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Preliminary evidence of diurnal rhythms in everyday behaviors associated with positive affect ☆

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ABSTRACT

The authors used the Electronically Activated Recorder (EAR) to track within-day variability in everyday behaviors associated with positive and negative affect across two samples. The EAR is a portable audio recorder that periodically samples snippets of ambient sounds from participants' momentary environments. The recorded sounds are then coded for different behaviors. The study tested whether previous findings regarding diurnal patterns in self-reported mood extend to naturalistically observed behavior. Across both samples, behavior associated with positive affect (i.e., socializing, laughing, and singing) varied according to a sinusoidal 24-h rhythm centered around participants' average waketime while behavior associated with negative affect (i.e., arguing and sighing) did not. Further, there was preliminary evidence that personality traits can moderate these rhythms (e.g., their amplitude).

1. Introduction

Mood is an essential feature if not the defining characteristic of ongoing conscious experience. As both philosophers and psychologists have noted, consciousness bereft of mood is rare or nonexistent (DeLancey, 1996; Watson, 2000). Such a constant presence implies an important function, and indeed, mood does more than just provide affective tone (e.g. "the blues" or "rose-colored glasses") to people's moment-to-moment phenomenological worlds.

In daily life, mood acts as a subtle yet pervasive causal agent. Mood states alter the way humans recall autobiographic memories (Miranda & Kihlstrom, 2005), make decisions (Loewenstein & Lerner, 2003), resist or fall prey to persuasion (Schwarz & Clore, 2007), perceive and are perceived by others (Forgas, 2003), and influence how people respond to social situations (Zajonc, 2000). Momentary moods even exert traceable effects on the immune system and the regulation of physical health (Kiecolt-Glaser, McGuire, Robles, & Glaser, 2002; Pressman & Cohen, 2005). Finally, mood dysregulation is a defining feature of many psychiatric disorders and is implicated in their onset, development, and recovery.

As pervasive as mood effects are, humans often remain largely unaware of the factors that are responsible for fluctuations in their moment-to-moment mood (Gilbert, 2006). It is a common experience to find oneself fumbling to understand why one is feeling a certain way. Not only are the causes of mood often beyond conscious access, but mood fluctuations themselves may go unrecognized. Therefore, it is important to develop a more complete understanding of patterns underlying variability in mood.

☆ Portions of the data presented here were used in Mehl, Vazire, Ramirez-Esparza, Slatcher, and Pennebaker (2007) for an analysis of sex differences in daily word use and in Vazire and Mehl (in press) for an analysis of the accuracy of self and other ratings of daily behavior. The analyses and findings reported here do not overlap with those reported in these papers.

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Over the past two decades, emotion researchers have made critical progress in identifying dispositional and contextual influences on everyday affective experiences. This article explores the role of a third component of daily mood fluctuations and their behavioral consequences: rhythmic processes, including both circadian and socio-cultural rhythms. It is well established using forced desynchrony protocols, the gold-standard in chronobiological methodology,[1] that there is a circadian component to self-reported mood (Boivin et al., 1997). More recently, a number of studies have further explored this phenomenon, noting that self-reported positive affect (PA) varies according to a daily rhythm, while self-reported negative affect (NA) does not (Murray, 2007; Murray, Allen, & Trinder, 2002; Thayer, 1997; Watson, Wiese, Vaidya, & Tellegen, 1999; Wood & Magnello, 1992). Some studies (e.g., Murray et al., 2002) have experimentally controlled for social interaction, thus buttressing the argument that the rhythm in PA is endogenous, biologically-driven (i.e., circadian) and not merely diurnal (i.e., a daily pattern with uncertain causation). The disparity in patterns has been linked to different motivational systems regulating PA and NA.

These findings raise a critical question—is the diurnal pattern confined to how people describe their inner mood landscape, or does it also surface in their affect-associated behaviors in the external world? Answering this question is important for at least two reasons. First, from a multiple-method perspective (e.g., Larsen & Prizmic-Larsen, 2006) it is critical to establish whether the evidence of diurnal patterns underlying affect generalizes across methods and replicates if affect is assessed free of self-report. Second, it is of theoretical interest to test the extent to which diurnal fluctuations in experienced affect "spill over" into observable behavior. Affect display is partially under conscious control and often modulated according to social norms (e.g., a churchgoer may feel like laughing during service but decide to suppress it; a student may feel like singing in class but realize it is inappropriate to do so). Finally, studying diurnal rhythms in affect-associated daily behaviors is also in line with Baumeister and his colleagues's recent plea for "affirmative action for action" (p. 401) research in social and personality psychology—a field that currently experiences a dearth of studies that measures "actual behavior" (Baumeister, Vohs, & Funder, 2007).

