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ORIGINAL PAPER

Latent Variable Mixture Modeling of Ecological Momentary Assessment Data: Implications for Screening and Adolescent Mood Profiles

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Abstract Ecological momentary assessment (EMA) studies typically rely on arbitrary decision rules for identifying and excluding invalid responses from the data. In addition, most studies treat independent variables as separate from each other even if their combinations might have importance above the independent contribution of each. Our study aimed to conduct an exploratory latent profile analysis of EMA data to demonstrate an empirical method of identifying invalid responses, and to provide a preliminary investigation of mood profiles. We recruited 20 adolescents between the ages of 13–18 to complete 4 surveys about their internal states each day for 20 days. Participants provided responses on study smartphones using an Android app developed by the study team. Our profile analysis revealed 9 independent profiles. We determined that 3 of these profiles consisted of invalid responses because the integers provided by the participant were nearly invariant. The invalid responses comprised 24.9% of the sample. We also identified 6 valid profiles that were labeled: fatigued (8.7%), good mood/energetic (19.9%), angry/depressed (2.3%), good mood (37.1%), angry (5.7%), and depressed (1.4%). One important implication of the current study is that researchers and clinicians should screen electronic diary data, especially for invariant responding. In addition, it is important for clinicians to note that more than one internal state may drive the mood of an adolescent patient.

Keywords Ecological momentary assessment (EMA) · Adolescent · Mood states · Latent profile analysis

Ecological momentary assessments (EMA) are repeated, near-real-time measures of thoughts, feelings, and behaviors in an individual's natural environment (Schiffman et al. 2008). Previous studies have utilized EMA methods to reliably assess mood and affective states, pain severity, energy level, health behaviors, risky lifestyle behaviors, and a range of symptoms in youth (Connelly and Bickel 2011; Cushing et al. 2017; Dunton et al. 2014; Rofey et al. 2010; Spook et al. 2013; Wenze and Miller 2010). EMA assessments based on technology are particularly well-suited for use with adolescents. In the United States, 92% of adolescents report going online daily and 88% of adolescents report owning or having regular access to a cellphone or smartphone (Lenhart 2015). Ninety percent of adolescents with smartphones also text regularly (Lenhart 2015). This high level of access and use implies that adolescents are familiar and comfortable with technologies through which EMA surveys can be delivered.

In addition, EMA methodologies appear to be a reliable, feasible, and acceptable data-collection method for adolescents. In a previous study about sedentary behavior, 9–13 year olds answered EMA surveys delivered via a smartphone application 4–7 times per day for 8 days with 77% compliance (Liao et al. 2014). Adolescents reliably

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completed smartphone-based electronic diary entries (3 times per day for 14 days) to track headache triggers 84% of the time (Connelly and Bickel 2011). When presented with longer study periods of up to 20 days (4 times per day), adolescents maintained a high rate of compliance, completing 81% of surveys (Brannon et al. 2016). In addition to complying with survey completion, most adolescents reported high levels of satisfaction in using the EMA smartphone application, reported that the EMA surveys were useful, and that they would use the EMA application again for health-related purposes. It is clear from these findings that EMA methodologies represent a valid data collection method and that technology-based EMA approaches are amenable to adolescents, most of whom already use similar technologies on a daily basis.

In addition to their obvious value for assessing adolescent experience, technology-based EMA methodologies are particularly well-suited to assess affect in adolescents. Overall, affect is a dynamic, time-variant construct which is often not readily observable (Wenze and Miller 2010). EMA methodologies enable the measurement of individual variability in fluctuating affective states over time. Typically, studies of affect in adolescence conceptualize affective constructs in isolation as either independent or dependent variables in multilevel regression models (e.g., Cushing et al. 2017; Dunton et al. 2014). An alternative conceptualization is to treat each construct as a contributor to an overall affective profile using latent variable mixture modelling (LVMM; Berlin et al. 2014). There are several possible advantages to a LVMM approach. First, by developing a response profile it may be possible to empirically identify patterns of invalid responding in the data. Currently, most EMA protocols rely on rational, but arbitrarily defined rules for exclusion of cases (e.g., fewer than 50% of responses completed, assessment windows of greater than 30 min; Schiffman 2014). By adding empirical decision rules to *a priori* rational criteria, investigators can have more confidence in their data. Although affective states have been previously examined in adolescents, combinations of these states may better describe an adolescent's holistic emotional status beyond comparisons between discrete variables. For instance, it may be useful to know that an adolescent's affect is best characterized as angry *and* depressed vs. evaluating the anger and depression independently.

