe and atypical features (e.g., episodic symptom recurrence, weight gain, and hypersomnia) compared to men (Kessler et al., 2005; Kornstein et al., 2000; Perugi et al., 1990; Preisig et al., 2001; Weissman & Klerman, 1977). However, not all women develop affective problems, making it especially important to understand what consistent and stable aspects of women’s emotional experiences track with risk for affective problems irrespective of an affective disorder diagnosis and account for their increased risk for affective problems.

An idiographic approach utilizing person-specific analyses that fit personalized models could be invaluable for developing new insights into patterns of AC including its consistency across individuals overall, and among women relative to men, more specifically, which mark complex constellations of affective dynamics that are stable within the individual. Despite the increasing popularity of individualized approaches and the potential of “precision psychology” (Stein & Smoller, 2018), empirical application of these methods is rare (Beltz et al., 2016; Wright & Woods, 2020). Despite their underutilization, they have potential to offer information on individual-level variation that could be profitably leveraged to develop a more nuanced nomothetic model that more directly represents individual-level heterogeneity in AC and its links to risk for affective problems.

Current Study

Person-specific analyses of AC are required to: (1) identify the degree of AC heterogeneity within individuals (as compared to the traditional two-factor, positive and negative affect model that characterizes variation between individuals), (2) to determine whether person-specific AC tracks with previous findings that AC varies by gender and dimensional reports of risk for affective problems, and (3) to utilize person-specific models to inform development of a more nuanced nomothetic approach to AC that directly accounts for between-person differences in within-person effects.

We accomplished each of these aims using intensive longitudinal affect data collected from young adults (i.e., during the period of highest risk for affective problems for both men and women; Center for Collegiate Mental Health, 2018) across each of 75 days. After fitting personalized models to estimate stable, person-specific AC, we aggregated the same data across people to replicate the traditional, mean-level AC (i.e., bivariate positive and negative affect). Next, we compared person-specific AC and mean-level factor scores as predictors of risk for affective problems (i.e., indicators of potential subthreshold psychopathology derived from daily personality measurements) by gender. We hypothesized that AC would pose differential risk for affective problems for men and women (i.e., women would be more vulnerable to risk due to AC), and compared to the traditional, nomothetic approach, personalized models would have incremental value in facilitating idiographic inferences (i.e., prediction of risk for affective problems by gender). Finally, commonality across person-specific models was reviewed and then used to develop an idiographically-informed nomothetic model of AC.

Method

Sample

Participants were drawn from a larger, 75-day intensive longitudinal study of exogenous hormone effects on gender differences in behavior (N=175) with University IRB approval. Other papers from this sample have examined cognition (Kelly & Beltz, *in press*), personality and physical health (Kelly et al., 2020), and biological influences on emotion variability (focusing on a biologically-informed subsample, who are not included here).

Participants included in the present analyses (i.e., young adults; n=56, 45.6% women, age: M = 21.70, SD = 3.24) were broadly inclusive of the university community and between the ages of 18 and 30 and were drawn from the unmedicated, control group to ensure that variation in use of hormone medication would not exert undue influence on results across individuals. Consistent with other studies utilizing data from this sample and with prior work showing that 20% missingness is the optimal threshold to conduct data analysis without imputation (Rankin & Marsh, 1985), we only included participants with response rates of at least 80% (i.e., 82% inclusion overall). Of the 28 women identified for initial inclusion in this study, two were excluded due to poorly fitting p-technique models.

Procedures

The larger study involved an initial hour-long laboratory-based intake session followed by 75 daily diaries. During the intake session, participants were compensated with course credit or $15 for providing consent and medication use information, and for completing a battery of questionnaires indexing various phenomena including baseline affect and other psychological phenomena that typically show gender differences, including personality and cognition.

Over the 75 days following the intake session, a subset of participants utilized an Internet-based device (e.g., computer, tablet, or smartphone) to complete an approximately 20-minute survey each day. Surveys were activated daily at 5pm, participants were directed to complete them after 8pm or before they went to bed, and they remained open for responses until 12pm on the next day. Online surveys queried a broad array of daily experiences, including affect, and participants were compensated for their time on a prorated basis (i.e., up to $200 total with $1 per day for < 80% completion or $2 per day for > 80% completion, and a bonus of $50 for > 90% completion).

Measurement

Day-to-day AC.—The Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) was used to operationalize AC in the present study. At an initial intake session, participants reported based on general, trait-level affect ($\alpha = 0.83$, average across subscales at intake) while each of the daily diaries indexed affect in the previous 24 hours. Magnitude of experiences for each of the 20 PANAS affect items was reported on a unipolar scale (i.e., 1 = "very slightly/not at all", 2 = "a little", 3 = "moderately", 4 = "quite a bit", 5 = "extremely") and permitted bivariate factor computation (positive and negative affect scales). Dynamics between PANAS items were estimated for each person using repeated observations across days and the resulting personalized model structure was retained as an index of AC (explained below).

Risk for affective problems.—The NEO Five Factor Inventory (NEO-FFI; Costa & McCrae, 1992) was used to measure present risk levels for affective problems, estimated via personality and affect subscales, at the intake session ($\alpha = 0.81$, average across subscales at intake). The magnitude of trait-like experiences for each of the 60 NEO personality items was reported on a unipolar scale at the intake session. Effects were estimated across all 5 subscales (e.g., Neuroticism, Extraversion, Openness, Conscientiousness, and Agreeableness) and rationally-derived subscales for anxiety and depression (Chapman, 2007; Saucier, 1998). Use of these dimensional measures is intended to capture variation in aspects of functioning that pose risk for affective problems rather than for diagnosing mental health conditions.