For the current study, we used the Electronically Activated Recorder or EAR (Mehl, 2007; Mehl, Pennebaker, Crow, Dabbs, & Price, 2001), a relatively novel unobtrusive observation method, to sample affect-associated behavior directly from the natural stream of daily life and independent of self-reports. The EAR tracks participants' real-world behaviors by periodically recording snippets of ambient sounds from their momentary environments. The sampled ambient sounds are then coded for aspects of participant's moment-to-moment social behaviors, interactions, and environments (Mehl, Gosling, & Pennebaker, 2006; Mehl & Pennebaker, 2003; Mehl, Vazire, Ramirez-Esparza, Slatcher, & Pennebaker, 2007).

This study extends prior research on diurnal rhythms in affect in four important ways: First, it subjects the hypothesis of diurnal rhythms in affect to a cross-method validation that is independent of self-reports and based on affect-associated behaviors that are socially important but infrequently studied (e.g., singing, arguing). Second, it tests whether the phenomenon is limited to the experience of affect or can extend to its behavioral expression in daily life. Third, it uses progress in statistical modeling and a theoretically specified mathematical function. Diurnal variability in affect is often studied by using repeated measures ANOVA on between 3 and 10 data points per person per day (e.g., Adan & Sanchez-Turet, 2001; Wood & Magnello, 1992); we directly fit a theoretically predicted sinusoidal curve to fine-grained EAR data consisting of more than 60 data points per person per day. Finally, we explore the idea that personality traits can moderate the identified diurnal patterns. Based on a recent finding that Neuroticism (N) may be associated with a lack of circadian rhythmicity in PA and a blunted amplitude in the core body temperature rhythm (Murray, Allen, Trinder, & Burgess, 2002), we examined whether N would be related to a blunted and Extraversion (E) to an amplified diurnal rhythm of PA-associated behaviors.

2. Methods

The data for this study were derived from two EAR projects that examined the personality implications of daily life. For details about Sample 1 see Mehl et al. (2006); for details about Sample 2 see Vazire and Mehl (in press).

2.1. Participants

Sample 1 consisted of 96 introductory psychology students at the University of Texas at Austin (47 females, mean age $M = 18.7$) who wore the EAR for approximately 3 days during their waking hours. Of these, 60 participants (29 females, mean age $M = 18.7$) were included in the analyses. Sample 2 consisted of 79 introductory psychology students at the University of Texas at Austin (42 females, $M = 18.7$) who wore the EAR for approximately 5 days during their waking hours. Of these 50 participants (30 females, mean age $M = 18.6$) were included in the analyses. In both studies, participants were excluded if their sleep patterns did not meet our inclusion criteria (see below).

[1] Forced desynchrony protocols place participants in a laboratory-controlled 28-h 'day' without cues to external clock time. The circadian pacemaker is unable to synchronize to this schedule, thus allowing individual circadian rhythms (sleep/wake, temperature, etc.) to proceed according to purely endogenous signals.

2.2. Procedures and measures

2.2.1. EAR system

The EAR system consisted of a digital voice recorder (SONY ICD-MS1), an external tie-clip microphone (OPTIMUS Tie Clip Microphone), and a controller chip (Mehl et al., 2001). The chip was programmed to produce 4.8 30 -s recordings per hour. Participants wore the EAR during their waking hours. They had an opportunity to erase recordings they did not want the researchers to hear. In both samples participants erased fewer than 0.1% of the sampled sound files. For more details about the EAR, including information about the method's obtrusiveness and participants' compliance with wearing the device see Mehl (2007) and Mehl and Holleran (2007).

2.2.2. EAR-derived affect-associated behaviors

Research assistants coded all of participants' EAR sound files for aspects of their momentary behaviors using a revised version of the Social Environment Coding of Sound Inventory (SECSI; Mehl et al., 2006). Each participant was coded by one research assistant. From the 32 available SECSI behaviors, we selected three behaviors *a priori* on the basis of their theoretical association with PA—Laughing, Singing (or whistling), and Socializing (defined as having a casual, non-instrumental social interaction)—and two behaviors on the basis of their theoretical association with NA–Arguing (defined as arguing with, yelling at, or otherwise expressing anger towards another person) and Sighing. Inter-coder agreement (ICC[2,k]) determined from standardized sets of training EAR recordings independently coded by all coders exceeded .70 for all five variables (for details see Mehl et al., 2006; Vazire & Mehl, in press). The raw binary codings were converted into relative frequency estimates by calculating the mean number of waking EAR recordings in an hour in which a coding category applied (e.g., the mean number of recordings per hour in which the participant was laughing or singing).

2.2.3. EAR-derived sleep times

Sleep-onset was determined by the coders as the time of the first of a series of "empty" (i.e. totally silent) nightly EAR recordings. Sleep-offsets were determined as the times of the first "active" (i.e. non-silent) EAR recording after a nightly sleeping period. Inter-coder agreement for determining whether a participant was sleeping was high (ICC[2,k] = .97). To maximize the accuracy of their codings, the coders further used information that participants' provided in basic activity diaries they completed at the end of each day of monitoring (cf. Mehl et al., 2001).