Our exploratory analysis aimed to identify latent affective profile clusters in adolescents. These profile clusters may enable novel approaches to managing intensive longitudinal data collected through EMA methodologies, permit identification of invalid responses in large data sets, and decrease the complexity of data analyses to increase accessibility and usability of EMA data in near-real-time. We predict that discrete, latent affective profile clusters will exist in a sample of typically developing adolescents. We also predict that some number of identified latent affective profile clusters will represent discrete patterns of invalid responses, which we can use to reliably remove invalid responses from complex data sets. This exploratory study is the first step in identifying latent psychosocial profile clusters in free-living, typically developing adolescents.

Method

Participants

We used flyers, emails, and social media postings to recruit 20 adolescents between the ages of 13 and 18 years from a small Midwestern university and the surrounding community. Parental consent and participant assent was obtained for minors prior to initiation of study procedures. For 18-year-olds, the participant provided written consent. The local Institutional Review Board approved all study procedures.

Procedures

Participants attended an initial visit at which they completed a baseline demographics questionnaire and learned to use study devices, including an Android smartphone (Google Nexus 4), which delivered ecological momentary assessment surveys through the PETE application. The PETE application is a native Android application that delivers surveys at either random or pre-specified intervals throughout the day (for a more extensive description of the technology see Brannon et al. 2016). Participants used the PETE application to answer questions assessing affect, clinical mood domains, and energy at four self-selected times per day (i.e., specific times in the morning, around lunch-time, late-afternoon, and evening) for 20 days. Each survey took approximately 3 min to complete and surveys were delivered at times ranging from 6:00am to 9:30 pm, with at least 2 h between each administration. Participants attended a final study visit after 20 days to return study equipment and could earn up to $40 based on the number of surveys completed.

Measures

Positive and negative affect

Participants completed the 10-item International Positive and Negative Affect Schedule-Short Form (I-PANAS-SF) to measure positive and negative affect (Thompson 2007). Participants were asked to respond to prompts such as "How upset are you feeling right now?" Response anchors

Table 1 Fit statistics for latent class analysis of affect in adolescents

Latent Classes	AIC	BIC	SSA-BIC	Entropy	Loglikelihood	-2LL	LMR Mean	Adjusted LMR	Adjusted LMR P-value	BLRT	BLRT P-value
2	37179.527	37317.762	37238.337	0.969	−18564.763	5169.722	195.764	5094.542	<0.0001	−21149.624	<0.0001
3	34885.753	35073.753	34965.736	0.972	−17408.877	2311.774	−147.198	2278.155	<0.0001	−18564.763	<0.0001
4	33771.480	34009.244	33872.634	0.875	−16842.740	1132.273	−20.165	1115.807	<0.0001	−17408.877	<0.0001
5	32894.819	33182.348	33017.145	0.881	−16395.410	849.661	81.672	881.650	<0.0001	−16842.74	<0.0001
6	32456.846	32794.140	32600.344	0.857	−16167.423	455.973	23.417	449.342	<0.0001	−16395.41	<0.0001
7	32025.939	32412.997	32190.609	0.871	−15942.969	448.907	373.856	442.379	0.4320	−16167.423	<0.0001
8	31599.488	32036.311	31785.329	0.877	−15720.744	444.451	890.391	437.988	0.6524	−15942.969	<0.0001
9	31225.042	31711.630	31432.056	0.886	−15524.521	392.445	−779.085	452.586	0.1555	−15754.153	<0.0001
10	30932.115	31468.468	31160.301	0.891	−15369.058	310.927	1201.043	306.405	0.7409	−15524.521	<0.0001