While the NEO-FFI is not a diagnostic tool, a pathoplastic relationship has been documented between higher order personality constructs and psychopathology risk, such that personality factors can broadly modulate the onset, severity, and course of clinically-relevant factors like affect (Widiger, 2011). For example, neuroticism has been specifically linked with internalizing disorders (Hettema et al., 2006; Miller & Pilkonis, 2006; Spinhoven et al., 2014) during the period of greatest risk for their development (e.g., during late adolescence and young adulthood). For this reason, we explored variation in affective complexity across all higher-order personality constructs. This approach is consistent with dimensional approaches to the study of clinically relevant psychological problems in those with and without diagnoseable disorders (e.g., NIH Research Domain Criteria; Kozak & Cuthbert, 2016) and has the advantage of capturing severity of premorbid risk during the developmental period where onset of affective problems is most common among men and women (i.e., among young adults sampled).

Statistical Analysis

Person-specific AC models.—Daily data were used to estimate person-specific factor structures (i.e., 40 within-person factor models) for affect data from the daily PANAS responses using p-technique (Jones & Nesselroade, 1990; Lee & Little, 2012; R. L. Russell et al., 2007; Stephenson, 1936; Wright et al., 2016) with quasi-maximum likelihood estimation (Hamaker et al., 2005) in LISREL. In contrast to traditional factor analysis (i.e., r-technique) that capitalizes on inter-individual variance from single, cross-sectional reports across many individuals (i.e., nomothetic approach), p-technique utilizes intra-individual variance from repeated measurements (i.e., intensive longitudinal data) from a single individual (i.e., idiographic approach). Variable associations are used to map the latent (i.e., unobserved) structure that connects them. To meet statistical assumptions of p-technique, invariant items (i.e., items with standard deviations of 0 across a participant's time series) were removed and models were fit to standardized residuals after regressing out linear time effects (Foster & Beltz, 2018).

The number of affect factors was determined for each person using an SEM-based sequential factor modeling approach (Lo et al., 2017; Molenaar & Campbell, 2009). Starting with a one-factor solution, exploratory models were fit sequentially (i.e., 1-factor then 2-factor and so on) and estimation concluded when three of four fit criterion thresholds were surpassed (Kline, 2016). Next, oblique rotation was conducted and a confirmatory model (using a regularization-like threshold of 0.05) was subsequently fit and evaluated with the same fit criterion thresholds. If confirmatory fit was unacceptable, a higher-order exploratory model was subsequently fit followed by an oblique rotation and confirmatory fit. Maximum significant factor loadings in the confirmatory solution were interpreted and factors were labeled. Using this approach, AC was operationalized as the person-specific factor structure solution for each individual. For each individual, these structures simultaneously captured temporal consistency in both granularity (i.e., number of factors detected across the 20 items, with more factors indicating more granularity) and covariation (i.e., patterns of clustering between specific items within a factor) across time for each individual.

Traditional, mean-level models of cross-sectional AC.—To facilitate comparison of person-specific and conventional approaches to modeling affect, full-sample, cross-sectional data from the first diary day was used to estimate traditional, bivariate structures for affect using r-technique (i.e., mean-level approach). Confirmatory model-fitting procedures were used to replicate the bivariate structure previously validated for the PANAS. Regression-based positive and negative factor scores were computed for use in subsequent analyses as an aid for identifying incremental predictive value of person-specific AC information.

Linking clinically relevant problems with AC using person-specific vs. traditional approaches.—Regression analyses were then used to test whether person-specific variation in AC (i.e., each person's number of p-technique affect factors) captured meaningful between-person variation in risk for affective problems. The number of affective factors were first modeled alongside the main and moderating effects of gender as predictors of risk for affective problems (i.e., 5 NEO factors and anxiety and depression rationally-derived NEO subscale scores) reported at intake.

Regression analyses were also used to test whether mean-level variation in positive and negative affect (i.e., factor scores estimated in r-technique) captured meaningful risk for affective problems reported at intake by gender. Differences between person-specific and mean-level associations with clinically relevant outcomes will highlight whether person-specific models capture unique variation in mental health risk. Post-hoc power analysis confirmed that 0.80 power is retained to detect a moderate effect with alpha=.05 for the focal between-person tests specified.

Drawing nomothetic conclusions from person-specific AC results.—Finally, person-specific patterns of AC (i.e., items loading on the same factor from p-technique solutions) were used to develop a nomothetic AC network via the Louvain method for community detection (Blondel et al., 2008) in Gephi (Bastian et al., 2009) wherein all person-specific adjacency matrices indicated whether the same emotions (i.e., PANAS items) loaded onto the same factor for a person. Commonalities across all matrices are reflected in the full sample network and separate networks of men and women. Network modularity and density reveal whether the traditional bivariate structure emerges at the group level and within each gender.

Results

Table 1 and Figures 1–5 present results from person-specific, mean-level, and idiographically-informed nomothetic models. Generally, results uncovered noteworthy individual-level heterogeneity in AC. Person-specific AC (i.e., the number of factors in the person-specific network; Figures 1 and 2) had incremental utility for differentiating additional risk for affective problems in men and women not otherwise predicted by traditional positive and negative affect scores (Table 1 and Figure 3). Additionally, nomothetic analysis of idiographic results confirmed the presence of positive and negative affect networks but illustrate their distinct dynamics (Figure 4), interconnections that constituted mixed emotions (e.g., "Jittery"), and the gender-specific dynamics of these networks (Figure 5).

Person-specific AC models.