Although no *a priori* restrictions were placed on participants' sleep schedules as part of the original studies, participants were excluded from our analyses if their waketimes differed by more than two standard deviations from one another or if they did not have a single block of sleep lasting longer than 5 h that concluded between 4 AM and 3 PM on at least two days of the study. These criteria were aimed at increasing the validity of the mean waketimes as a proxy of circadian phase (see below). By excluding participants with highly erratic sleep schedules we sought to maximize the generalizability of the findings. As shown in Table 1, Sample 1 participants woke up somewhat earlier than Sample 2 participants, $t = 3.01$, $p < .01$.

2.2.4. Standardization of sleep times

Because we hypothesized that the affect-related behaviors are driven in part by an endogenous component, and given the individual variability in sleep/activity schedules, it was necessary to standardize the data according to each participant's ostensible circadian phase. We converted the timescale from clock time to one more closely approximating circadian time. Prior research has shown that sleep offset is highly correlated with circadian phase, particularly for individuals on self-selected, unrestricted sleep schedules—such as the students in our two samples (Burgess & Eastman, 2005; Burgess et al., 2003). Thus, in the absence of a physiological circadian measure (e.g., core body temperature), sleep offset provides a proxy for circadian phase. Specifically, each participant's mean sleep-offset over the length of the study was subtracted from all their timepoints. Thus, a timepoint falling exactly at their mean sleep-offset would be designated as 0, a timepoint falling 8 h after their mean sleep-offset would be designated as 8. This newly calculated time variable represents the hours after the mean waketime and was labeled $\text{Time}_{\text{relative to average waketime}}$.

2.2.5. Personality measures

We assessed personality using the 44-item Big Five Inventory (BFI; John & Srivastava, 1999) in Sample 1 and the BFI and the Revised NEO Personality Inventory (NEO-PI-R; Costa & McCrae, 1992) in Sample 2. Sample 1 participants rated themselves on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). Sample 2 participants rated themselves twice (three

Table 1
Demographics across Samples 1 and 2

	Sample 1 (*N* = 60)		Sample 2 (*N* = 50)	
	M	*SD*	*M*	*SD*
Age (in years)	18.67	0.86	18.60	1.29
Waketime	9:42	0:44	10:29	1:17
Study length (in days)	2.85	0.40	5.98	0.82

Table 2
Basic psychometric information about the personality measures in Sample 1 and 2

Personality measure	Sample 1 ($N = 60$)		Sample 2 ($N = 50$)		
	M (*SD*)	Rel.	M (*SD*)	Time1-time2 correlation	Rel.
BFI-E	3.61 (0.92)	.90	4.67 (1.03)	.89	.88
BFI-N	3.44 (0.82)	.87	4.31 (0.93)	.85	.90
NEO-N	na	na	4.02 (0.92)	.89	.89
NEO-DEP	na	na	3.98 (1.31)	.81	.90

Note. Sample 1 ratings are based on a scale ranging from 1 (strongly disagree) to 5 (strongly agree). Sample 2 ratings are based on a scale ranging from 1 (strongly disagree) to 7 (strongly agree). The BFI scores in Sample 1 are based on the participants' self-ratings. The BFI scores in Sample 2 are based on the average of two self-reports (three weeks apart) combined with reports from three informants that knew the participants well. The NEO-PI-R scores are based on the average of two self-reports. Rel., Reliability (Cronbach's alpha).

weeks apart) using a scale ranging from 1 (strongly disagree) to 7 (strongly agree). We also obtained BFI ratings of each Sample 2 participant from three informants who knew the participant well (Vazire, 2006). The participants' BFI scores in Sample 2 are based on the average of their two self-reports combined with the three informant reports, and their NEO-PI-R scores are based on the average of their two self-reports. Table 2 shows the means and reliabilities for the personality measures assessed in Samples 1 and 2.

2.2.6. Data analytic strategy

Hierarchical linear modeling (HLM) was employed to test for 24-h diurnal rhythms in the within-person pattern of the five selected behaviors. This approach to modeling change includes (1) a level-1 submodel that estimates how individuals change over time and (2) a level-2 submodel that estimates how these changes vary across individuals. By simultaneously addressing both sources of variance and allowing for non-independence of observations, HLM provides more precise standard errors of parameter estimates than ordinary least squares regression, resulting in more accurate hypothesis testing (Singer & Willett, 2003). Furthermore, HLM can model periodic trends directly within-person (as compared to only aggregated across individuals), thereby providing a conceptually more adequate and statistically more powerful approach than the cosinor analysis techniques traditionally used to study circadian rhythms (e.g., Clark, Watson, & Leeka, 1989).