AIC Akaike information criteria, *BIC* Bayesian information criteria, *SSA-BIC* Sample-size adjusted Bayesian information criteria, *-2LL* Two times the Log-likelihood difference, *LMR* Lo-Mendell Rubin Likelihood ratio test, *BLRT* Bootstrap Likelihood ratio test

included “Not at all” and “Extremely”. The I-PANAS-SF includes 5-items each for positive and negative affect. The scales demonstrated good internal consistency in the current sample ($\alpha_{positive\,=}$ .87, $\alpha_{negative\,=}$ .85). In addition, previous studies have demonstrated good test-retest reliability ($r =$ 0.84), and convergent validity between the positive and negative affect subscales (Thompson 2007).

Other dimensions of mood and affect

To assess other dimensions of mood and affect, the three highest loading items from five subscales of the Profile of Mood States (POMS) were administered (McNair et al. 1971). In each case, the prompt consisted of wording such as, “Since the beep last went off how ANGRY have you been feeling?” Response options included “Not at all”, “A little”, “Moderately”, “Quite a bit”, and “Extremely”. In the current sample, internal consistency for the constructs of interest was uniformly high: 1) anger ($\alpha = .92$); 2) fatigue ($\alpha = .90$); 3) energy ($\alpha = .86$); 4) friendliness ($\alpha = .86$); 5) anxious ($\alpha = .85$); 6) depressed ($\alpha = .89$).

Data Analysis

We entered data from the PETE app and baseline demographic information into an SPSS database. We created affective trait scores by averaging responses across survey items for each trait, and calculated descriptive statistics using SPSS version 22 statistical software. We then analyzed affective profile clusters using latent variable mixture modelling in Mplus version 6 statistical software.

Model Estimation

We used an exploratory analysis to identify the optimal number of latent classes of affective profiles, or the optimal number of affective variables that cluster together into meaningful groups, in this sample of adolescents. We determined optimal model fit by comparing fit statistics across models with differing numbers of latent classes, including the Bayesian Information Criteria (BIC), Akaike Information Criteria (AIC), and loglikelihood (-2LL; Berlin et al. 2014). Smaller values of each of these indices of model fit generally indicate more optimal model fit, although some subjective interpretation is required. We also calculated entropy, a measure from 0–1 where larger values indicate better model fit; and Lo-Mendell Rubin likelihood ratio tests (LRT) and parametric bootstrapped likelihood ration tests (BLRT) to determine whether models differing by one class were significantly different from one another (Berlin et al. 2014). These model fit statistics are presented in Table 1.

Table 2 Descriptive statistics of the study sample

Child demographics	Mean ± SD ($n = 20$)	Parent demographics	Mean ± SD ($n = 20$)
Sex	60% male	Parent Age	
Age (years)	15.65 ± 1.60	Maternal Age	43.75 ± 6.44
Race/Ethnicity		Paternal Age	48.65 ± 9.77
White/Caucasian	80%	Parent Marital Status	
American Indian	10%	Married	75%
Asian	5%	Divorced/Separated	20%
Latino	5%	Single, Never Married	5%
Annual Family Income		Parent Education Level	
$21,000–30,999	5%	High School	25%
$31,000-$40,999	0%	College	42.5%
$41,000–50,999	10%	Master's	20%
$51,000–60,999	10%	Graduate Degree	10%
> $61,000	70%	Unknown	2.5%
Unknown	5%		

Table 3 Descriptive statistics (Mean ± SD) and correlations of affective variables

	Affective Variables from POMS		Affective Variables from I-PANAS					
	Positive Affect	Negative Affect	Anger	Fatigue	Energy	Friend-liness	Anxious	Depressed
Positive Affect	2.58 ± 1.01							
Negative Affect	.381**	1.60 ± 0.89						
Anger	.307**	.737**	1.80 ± 1.06					
Fatigue	.194**	.589**	.586**	2.13 ± 1.12				
Energy	.623**	.323**	.213**	.100**	2.25 ± 1.10			
Friendliness	.504**	.113**	.049*	.152**	.559**	2.66 ± 1.07		
Anxious	.361**	.729**	.601**	.545**	.379**	.249**	1.67 ± 0.94	
Depressed	.259**	.759**	.684**	.556**	.279**	.127**	.703**	1.51 ± 0.92