Noteworthy heterogeneity was observed in AC across individuals, with a range of 2 to 8 factors identified. Fit criteria and final factor solution averages indicate generally excellent fit (i.e., averages: RMSEA = 0.03, CFI = 0.97, SRMR = 0.08; values by individual are presented in Supplemental Table 1). In Figure 1, a frequency graph is presented to depict instances of each level of AC (i.e., 2–8) across individuals. Only one individual exhibited the traditional bivariate structure while the majority of individuals exhibited greater AC. More than 73% of the sample exhibited an AC of 5 or more factors. Notably, no two person-specific models had identical composition. Even across individuals whose person-specific model contained the same number of factors, item associations varied, suggesting that specific patterns of covariation were heterogeneous even among those with the same AC granularity. Despite being obliquely rotated, factor correlations were small (i.e., average magnitude within-individuals: 0.19), suggesting that affect factors capture unique variance with minimal overlap.

To highlight the breadth of heterogeneity in AC observed across person-specific models, Figure 2 depicts solutions for different individuals who exhibited three-, five-, and seven-factor structures (by convention *provisional*, *subjective* factor labels are included to facilitate interpretation of variation across factors and individuals). The individual with the 3-factor structure (Figure 2A) exhibits one factor comprised of positive items (labeled Zeal) and two factors each comprised of negative items, highlighting that this individual exhibited strong linkage between jitteriness and hostility (On Edge) that remains unrelated to other typically negative experiences like irritability or distress (Distress).

The individual with the 5-factor solution (Figure 2B) – the most common AC granularity – exhibited an affect structure that was moderately compartmentalized with traditionally negative and positive items mixed across categories. Specifically, a structural link between traditionally positive items like strength and determination and traditionally negative items like jitteriness and alertness (Anxious Arousal) was evident.

By contrast, the individual with the 7-factor solution (Figure 2C) exhibited highly compartmentalized affective experience dramatically different from the traditional bivariate model. For this individual, constituent items for some factors included a mix of traditionally positive and negative items (e.g., a factor comprised of interested, attentive, and jittery labeled Vigilance, or the factor comprised of strong, active, upset, hostile, and irritable labeled Agitation). Across individuals, AC ranged by degree of affect compartmentalization (e.g., negative items spread across Distress and On Edge factors for one individual and across Anxious Arousal, Anguish, and Fearful Vigilance for another) and degree of positive and negative item mixture within factors (e.g., total separation across Zeal and Distress factors for one individual and a mixture of both across Vigilance and Agitation for another individual).

Across personalized models, emotions were either clustered into unique factors reflecting polarity (i.e., comprised of positive or negative items only) or some combination of traditional positive and negative emotions (i.e., "mixed"). Factors with items exclusively from one polarity (i.e., all constituent items were either exclusively positive or exclusively negative) were detected across only 16.1% of individuals and represented 60.3% of person-specific factors estimated across people overall. Polarity factors were detected in personalized models of men (22.6%) more often than women (8%). Across individuals, the prevalence of negative item only factors (83.9% of individuals with at least 1) exceeded that of positive item only factors (75% of individuals with at least 1). For men, positive item only factors were more prevalent than negative item only factors (80.6% vs. 77.4%). For women, the opposite was true, such that negative item only factors were more prevalent than positive item only factors (92% vs. 68%).

By contrast, "mixed" factors (i.e., comprised of both traditionally negative and positive items) were detected across 83.9% of individuals and comprised 39.6% of person-specific factors estimated across people overall. Mixed factors were detected in personalized models of women (92.0% of women with at least 1) more often than men (77.4% of men with at least 1). Mixed factors were the most prevalent factor type (vs. positive only and negative only) in the personalized model for each gender (e.g., for 64% of women and 35.5% of men). Additionally, at the item-level, some emotion items exhibited higher rates of appearance in these mixed emotion factors. For example, as seen in Figure 2A–C, "jittery" exhibited between-person variation in its loading onto otherwise positive or negative factors, highlighting that the same item may exhibit considerable idiographic variation in its specific covariation with other emotions across individuals.

Linking clinically relevant problems with AC using person-specific vs. traditional approaches.

The traditional bivariate positive and negative affect structure was replicated using a confirmatory r-technique on the first day PANAS ratings from the full sample (Figure 2D). Person-specific AC captured unique variance in risk for affective problems that was not captured by the mean-level approach. In the person-specific regression model (Table 1 and Figure 3), AC alone did not relate to risk for affective problems until gender was considered (i.e., in interactions). Though men and women did not differ significantly on AC, the influence of AC risk for affective problems was opposite in men and women. For men, less granularity in AC (i.e., fewer factors) was associated with higher anxiety scores ($\beta = -0.40$, $p < 0.05$) scores, but for women, more granularity in AC (i.e., more factors) was linked with more anxiety.

In the mean-level model (Table 1), positive and negative factor scores (from the first day of diary data that replicated the two-factor structure) predicted variation in risk for affective problems. Only main effects of the bivariate factors were observed for conscientiousness (i.e., positive affect factor, $\beta = 0.47$, $p < 0.05$), neuroticism (i.e., negative affect factor, $\beta = 0.55$, $p < 0.001$), depression (i.e., negative affect factor, $\beta = 0.50$, $p < 0.01$), and anxiety (i.e., negative affect factor, $\beta = 0.49$, $p < 0.01$) subscales. Notably, bivariate factor scores did not differentiate affective problems by gender.

Drawing nomothetic conclusions from person-specific AC results.

Network models reflecting frequency of effects (i.e., commonality extracted from person-specific adjacency matrices of AC) are depicted for the full sample in Figure 4 and separately by gender in Figure 5. In the full sample network utilizing information across all person-specific models, community detection uncovered distinct positive (green nodes) and negative (red nodes) affect communities (modularity of 0.23), suggesting that, in aggregate, the heterogeneity in AC at the individual level largely supports the bivariate positive and negative model overall (Figure 4) and separately within each gender (Figure 5).