In this special case of HLM, the presence of a 24-h diurnal pattern is determined by a significant fit of the data to a sinusoidal curve, or sine wave, with a period of 24 h. An equation representing a sinusoidal curve (i.e., the cosinor model) is used at level-1 (Ching, Fok, & Ramsay, 2006). The simplest form of this equation is $f(t) = c_0 + c_1\sin(2\pi t/P)$, with time ($t$) and period ($P$). The periodic function has its baseline value c_0 at the origin ($t = 0$), rises to $c_0 + c_1$ at $t = P/4$, drops to $c_0 - c_1$ at $t = 3P/4$, and returns to baseline at $t = P$. This captures the periodic effect if the phase begins at $t = 0$. To allow a phase shift, a cosine term is included as regressor, resulting in $f(t) = c_0 + c_1\sin(2\pi t/P) + c_2\cos(2\pi t/P)$. Sinusoids that begin at a phase 90 degrees (i.e., 6 h if $P = 24$ h) after $t = 0$ are better captured by the cosine term. Furthermore, in addition to allowing the sinusoidal pattern to begin at any phase, including both sine and cosine terms in the equation permits the modeling of nonsymmetrical curves. We created separate sine ($\sin(2\pi t/P)$) and cosine ($\cos(2\pi t/P)$) parameters, with $t = \text{TIME}_{\text{relative to average waketime}}$ and $P = 24$ h.[2]

3. Results

3.1. Preliminary analyses

Preliminarily, we fitted two simple models (the unconditional means and unconditional growth models) for each of the five behaviors (1) to estimate the overall variability in the behaviors; (2) to assess the extent to which this variability resided within or between people; and (3) to test for any linear change in the behaviors over the course of a day. Analyses confirmed the existence of significant within- and between-person variability and indicated that (with one exception) the within-person variability did not fit a linear trend.[3]

3.2. Analysis of within-person periodic change

To test the hypothesis that within-day variability in behaviors associated with PA but not NA follows a diurnal pattern, we fitted a series of models with sinusoidal curves at level-1. Figs. 1(A–F) and 2(A–D) show the observed data (aggregated across days) for each behavior in the two samples, as well as the respective predicted data based on the coefficients from each cosinor model. Because participants' data were standardized according to their own mean waketimes, the time scale

[2] Analyses were run using HLM 6. To test the influence of autocorrelated residuals, we also re-ran all Level 1 analyses on SPSS 14.0 using different error structures. These analyses consistently yielded very similar coefficients and significance levels for the fixed effects.

[3] Although the Sample 2 Singing data showed a significant daily linear trend, the periodic change effect remained significant with the linear effect in the model. Reported results are based on the model without a linear trend.