Note. Descriptive statistics and correlations of affective variables after classes of invalid responders were removed are included as Supplemental material. *POMS* Profile of Mood States, *I-PANAS* International Positive and Negative Affect Scale

**$p < .001$; *$p < .05$

Results

Participants

Twenty adolescents (M age = 15.65, $SD = 1.60$) enrolled in the study and completed the protocol. Participants were majority Caucasian (80%), male (60%), and middle-to-high income (70% reported family income ≥ $61,000 per year). Other represented ethnicities were American Indian (10%), Asian (5%), and Hispanic (5%). Descriptive statistics, average affective trait scores, and correlations between study variables are reported in Table 2 and Table 3.

Based on interpretation of the model fit statistics (Table 1), the addition of each successive class enhanced model fit. A 9-class model displayed optimal model fit, with better model fit than an 8-class model. A 10-class model added an additional small class, but did not appear to fit the data better than the 9-class model. Therefore, we retained the 9-class model to avoid parsing the data into a larger number of poorly populated classes. The probability of latent class membership for each successive model is detailed in Table 4.

Profiles of Invalid Responders

In the 9-class model, three classes representing 24.9% of responders selected rote responses across nearly all items. These three classes included Class 4 (15.0% of responders), who we labeled as Low Responders to each scale, Class 5 (7.8%), labeled as Moderate Responders, and Class 9 (2.1%), labeled as High Responders. These response classes indicated that a quarter of adolescents demonstrated a set of responses best represented by uniformly low, moderate, and high profiles. For example, a member of the Low Responder profile may have selected "1" on the Likert scale for nearly all questions. These profiles likely represent invalid