Despite this general replication, the idiographically-informed approach led to important nuance in this nomothetic model as it uncovered unique dynamics within each factor network and across items. First, the community of positive items appears to have greater density (i.e., line thickness) relative to negative emotions, suggesting the AC network properties for these communities differ. Second, communities were not as separate for women as they are for men. Specifically, women exhibited greater spread, reflected in lower modularity (i.e., 0.20 for women < 0.25 for men), and lower density (0.98 with an average weighted degree of 106.2 for women < 1 with an average weighted degree of 147 for men) and this was especially true for the negative emotion network. Finally, as was noted in earlier discussion of commonality across personalized models, some items exhibited similar rates of connection with both communities (e.g., “Jittery”), suggesting that these items may be commonly implicated in “mixed” emotional experience.

Discussion

The present study detected noteworthy heterogeneity in AC – as measured by person-specific factor solutions estimated from 75 daily reports of emotion. Findings replicated the range detected in an earlier study (Larsen & Cutler, 1996). Convergence of evidence across these studies suggests that heterogeneity in AC may be a robust phenomenon that undermines models of specific emotions that assume AC effects are common and uniform for all people. Critically, women had higher rates of negative only item factors and mixed item factors relative to men. Results suggest that personalized models of AC may capture incremental variation in risk for affective problems by gender not otherwise captured by traditional, nomothetic models. Specifically, more AC was associated with higher levels of risk for affective problems (anxiety subscale score) in women but lower levels of risk in men. More work is needed to further replicate these findings and delineate the role affective complexity plays in the etiology and course of clinically-relevant affective problems. Finally, common effects in personalized models (i.e., loading of two emotions on the same factor) were then used to construct a nomothetic representation of AC. This “bottom-up” representation of emotions generally replicated the bivariate (i.e., positive and negative affect) solution documented using traditional approaches but reflected some nuance for men and women and has the added benefit of accurately describing emotions of individuals (unlike the traditional approach).

Present findings have several important implications. First, they are consistent with idiographic effects observed in past work on affect (Barrett, 2009; Larsen & Cutler, 1996) and personality (Borkenau & Ostendorf, 1998; Wright et al., 2016) wherein individuals exhibit abundant variation that likely undermines the generalizability of mean-level models to individuals. Additionally, observed gender moderation of AC influences on risk for affective problems is consistent with recent work highlighting opposing signatures for risk for affective problems across men and women (Barrett, 2009; Larsen & Cutler, 1996; Seney et al., 2018) and provides additional evidence that personalized treatment approaches for affective symptoms (Fisher et al., 2019) may help maximize individual well-being. These findings concern dimensional levels of anxiety in a community sample, though, indicating that specific work is needed to understand how AC confers more/less risk for clinical diagnoses by gender. Importantly, bivariate factor scores did not differentiate affective problems by gender, suggesting that mean-level scores alone may have limited utility for explaining different rates of affective disorder diagnosis in men and women. One possibility is that the gender-specific patterns of covariation in AC (e.g., higher proportion of negative only and mixed emotion factors observed across personalized models of women) could confer emotional experiences that are inherently more intense or challenging to regulate (e.g., when a positive emotion also leads to a negative emotion) and, consequently, increase risk for affective problems and disorder.

The present findings additionally demonstrate the incremental descriptive and predictive value of developing person-specific models for AC. Importantly, the particular idiographic approach demonstrated that stable, person-specific structure in AC (i.e., consistent granularity and covariation between specific emotional states over time) is evident and may serve as both an antecedent and consequence for other psychological factors like social identity (e.g., gender) and mental health (e.g., risk for affective problems). Given the broad ambit linked with emotional experiences, other psychological factors like cognition (e.g., intelligence) or language (e.g., emotion word processing) may also be inherently connected with AC structures as antecedents, consequences, or ancillary phenomena. Importantly, we are not able to yet provide insight into exactly how these AC structures develop, the rate and implications of change in them, what factors predict their differentiation across individuals, and the extent to which they mark etiological or maintaining mechanisms for affective problems. Thus, there is an abundance of opportunity for future work to explore these aspects of AC– with a specific focus on integrating the unique contributions of idiographic and nomothetic inferences demonstrated in this study.

As traditional studies aim to draw inferences about the nature of emotions instead of individuals, this study uniquely leveraged a non-traditional, person-specific approach to capture heterogeneity in AC and derive “bottom up” conclusions about the nomothetic nature of AC. Integration of idiographic and nomothetic models in this manner can maximize correspondence between nomothetic conclusions with individual variation in AC in a manner that is superior to estimation of average effects, as has been done in other psychological domains, such as neuroscience (Gates & Molenaar, 2012). While the bivariate positive and negative structure was largely replicated, these analyses revealed distinct dynamics across these networks and by gender such that connections between negative emotional states were stronger, especially for women, but women also experienced more extensive connections between traditionally positive and negative items, suggesting higher rates of “mixed” emotional states. Additionally, community detection highlighted that some items (e.g., “jittery”) exhibit more linkage with experiences across positive and negative networks relative to other items. When taken together, these results confirm not only that AC is person-specific as a function of granularity and covariation within traditionally positive and negative affective networks, but also as a function of some aspects of gender identity and the degree to which items have specific operations in bridging connections between traditional networks. Overall, development of this idiographically-informed nomothetic model highlights that integration of the two approaches likely augments the accuracy, nuance, and generalizability of nomothetic inferences.

While numerous strengths of the present study are evident, there are also important limitations to note. Although p-technique leverages data collected across many time points for each individual to estimate stable aspects of AC that may be especially helpful in predicting variation in persistent affective experiences like anxiety symptoms, it does not evaluate change over time within an individual (i.e., affective experiences that linger across days are not modeled) or in response to acute shifts in social or environmental effects (e.g., situational stress as per the Dynamic Model of Affect; (Reich et al., 2003; Zautra et al., 2000). Therefore, the present results may have limited generalizability for understanding temporal dynamics of AC. Additionally, p-technique models were developed using iterative model-fitting procedures that may be somewhat influenced by measurement error, though the degree and nature of the heterogeneity detected is not expected to be significantly influenced by this. Building upon the present results, though, person-specific applications of other analysis techniques (e.g., dynamic factor and regime change models) and further evaluating temporal effects like cyclic variation detected in other studies (Fisher & Bosley, *in press*; Houben et al., 2015; Rabinowitz & Fisher, 2020) will be fruitful for future characterization of daily affective dynamics and their links with AC and even affective symptom onset, escalation, and remission.