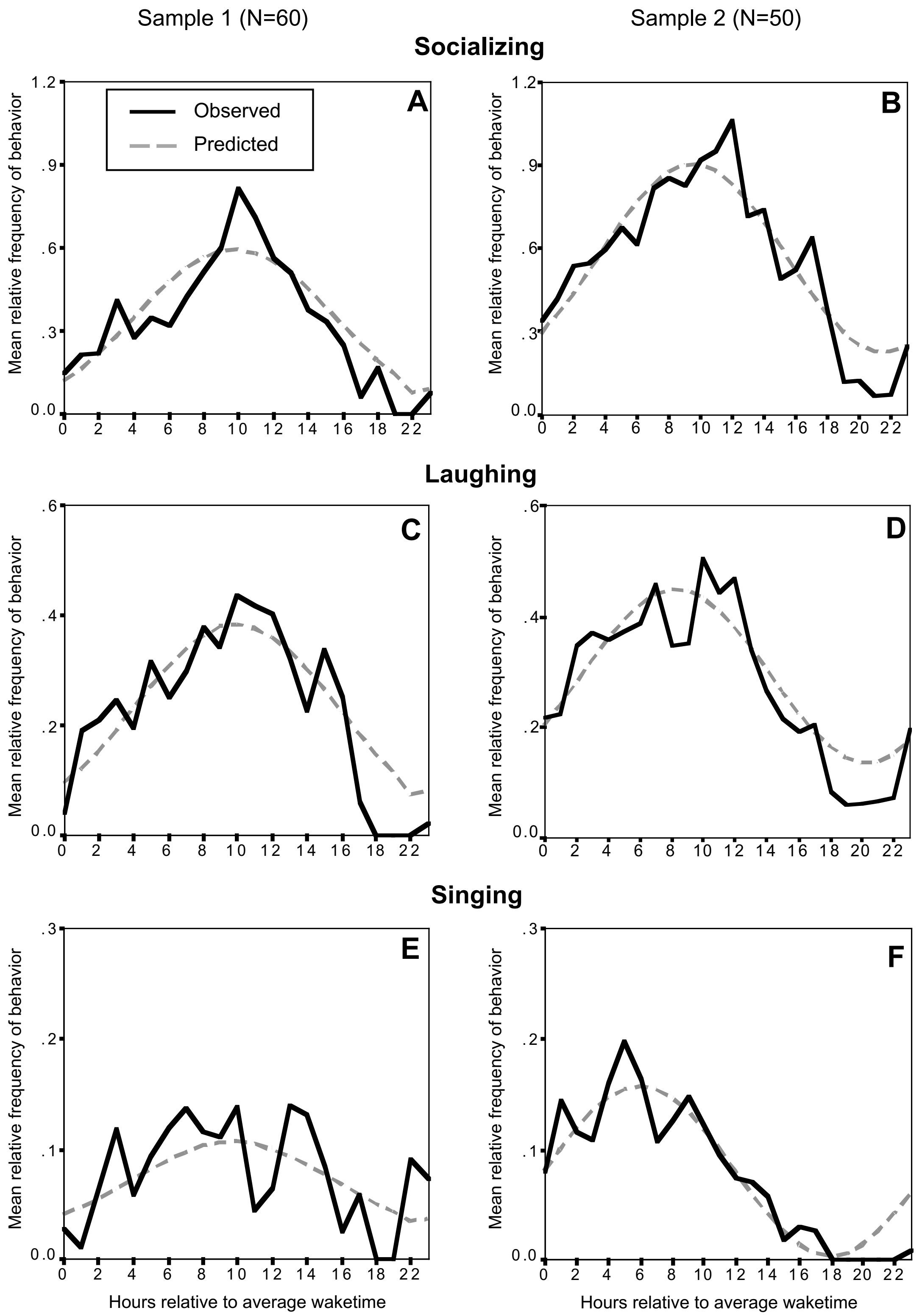

Fig. 1. Relative frequency of behaviors associated with positive affect across 24 h after the average waketime. The solid line represents the observed data (aggregated across days) for each behavioral variable, while the hatched line represents the predicted data based on the specific coefficients from each HLM-derived cosinor model.

begins at the mean waketime. Because the multi-day sampling and the variability in waketimes ensured that we had valid data points for any hour within the 24-h cycle (though fewer at the very beginning and the very end), the time scale extends over the full 24 h. That way, for example, the predicted value of socializing at 22 h after mean waketime is based on data points that participants provided who at that time in the day were either (1) still engaged in casual conversations with others, or (2) 2 h prior to their mean waketime and already engaged in social activity (while the rest of the sample was sleeping).