Table 4 Average probability of latent class membership by model

2-Class Model	1	2							
1, n = 1565, 0.84049	**0.995**	0.005							
2, n = 297, 0.15951	0.026	**0.974**							
3-Class Model	1	2	3						
1, n = 346, 0.18582	**0.963**	0.002	0.035						
2, n = 50, 0.02685	0.016	**0.984**	0.000						
3, n = 1466, 0.78733	0.007	0.000	**0.993**						
4-Class Model	1	2	3	4					
1, n = 574, 0.30827	**0.907**	0.089	0.004	0.000					
2, n = 898, 0.48228	0.068	**0.923**	0.008	0.000					
3, n = 343, 0.18421	0.011	0.022	**0.966**	0.001					
4, n = 47, 0.02524	0.000	0.000	0.001	**0.999**					
5-Class Model	1	2	3	4	5				
1, n = 812, 0.43609	**0.918**	0.070	0.012	0.000	0.000				
2, n = 575, 0.30881	0.080	**0.908**	0.012	0.000	0.000				
3, n = 249, 0.13373	0.039	0.020	**0.915**	0.027	0.000				
4, n = 180, 0.09667	0.000	0.000	0.036	**0.964**	0.000				
5, n = 46, 0.02470	0.000	0.000	0.000	0.002	**0.998**				
6-Class Model	1	2	3	4	5	6			
1, n = 278, 0.14930	**0.907**	0.001	0.000	0.091	0.000	0.000			
2, n = 239, 0.12836	0.004	**0.916**	0.008	0.048	0.000	0.025			
3, n = 365, 0.19603	0.000	0.006	**0.894**	0.100	0.000	0.000			
4, n = 754, 0.40494	0.057	0.014	0.065	**0.864**	0.000	0.000			
5, n = 46, 0.02470	0.000	0.000	0.000	0.000	**0.997**	0.003			
6, n = 180, 0.09667	0.000	0.040	0.000	0.000	0.000	**0.960**			
7-Class Model	1	2	3	4	5	6	**7**		
1, n = 275, 0.14769	**0.910**	0.000	0.000	0.089	0.000	0.001	0.000		
2, n = 52, 0.02793	0.007	**0.925**	0.000	0.009	0.024	0.035	0.000		
3, n = 369, 0.19817	0.000	0.001	**0.894**	0.100	0.000	0.006	0.000		
4, n = 748, 0.40172	0.057	0.002	0.061	**0.871**	0.000	0.010	0.000		
5, n = 140, 0.07519	0.000	0.006	0.000	0.000	**0.968**	0.021	0.005		
6, n = 236, 0.12675	0.002	0.012	0.007	0.045	0.018	**0.917**	0.000		
7, n = 42, 0.02256	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**		
8-Class Model	1	2	3	4	5	6	7	8	
1, n = 265, 0.14232	**0.909**	0.005	0.000	0.000	0.000	0.086	0.000	0.000	
2, n = 165, 0.08861	0.005	**0.908**	0.026	0.020	0.009	0.031	0.000	0.000	
3, n = 105, 0.05639	0.001	0.039	**0.899**	0.013	0.010	0.039	0.000	0.001	
4, n = 145, 0.07787	0.000	0.033	0.011	**0.948**	0.000	0.000	0.000	0.009	
5, n = 357, 0.19173	0.000	0.002	0.001	0.000	**0.898**	0.099	0.000	0.000	
6, n = 725, 0.38937	0.054	0.011	0.004	0.000	0.066	**0.865**	0.000	0.000	
7, n = 42, 0.02256	0.000	0.000	0.000	0.000	0.000	0.000	**0.998**	0.002	
8, n = 58, 0.03115	0.000	0.000	0.000	0.040	0.000	0.000	0.004	**0.956**	
9-Class Model	1	2	3	4	5	6	7	8	9
1, n = 159, 0.08539	**0.905**	0.010	0.000	0.010	0.006	0.041	0.027	0.001	0.000
2, n = 360, 0.19334	0.003	**0.897**	0.000	0.000	0.000	0.098	0.002	0.000	0.000
3, n = 44, 0.02363	0.000	0.000	**0.953**	0.000	0.035	0.000	0.008	0.004	0.001
4, n = 263, 0.14125	0.004	0.000	0.000	**0.916**	0.000	0.080	0.000	0.000	0.000
5, n = 149, 0.08002	0.030	0.000	0.006	0.000	**0.942**	0.000	0.016	0.006	0.000

Table 4 continued

6, n = 717, 0.38507	0.013	0.063	0.000	0.052	0.000	**0.870**	0.002	0.000	0.000	
7, n = 105, 0.05639	0.029	0.008	0.000	0.002	0.010	0.037	**0.913**	0.000	0.000	
8, n = 25, 0.01343	0.005	0.000	0.000	0.000	0.029	0.000	0.000	**0.965**	0.000	
9, n = 40, 0.02148	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	
10-Class Model	1	2	3	4	5	6	7	8	9	10
1, n = 255, 0.13695	**0.916**	0.000	0.000	0.000	0.081	0.000	0.000	0.002	0.000	0.000
2, n = 355, 0.19066	0.000	**0.897**	0.000	0.000	0.098	0.000	0.000	0.002	0.000	0.003
3, n = 31, 0.01665	0.000	0.000	**0.944**	0.017	0.000	0.000	0.032	0.000	0.002	0.005
4, n = 27, 0.01450	0.000	0.000	0.004	**0.974**	0.000	0.000	0.022	0.000	0.000	0.000
5, n = 676, 0.36305	0.052	0.063	0.000	0.000	**0.872**	0.000	0.000	0.007	0.000	0.005
6, n = 40, 0.02148	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000	0.000	0.000
7, n = 103, 0.05532	0.000	0.000	0.003	0.010	0.000	0.000	**0.943**	0.000	0.044	0.001
8, n = 173, 0.09291	0.009	0.008	0.000	0.001	0.053	0.000	0.000	**0.894**	0.024	0.012
9, n = 107, 0.05747	0.000	0.000	0.000	0.000	0.000	0.000	0.040	0.040	**0.918**	0.002
10, n = 95, 0.05102	0.002	0.008	0.000	0.000	0.052	0.000	0.000	0.016	0.016	**0.908**

response sets given that it is not plausible that an adolescent concurrently felt "Extremely Fatigued" and "Extremely Energetic," at the same time. Excluding these three classes of invalid responses left six meaningful clusters of affective variables.