Moreover, the present study used a community-based sample in the developmental period of greatest risk for affective problem onset (i.e., young adulthood). A hallmark of modern dimensional approaches to understanding the development of psychopathology (e.g., as per NIH Research Domain Criteria; Kozak & Cuthbert, 2016) is the evaluation of experiences common to all individuals and their linkage with functional problems on a continuum. Despite the use of this approach to identify levels of clinical problems (vs. diagnostic categories) and establish vital “baseline” expectations for these person-specific affective processes in young adulthood, study participants did not undergo a clinical evaluation. High levels of these personality and affect subscale scores – while demonstrating robust links with onset of psychopathology in the broader literature – may not always precede a diagnoseable disorder. As we focused on the development period of greatest risk for affective problems (i.e., a young adult sample ranging in age from 18 to 30), findings may also not precisely generalize to older or younger individuals and/or individuals exhibiting clinically severe affective phenotypes in young adulthood. Consequently, it will be critical for future work to conduct focal sampling approaches across these populations to understand links between AC and the severity of affective disorders across development and the more severe range of the risk for affective problems dimension.

In conclusion, use of idiographic person-specific and nomothetic mean-level approaches are likely to yield different conclusions about affective experiences of the individual. Although both approaches reach similar conclusions about a bivariate positive-negative nomothetic structure of emotion overall, they vary fundamentally in whether or not that structure describes individuals and the degree of nuance they capture in variation in focal phenomena like AC. Results from the present study show that by relying on intensive longitudinal data, a person-specific approach can be leveraged to maximize the individual-relevance of basic and applied studies by creating individualized emotion structures of AC without precluding the pursuit of identifying universal mechanisms. Integration of idiographic and nomothetic approaches is critical for identifying the consistency of effects across individuals that would warrant conclusion that a universal “mechanism” underlies phenomena like AC or if more personalized approaches are needed to understand and treat differential risk for persistent emotional states like depression or anxiety symptoms. As sources and quantities of data grow and the feasibility and imperative of using data from individuals’ daily lives increases, concrete practice of personalized science becomes possible.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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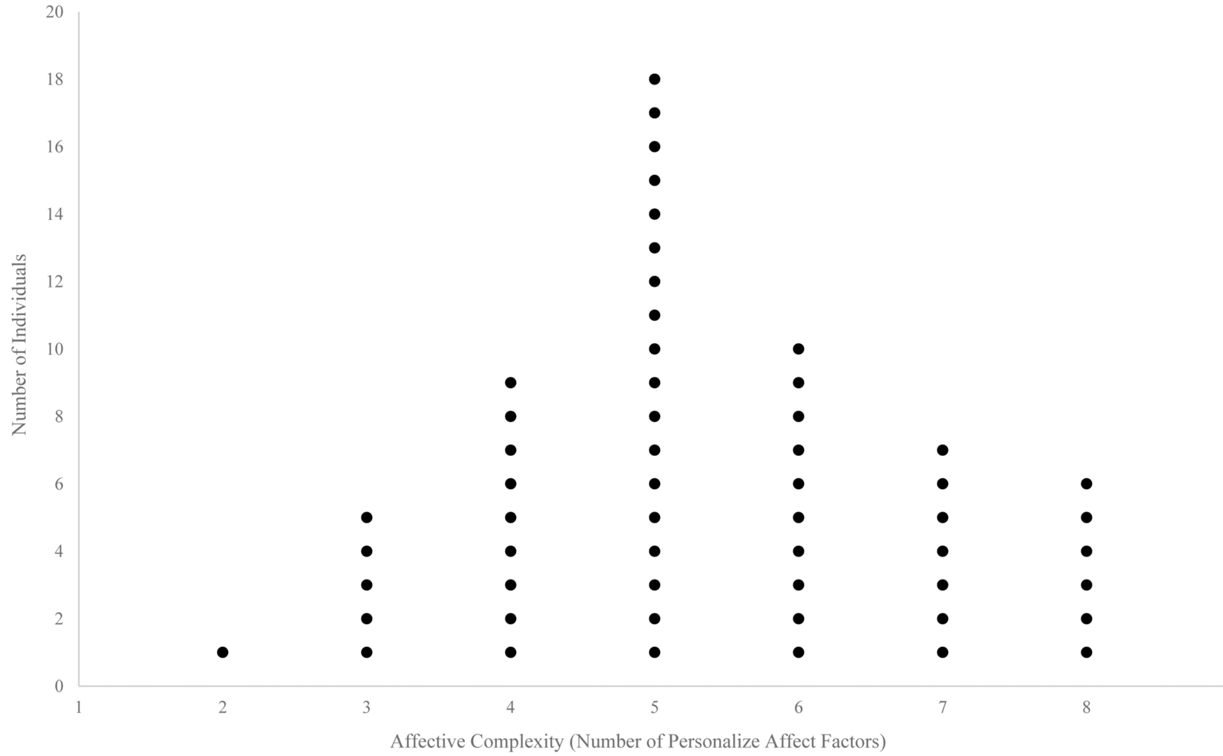

Figure 1.
Affect factor count frequencies across person-specific confirmatory models