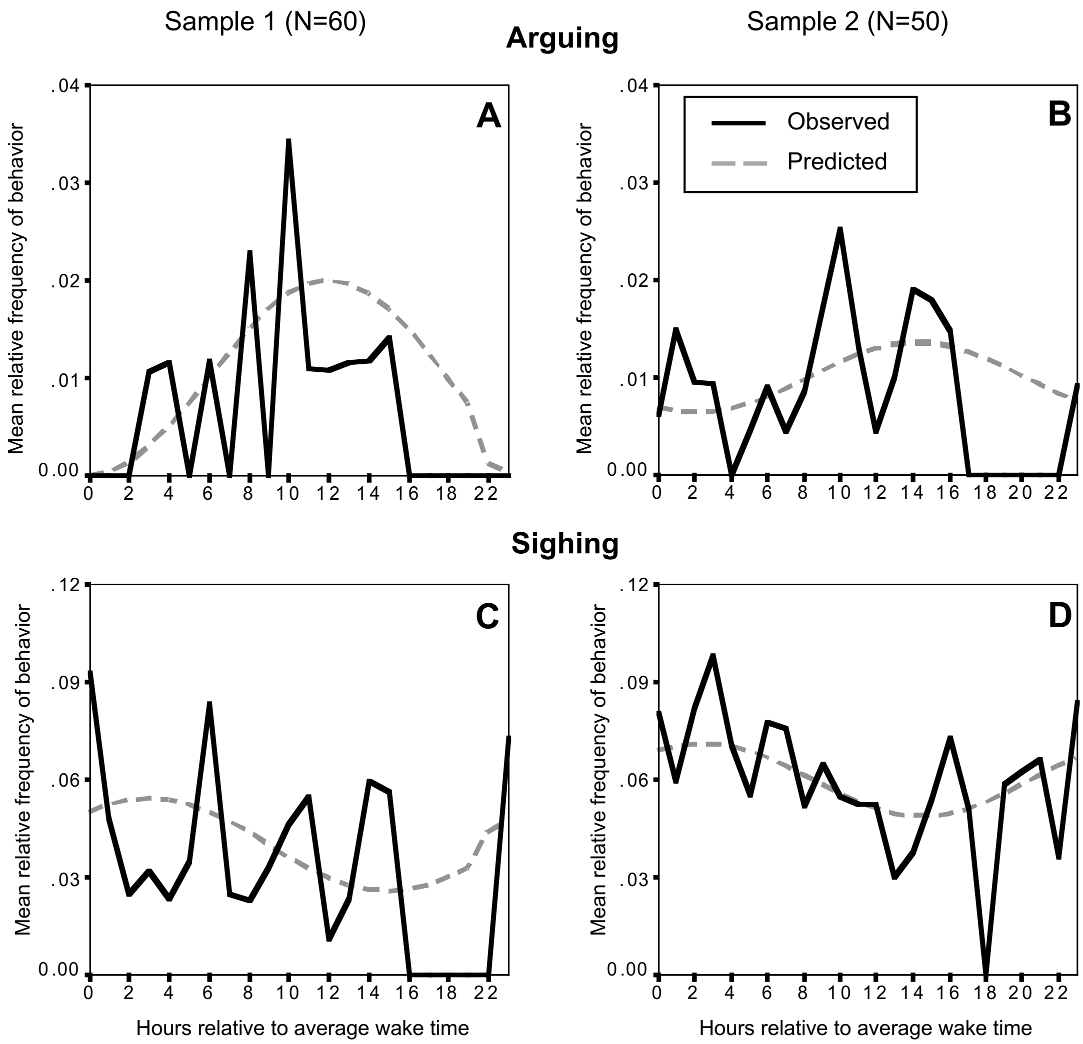

Fig. 2. Relative frequency of behaviors associated with negative affect across 24 h after the average waketime. The solid line represents the observed data (aggregated across days) for each behavioral variable, while the hatched line represents the predicted data based on the specific coefficients from each HLM-derived cosinor model.

3.2.1. PA-associated behaviors

For Socializing, in both samples we found significant sine (γ_{10} = .14, p < .001, d = .47 and γ_{10} = .21, p < .001, d = .54) and cosine terms (γ_{20} = −.22, p < .001, d = −.63 and γ_{20} = −.27, p < .001, d = −.73), supporting the presence of periodic change in socializing within each day. Both sine and cosine terms were also significant for Laughing across Samples 1 and 2 (γ_{10} = .09, p < .01, d = .35 and γ_{10} = .13, d = .69, p < .001; γ_{20} = −.13, d = −.83, p < .001 and γ_{20} = −.09, p < .001, d = −.49). Finally, only the cosine term in Sample 1 was significant for Singing (γ_{20} = −.03, p < .05, d = −.83), indicating that periodic change was present with a phase beginning closer to 6 h after the mean waketime; while only the sine term in Sample 2 was significant for Singing (γ_{10} = .08, p < .001, d = .79), indicating that periodic change was present with a phase beginning close to the mean waketime. Thus, we found consistent evidence of the presence of a sinusoidal diurnal rhythm (by means of fit to either a sine or a cosine wave) for all three selected PA-associated behaviors.

Due to socio-cultural (i.e. schedule) constraints, the opportunity to socialize likely increases from morning until late afternoon and declines in the evening as people return to their socially more restricted home environments. To account for variance in our cosinor model that is associated with variability in socializing, we ran another set of analyses that included socializing as an additional level-1 predictor. Both Laughing and Singing retained their significant fits to the cosinor model after accounting for the variance associated with Socializing (Laughing, Samples 1 and 2, respectively: γ_{10} = .06, p < .05, d = .27 and γ_{10} = .06, p < .001, d = .51; Singing, Samples 1 and 2, respectively: γ_{20} = −.03, p < .05, d = −.27. and γ_{10} = .07, p < .001, d = .71).

The possible high variability of waketimes in college students as sampled in the two studies raises the question about whether the findings generalize to both those with late and early waketimes. Conceptually, different sleep schedules among participants add noise to the measurements and thereby make it more difficult to reliably detect a signal (i.e., sinusoidal patterning). Empirically, we compared the patterns for participants with relatively early versus late waketimes by including a

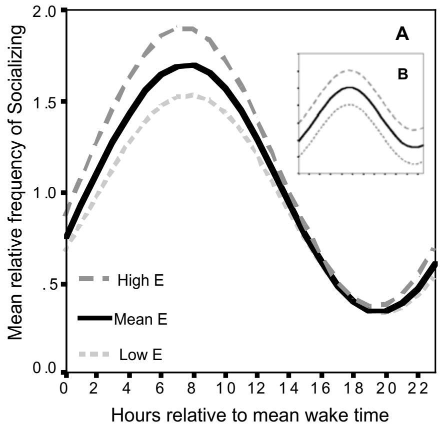

Fig. 3. Effect of varying levels of Extraversion (Mean BFI-E ± 1 *SD*) on predicted pattern of Socializing (A). With significant effects on both the intercept (mesor) and the sine term in Level 1, E moderates both the mean level and the shape of the curve. In contrast, the inset figure (B) depicts an effect only on the intercept (per the effect of varying levels of Neuroticism on Socializing).

dichotomous level-2 moderator (earlylate) based on a median split. In Sample 1, 'earlylate' was not a significant moderator for any of the behaviors. In Sample 2, which was more heterogeneous for waketime, 'earlylate' emerged as a significant moderator for Socializing and Laughing ($\gamma_{11} = .20$, $p < .05$, $d = .56$ and $\gamma_{11} = .13$, $p < .01$, $d = .80$) and showed a trend towards significance ($\gamma_{11} = .04$, $p = .08$, $d = .50$) for Singing. Later waketimes were associated with larger sine term effects indicating higher "circadian" amplitudes.