Latent Affective Profiles

Latent affective profiles described adolescents' mean ratings for positive affect, negative affect, anger, fatigue, friendliness, energy, anxious, and depressed; and how ratings clustered together across individuals and time points. The largest class (Class 6, 37.1% of responders) displayed moderate positive affect and friendliness with low anxiety and depression, which we labeled Good Mood. Another Good Mood/Energetic profile (Class 2, 19.9%) exhibited high positive affect, energy, and friendliness with low negative affect, fatigue, anxiety, and depression. A third class (Class 1, 8.7%) displayed high fatigue and blunted response on all other items, which we labeled Fatigued. Two additional classes displayed high anger and low energy with either high depression (Class 3, 2.3%) or low depression (Class 7, 5.7%), and were labeled Angry/Depressed and Angry, respectively. The final class, labeled Depressed, (Class 8, 1.4%) displayed blunted affect and high depression, with moderate responses on all other traits. All latent profiles are displayed in Fig. 1.

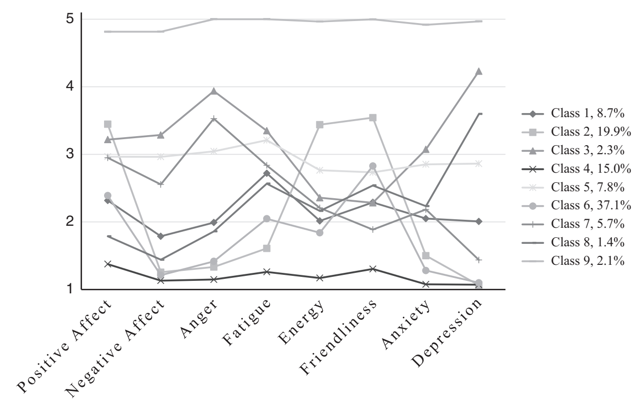

Fig. 1 Nine-class model of complex latent affective profiles in adolescents. Class 1 (Fatigued); Class 2 (Good Mood/Energetic); Class 3 (Angry/Depressed); Class 4 (Low Responders); Class 5 (Moderate Responders); Class 6 (Good Mood); Class 7 (Angry); Class 8 (Depressed); Class 9 (High Responders)

Discussion

Findings from the current study suggest that screening of adolescent EMA data may be improved by the use of LVMM as an empirical approach to identify invalid response sets. Specifically, the current analysis revealed that nearly one quarter of responses could best be characterized as a response set that should be considered for exclusion from further analysis. Moreover, this analytical step in data cleaning may allow investigators working with intensive longitudinal data to step beyond static *a priori* decisions for data cleaning. Many responses may be invalid for reasons other than incomplete surveys or long response times, which are common *a priori* classifications used to identify invalid responses in the current literature (Schiffman 2014). For example, identifying invalid responses using an *a priori* approach would exclude all data from three participants in our study who answered less than 50% of survey items. Our novel approach to identifying latent profiles of invalid responses allowed the inclusion of surveys that these three individuals did complete, while concurrently identifying completed survey responses that were invalid.

The ability to identify invalid responders in EMA data is especially important because these large data sets likely contain more entries than can be hand searched. It is likely that invalid responses may not be easily identified by simple count strategies that search for strictly uniform responding. Indeed, visual inspection of the invalid classes identified in Fig. 1 make it clear that High Responders did not uniformly select "5" when completing their surveys. However, their overall pattern of responding is so near the ceiling of the scales that the responses are logically inconsistent. That is, it is unlikely that an individual felt high levels of depression, anger, and positive affect (among others) all at the same time.