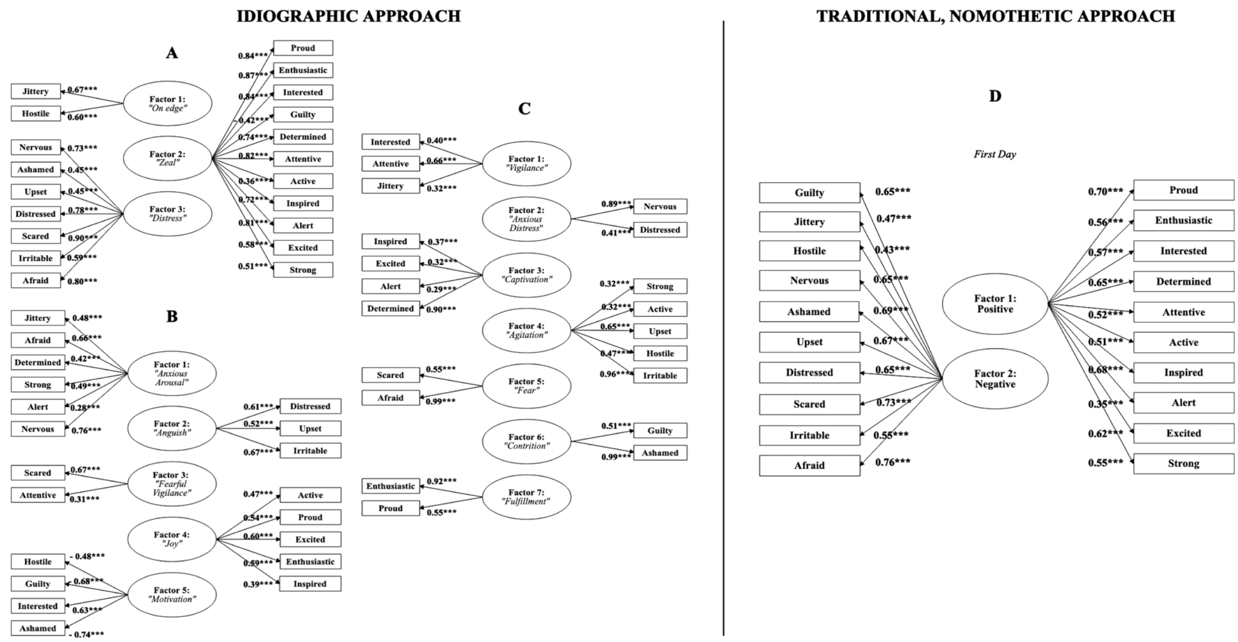

Figure 2. Comparison of idiographic and nomothetic affect structures

Note: Idiographic models A, B, and C each represent affect structure for a unique individual exhibiting 3-factor (Person A), 5-factor (Person B), and 7-factor (Person C) solutions. Factor labels in parentheses reflect hypothetical monikers specific to that individual. Nomothetic models depicted under D were estimated across the entire sample on the first day of the daily diary period to replicate the traditional bivariate factor structure. All models meet excellent fit criteria thresholds (i.e., RMSEA < 0.08, NNFI > 0.95, CFI > 0.95, SRMR < 0.10).

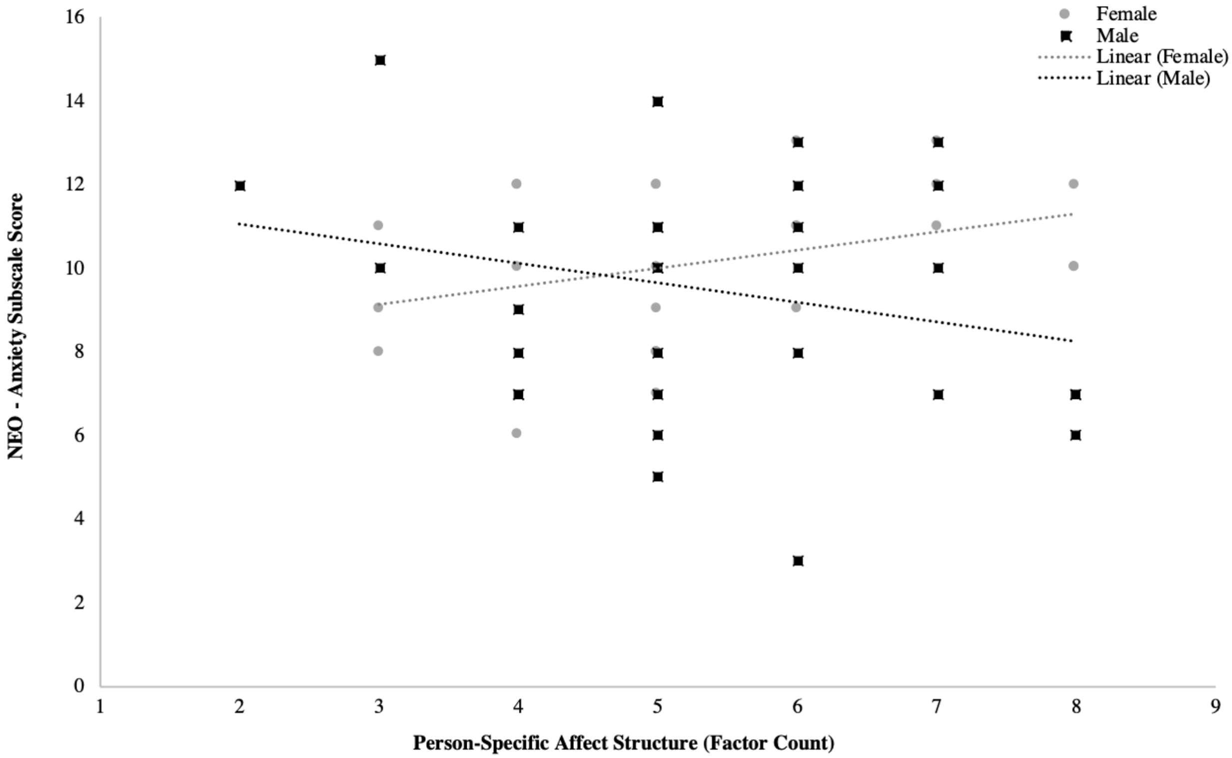

Figure 3.