A possible explanation for this difference lies in the sleep/wake schedule-circadian clock relationship. Given that college students tend to have delayed circadian phases (i.e. habitually get up relatively late), it is thus likely that those with later waketimes are more aligned with their biological rhythms than those with earlier waketimes who might be on a schedule that is at odds with their circadian clock. As a result, waketime would be a less valid proxy of circadian phase in the early group, thus reducing the amplitude of their diurnal patterning (and the cosinor model fit). This is consistent with indications of higher correlations between later waketimes and circadian rhythms in other samples (e.g., Burgess et al., 2003).

3.2.2. NA-associated behaviors

Neither Arguing nor Sighing significantly fit the cosinor models in either sample, indicating that no 24-h periodic pattern of systematic change existed in these data (all *ps* $\geqslant .10$; see Fig. 2).

3.3. Further exploratory analyses: Individual differences in within-person periodic change

In a set of exploratory analyses, we added the level-2 covariates to examine whether affect-related personality traits could systematically explain variability in the intercepts and periodic patterns of the PA-associated behaviors. For both the level-1 only cosinor model and all subsequent cosinor models involving level-2 variables, nonsignificant fixed effects were dropped and the models re-run until only significant effects remained.[4]

The strongest findings concerned dispositional effects on the overall level of the behaviors, with effect sizes ranging from $d = .26$ to .41 (detailed results are available upon request). E was generally related to an overall greater frequency and N to an overall lower frequency of PA-associated behaviors (i.e., E and N had significant effects on the intercept of the cosinor model). However, these findings are not directly relevant to the question of diurnal rhythms (i.e. periodic change) in daily behaviors.

More importantly with respect to circadian processes, we found suggestive evidence (i.e., small-to-medium effect sizes) that affective personality traits can moderate the periodic change parameters of PA-associated behaviors. BFI-E significantly predicted the sine term of Socializing in Sample 1 ($\gamma_{11} = .09$, $p < .05$, $d = .30$), and showed a trend towards significantly predicting the sine term of Socializing in Sample 2 ($\gamma_{11} = .09$, $p = .09$, $d = .25$). Consistent with an amplification function, visual analysis of Fig. 3 shows that higher levels of E manifest as a higher amplitude in the positive portion of the sinusoidal curve of Socializing.[5]

With regard to Laughing, NEO-DEP showed a trend towards significantly predicting the sine term in Sample 2 ($\gamma_{11} = -.03$, $p = .07$, $d = -.26$) and BFI-N showed a trend towards significantly predicting the cosine term in Sample 1 ($\gamma_{21} = -.04$, $p = .09$, $d = -.22$). Thus, in contrast to the impact of E, higher levels of sub-clinical depression and N were related to a more blunted Laughing rhythm.[6] Neither E nor N was significantly associated with the change parameters of Singing, Arguing, or Sighing.

[4] The models are available upon request.

[5] Because amplitude is not specifically modeled in our equation, we combined visual analysis with examination of the MLM coefficients in order to enhance interpretation of the moderation results.

[6] These results were also confirmed via visual analysis, but the graphs were somewhat redundant with Fig. 3 and were thus omitted for the sake of brevity.

4. Discussion

In summary, across two independent samples, we found that three behaviors associated with PA (socializing, laughing, and singing) followed 24-h sinusoidal patterns centered around participants' mean waketimes. Even after accounting for the variance associated with socializing, both laughing and singing retained significant fits to the cosinor model, supporting our hypothesis—but effectively not ruling out the possibility—that they are not entirely driven by socio-cultural, environmental factors (i.e., time-of-day-associated opportunities to socialize and therefore laugh or sing) and may follow an endogenous circadian regulation. Also as predicted, there was no evidence of systematic, time-of-day related variability in the two behaviors associated with NA (arguing and sighing) in either sample.

Although the effects of affective personality traits on the PA-associated behaviors were stronger for the overall frequency (i.e. intercepts) of the behaviors than for the circadian patterning, all observed effects (extraversion's amplification and subclinical depression's blunting of the sinusoidal curve) were consistent with prior research and theorizing (e.g., circadian blunting in association with depression, Souetre et al., 1989), suggesting that this area may merit further investigative efforts.

The findings from this study have important theoretical implications and are consistent with the theory of divergent biobehavioral systems underlying PA and NA (Watson, 2000). It is now well understood that under normal conditions, PA and NA operate largely independently of each other. According to the theory, this is hypothesized to be a result of the fact that they are regulated by different motivational systems. Specifically, the systematic diurnal pattern of PA may be the manifestation of an underlying Behavioral Approach System (BAS) that is motivating engagement of the environment during the day (the time of maximum reward and minimum risk). In contrast, the stability of NA in the absence of aversive stimuli is hypothesized to be the manifestation of a reactive Behavioral Inhibition System (BIS). Also, we should note recent discussions around the idea that the negative emotion anger (and thus arguing) may counterintuitively involve the BAS (e.g., Harmon-Jones, 2007). Although our data cannot definitively link arguing to either motivational system, the data do suggest that arguing does not occur in a systematic diurnal pattern like the PA-associated behaviors and may better be classified with NA-associated behaviors in this regard.