Beyond the findings that can help to inform data accuracy, the current report provides preliminary evidence for mood profiles that may warrant additional study in adolescents. The person-centered approach to data analysis reveals that it may be important to consider mood states concurrently with each other when collecting intensive longitudinal data, rather than treating each variable independently (i.e., a variable centered approach). A study utilizing latent growth curve modeling to show trajectories of internalizing from adolescence to adulthood suggested that focusing on profiles derived from patterns of different symptoms may be more useful in guiding adolescent interventions than using the broad label of internalizing (Betts et al. 2016). Moreover, Merikangas et al. (2003) argued that mood profiles are less likely to be subject to fluctuations and better able to demonstrate continuity than are syndromes, which is particularly important for longitudinal studies. It remains to be seen whether there is incremental validity in closely related classes (e.g., Angry/Depressed vs. Depressed). However, we would hypothesize that a participant who experiences two concurrent negative emotions may experience greater overall distress, with possible physiological implications, than one who experiences only one negative emotion. Future studies that collect psychophysiological data such as heart rate variability in real time may help to shed light on this hypothesis (Brannon et al. 2016).

Finally, by combining eight psychological states into one class, the current study adds computational efficiency to predictive models of affective and physical feeling states. A multilevel model examining these eight constructs would require at least 17 independent variables (i.e., one predictor for time, and a within and between person variance component for each of the state variables). Such a model is unlikely to converge and the most computationally efficient strategy would be to break the analysis down into eight independent models. Estimating a large number of models, however, would dramatically increase the likelihood of a Type 1 error. This number of models may also result in various written products rather than a single manuscript describing the overall effect of psychological states on a dependent variable of interest. This is not ideal as it may limit a reviewer's ability to detect Type 1 error if models are published in multiple manuscripts. The current approach allows future studies to: (1) Complete a data screening step (i.e., identify invalid response sets), (2) Remove invalid responses from the analysis, and (3) Use a computationally efficient multivariate approach to hypothesis testing.

The contributions that can be made by our use of profile analysis must be tempered by this study's limitations. This study contained a small sample of majority Caucasian and middle-class adolescents. Findings should be replicated in larger, more diverse samples before making generalizations. In addition, this was an exploratory approach to identify clusters of affective states in adolescents and the 9-factor structure described in the current study may not be appropriate for all adolescents. A confirmatory approach should be used to reproduce latent affective profiles in a broader population of adolescents, to determine whether the profiles identified in this study hold true across adolescents and whether these profiles have clinical utility. Finally, due to the repeated measurements in the data there are dependencies that create a multilevel structure to these data that is not modeled in the current analysis.

In spite of these limitations, this study successfully demonstrated a novel approach to analyzing person-centered descriptors and identifying sets of invalid responding in intensive longitudinal data, a method of data capture in which it is notoriously difficult to identify invalid responses. The study also provided preliminary evidence for mood profiles in adolescents, which, if validated by future studies, may be useful for longitudinal research and intervention. This study moved the literature beyond investigations that demonstrate that EMA is an accurate data collection tool (Liao et al. 2014) and those that have conducted regression analysis with one affective construct per equation to consider the potential of modeling internal states as profiles (Cushing et al. 2017). Future investigations should examine associations between latent affect profiles and physiological states in adolescents, and determine whether specific mood profiles in adolescents are predictive of health behaviors, such as physical activity, diet, and sleep. Additionally, future studies should determine whether these kinds of models yield the same conclusions as those that consider each internal state independently.

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Author Contributions C.C.C. obtained funding for the project; conceptualized the work; provided substantial original writing; conducted the statistical and methodological design; conducted the statistical analyses; collected the data; editing the work; and supervised/mentored A.M.M., C.M.B. & L.P.H. A.M.M. collaborated in the conceptualization of the work, provided substantial original writing, and edited the work. C.M.B. collaborated in the conceptualization of the work, provided substantial original writing, and edited the work. C.J.C. collaborated in the conceptualization of the work, designed the PETE app and oversaw its use, and edited the work. L.P.H. collaborated in the conceptualization of the work, provided substantial original writing, and edited the work.

Compliance with Ethical Standards The current study fully complies with the American Psychological Association Code of Ethics.

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Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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