Person-specific affect structure predicts between-person variation in anxiety at intake

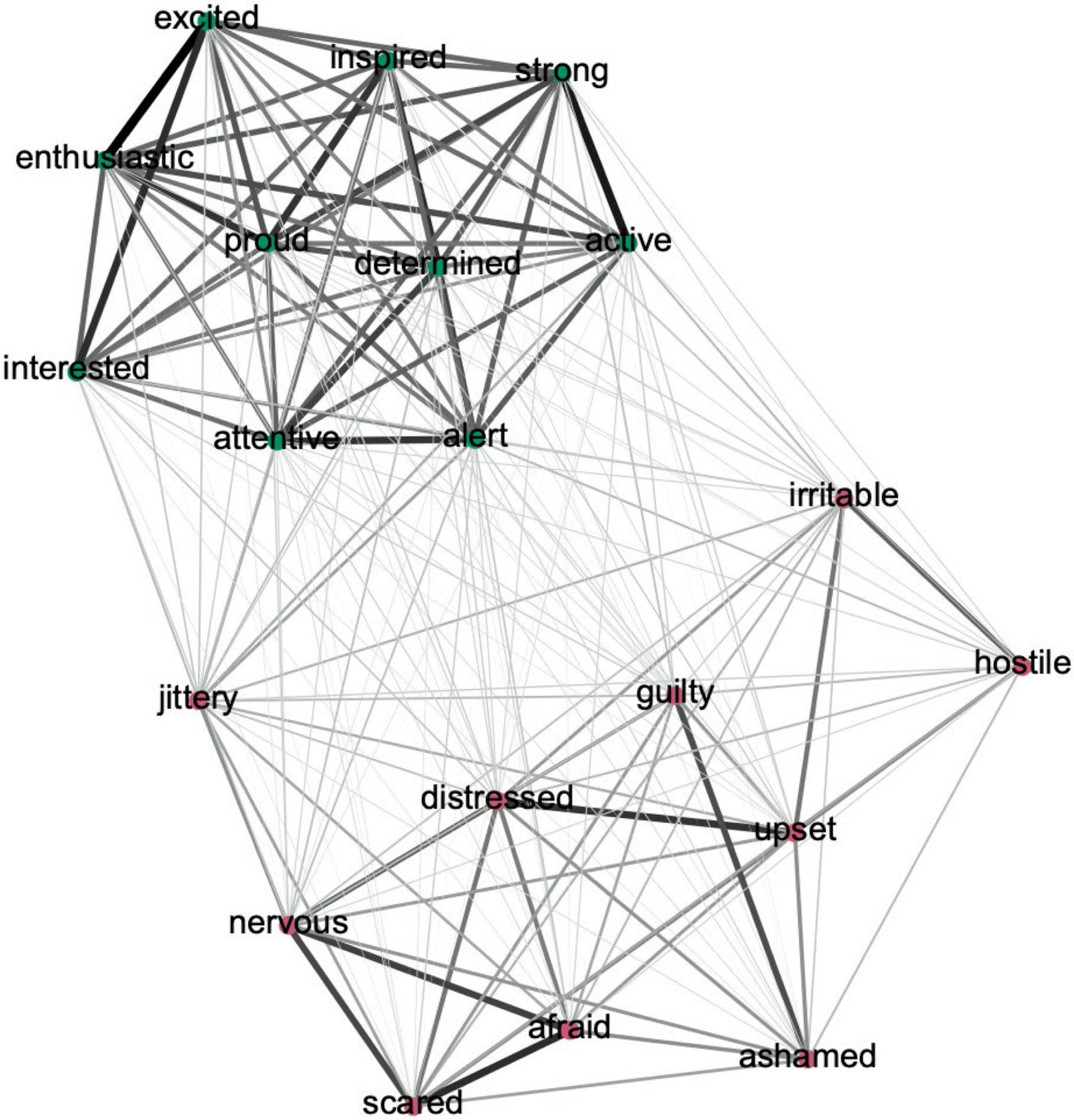

Figure 4.
Idiographically-informed nomothetic community detection model of affective complexity network for the full young adult sample