It is possible that a circadian rhythm in the activity of the BAS may underlie the observed diurnal pattern of both PA and its associated behaviors and optimally prepare humans for engagement of the environment during the day. This hypothesis is supported by the existence of a *positivity offset*, a "weak [approach] motivational output" when the environmental input is at "zero" (Cacioppo, Gardner, & Berntson, 1999). The positivity offset translates into mild-to-moderate PA-levels and low NA-levels in daily life in the absence of affect-eliciting events. Paralleling the theoretical link between PA and the BAS, the positivity offset is thought to be an adaptation of an appetitive motivational system, which ensures that organisms in neutral environments will still be motivated to investigate novel stimuli. Given this phenomenon and that the BAS should be stimulating engagement of the environment during daytime in humans, one would expect to find the systematic daily rise and fall of socializing that we observed in our samples.

Whatever ultimately the cause of the diurnal patterning, the findings have methodological implications for the assessment of PA-associated behaviors. Our findings suggest that behavioral scientists should test for and potentially control time-of-day effects that influence the frequency of such behaviors. These effects are routinely considered in research involving well-known circadian rhythms such as in the case of cortisol, for which failing to control for time-of-day (or better yet, individual circadian phase) could yield biased change scores. In a parallel scenario, if an investigator measures laughing during late afternoon at Time 1 and during the morning at Time 2, an observed decrease could in part be due to measuring the behavior near its nadir versus its peak.

Finally, a diurnal rhythm in PA also has practical implications. An interesting parallel can be drawn with chronopharmacology in which the efficacy of medications depends on the time of administration (e.g., blood pressure-lowering drugs are at peak effectiveness soon after waking, when cardiovascular risk is highest; (Smolensky & Haus, 2001). Similarly, the systematic pattern in PA suggests that certain activities may be more effectively accomplished at particular times. For example, a psychotherapist might enhance the effectiveness of a behavioral activation intervention for depression by taking advantage of the peak in PA during the latter part of the day. This planning of activities considering diurnal mood dynamics is in line with previous recommendations (Thayer, 1997). With this in mind, it is important to remember that the data were standardized according to waketime. For example, given that the peak in laughing occurred 10–12 h after waking, we might estimate that an average working adult who arises at 7 AM might expect this peak to occur between 5 and 7 PM.

The findings raise important questions for future follow-up research. Perhaps most important is the question of the extent to which the observed rhythms have circadian and/or socio-cultural underpinnings, a question which probably requires a novel experimental design to answer convincingly. (As noted above, the required laboratory setting of the forced desynchrony paradigm is inappropriate for observation of naturalistic behavior.) For example, would utilizing light to shift the rhythm in the central circadian pacemaker also shift the behavioral patterns, thus indicating that their causal chain includes signals from the pacemaker? An incremental step towards establishing stronger evidence of circadian regulation in future studies would be to include a direct physiological measure of participants' circadian phase (e.g., core body temperature) rather than relying on the mean waketime as an observable proxy thereof (thus perfectly confounding circadian effects with those due to time spent awake). Admittedly, as it stands, it is ultimately impossible for this study to provide unambiguous evidence for the circadian nature of the effects. Although there is converging support for the fact that the sinusoidal pattern we identified in everyday behaviors associated with PA is likely not just a result of social zeitgebers such as a person's daily schedule, at the most basic level, this study only unambiguously identified diurnal rhythms that are centered around a person's mean wake-up time (rather than the time of the day).

Further, future research should replicate this finding using more diverse sets of affect-associated behaviors, not only those that can readily be detected from ambient sounds. Finally, previous findings have occasionally been inconsistent with regard to the lack of diurnal patterning to self-reported NA (e.g., Stone, Smyth, Pickering, & Schwartz, 1996). Thus, future studies should include NA-associated behaviors with higher base rates that can help rule out the possibility that the apparent lack of diurnal patterning for arguing and sighing in this study was in part driven by a floor effect.

To conclude, the preliminary nature of our findings demands that all above interpretation remain speculative. With this caution in mind, our data extend previous reports of diurnal rhythmicity in PA in consequential ways. Specifically, they imply that there is not only a systematic pattern to how individuals are feeling on a momentary basis, but potentially also to how momentary feelings translate into action. In contrast to the stance that mood affects cognition more than action (Davidson, 1994), our findings suggest that positive mood patterns, while subtle and often unnoticed in conscious daily experience, may be shaping the *timing* of our behavior in ways critically important to our success in endeavors both personal and professional.

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