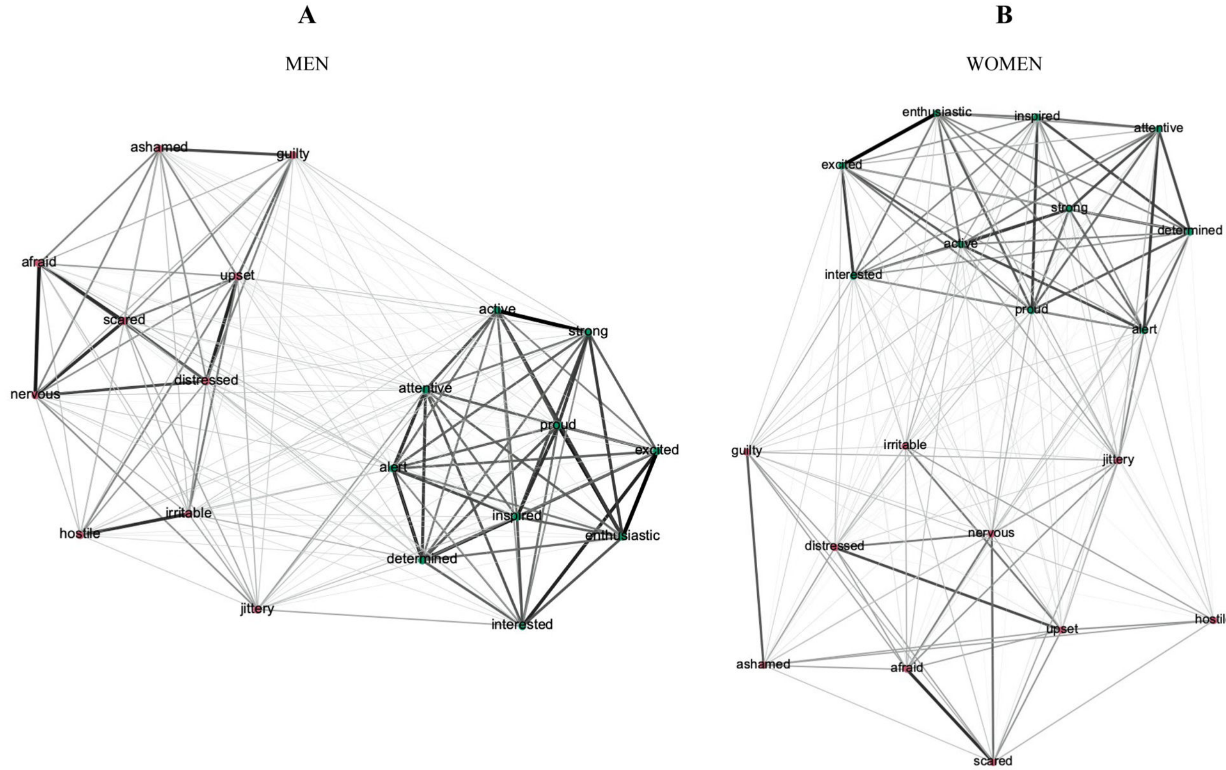

Figure 5.
Idiographically-informed nomothetic community detection model of affective complexity networks by gender

Table 1.

Person-specific and mean-level model prediction of risks for affective problems by gender

Person-Specific Model	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness	Depression	Anxiety
Gender							
β (SE)	−0.01 (−0.08)	−0.16 (0.14)	0.26 (0.14)	−0.17 (0.13)	−0.34 (0.15)	0.06 (0.21)	−0.13 (0.22)
CI (95%)	(−0.37, 0.34)	(−0.45, 0.11)	(−0.01, 0.57)	(−0.46, 0.10)	(−0.69, 0.10)	(−0.33, 0.51)	(−0.67, 0.22)
Affective Complexity (AC)							
β (SE)	0.33 (0.09)	0.12 (0.07)	−0.09 (0.07)	−0.01 (0.07)	−0.29 (0.07)	0.28 (0.10)	0.26 (0.11)
CI (95%)	(−0.03, 0.32)	(−0.10, 0.18)	(−0.18, 0.11)	(−0.14, 0.14)	(−0.26, 0.34)	(−0.06, 0.36)	(−0.07, 0.37)
AC × Gender							
β (SE)	−0.40 (0.12)	−0.03 (0.09)	0.08 (0.10)	0.13 (0.09)	0.34 (0.10)	−0.23 (0.14)	−0.40 (0.15) *
CI (95%)	(−0.47, −0.01)	(−0.20, 0.18)	(−0.16, 0.23)	(−0.13, 0.25)	(−0.02, 0.37)	(−0.44, 0.13)	(−0.60, −0.002)
Mean-Level (2-Factor) Models	**Neuroticism**	**Extraversion**	**Openness**	**Agreeableness**	**Conscientiousness**	**Depression**	**Anxiety**
Gender							
β (SE)	−0.02 (0.14)	−0.13 (0.13)	0.25 (0.15)	−0.17 (0.14)	−0.33 (0.14) **	0.03 (0.17)	−0.14 (0.16)
CI (95%)	(−0.30, 0.25)	(−0.40, 0.13)	(−0.02, 0.57)	(−0.46, 0.10)	(−0.67, −0.10)	(−0.30, 0.40)	(−0.57, 0.09)
Positive Factor (PA)							
β (SE)	−0.12 (0.14)	0.15 (0.13)	0.38 (0.15)	0.08 (0.14)	0.47 (0.14) *	0.00 (0.17)	−0.08 (0.16)
CI (95%)	(−0.36, 0.19)	(−0.18, 0.35)	(−0.07, 0.52)	(−0.23, 0.33)	(0.02, 0.58)	(−0.35, 0.35)	(−0.40, 0.25)
Negative Factor (NA)							
β (SE)	0.55 (0.11) ***	−0.06 (0.11)	0.19 (0.12)	−0.40 (0.12)	−0.26 (0.12)	0.50 (0.15) **	0.49 (0.14) **
CI (95%)	(0.17, 0.63)	(−0.25, 0.19)	(−0.14, 0.36)	(−0.47, 0.01)	(−0.40, 0.08)	(0.13, 0.72)	(0.18, 0.72)
*Gender*PA*							
β (SE)	−0.19 (0.17)	0.30 (0.16)	−0.29 (0.18)	−0.22 (0.17)	−0.22 (0.17)	−0.34 (0.21)	−0.08 (0.20)
CI (95%)	(−0.51, 0.16)	(−0.11, 0.53)	(−0.571, 0.15)	(−0.50, 0.19)	(−0.52, 0.17)	(−0.78, 0.07)	(−0.48, 0.31)
*Gender*NA*							
β (SE)	0.02 (0.16)	0.00 (0.15)	−0.02 (0.17)	0.32 (0.16)	0.15 (0.16)	−0.04 (0.20)	0.23 (0.19)
CI (95%)	(−0.29, 0.34)	(−0.30, 0.30)	(−0.35, 0.33)	(−0.08, 0.57)	(−0.19, 0.46)	(−0.44, 0.36)	(−0.08, 0.67)

Note:

* $p < 0.05$,

** $p < 0.01$,

*** $p < 0.001$