Dynamic fluctuations of emotional states in adolescents with delayed sleep phase-A longitudinal network modeling approach

Elovainio, Marko

2020-11-01

Elovainio , M , Kuula , L , Halonen , R & Pesonen , A-K 2020 , ' Dynamic fluctuations of emotional states in adolescents with delayed sleep phase-A longitudinal network modeling approach ' , Journal of Affective Disorders , vol. 276 , pp. 467-475 . https://doi.org/10.1016/j.jad.2020.07.050

http://hdl.handle.net/10138/332500
https://doi.org/10.1016/j.jad.2020.07.050

14.5.2020

Manuscript

Dynamic fluctuations of emotional states in adolescents with delayed sleep phase—a longitudinal network modeling approach

Marko Elovainio, PhD [1,2]
Liisa Kuula, PhD [1]
Risto Halonen, MPsyc [1]
Anu-Katriina Pesonen, PhD [1]

[1] SleepWell Research Program Unit, Department of Psychology and Logopedics, Faculty of Medicine, University of Helsinki, Finland
[2] National Institute for Health and Welfare, Finland

Correspondence: Marko Elovainio, University of Helsinki, P.O. Box 9, 00014, Helsinki, Finland
Phone: +358 50 3020621, email: marko.elovainio@helsinki.fi

Word count for abstract / main text: / 250 / 3531
Number of tables and figures: 1 Table / 3 figures

Funding: Academy of Finland

ABSTRACT

Background: Very late sleep rhythms are risks for social adjustment problems in adolescence. Using ecological momentary assessment data, we quantified and visualized temporal and contemporaneous within-persons dynamical relations of sleepiness and emotions in adolescents with and without late sleep rhythms.

Methods: We analyzed a temporal network via multilevel vector autoregression (mlVAR) modeling and a contemporaneous network through the partial associations between the residuals of temporal and the between-subject multilevel models. We tested whether these networks were different between those with a late circadian rhythm [concurrent delayed sleep phase (DSP) N = 172, 37% boys, 63% girls] and those without (N = 143, 22% boys, 78% girls).

Results: In adolescents without DSP, the temporal networks showed continuity only for low mood from the previous to the following time point. In adolescents with DSP, there were more predictable patterns of emotions. Feelings of depression led to a decrease of positive emotions and increase of irritation and anxiety. The contemporaneous networks showed clusters of positive and negative emotions in both groups and sleepiness decreased the experience of positive emotions concurrently.

Limitations: DSP in our current study was based only on one out of three diagnostic criteria of the full disorder (DSM-5) and it was assessed only once.

Conclusions: These findings indicate that the dynamic organization of emotions and sleepiness is different in adolescents with and without DSP. DSP adolescents have more predictable and maladaptive emotional patterns during the day. Results provide new insight about why individuals with DSP are at a heightened risk for decreased emotional adjustment.

INTRODUCTION

Globally, adolescents are sleeping fewer hours than they need (Owens, Adolescent Sleep Working et al. 2014). This is followed by daytime sleepiness and symptoms of fatigue. Recent surveys indicate a very high prevalence for hypersomnolence symptoms (>40% in U.S. youth), excessive daytime sleepiness (>60% in Brazilian youth), or mild daytime sleepiness (>20% in Chinese youth) during adolescence (Kolla, He et al. 2019, Meyer, Ferrari Junior et al. 2019, Wang, Liu et al. 2019). Not surprisingly, daytime sleepiness has been associated with poorer sleep and a higher risk of having mental health problems (Kolla, He et al. 2019).

To better understand adolescent development and the underlying processes, a closer look at the dynamics of daytime sleepiness and emotional processes is needed. While a body of evidence shows that quality of sleep and related alertness are associated with negative and positive emotional states (Caldwell, Caldwell et al. 2004, Kahn-Greene, Killgore et al. 2007, Paterson, Dorrian et al. 2011, Watling, Pawlik et al. 2017), little is known about their temporal dynamics. Most of the studies have attempted to examine these associations independently (e.g., the effects of sleepiness on emotions and the effects of emotions on sleepiness), but such separation does not reflect the complexity of their mutual dependencies. Moreover, there appears to be a “vicious cycle” as daytime sleepiness may compromise emotional regulation, which in many cases leads to increased negative emotion that in turn disrupts sleep, leading to further impairments in alertness and emotional wellbeing (Mauss, Troy et al. 2013). Understanding these dynamic and complex co-occurring processes and their underlying mechanisms is of great importance to understand developmental processes in adolescence, often driven by the common condition of chronically insufficient sleep (Shochat, Cohen-Zion et al. 2014).

Regarding the dynamics between daytime sleepiness and mood in adolescence, one group of adolescents is of specific interest: adolescents having a very late sleep rhythm, or delayed sleep phase (DSP), which is a subclinical form of the delayed sleep phase disorder (DSPD). DSP is often defined as having some of the three symptoms of the full disorder—most often the persistently very late sleep rhythm. In population-based studies, this has been operationalized, for example, as falling asleep after 1 a.m. at least 3 days per week (Danielsson, Markstrom et al. 2016). DSP in adolescence is often followed by negative consequences in school performance (Gradisar and Crowley 2013), and it has been associated with depression, anxiety, and symptoms of ADHD (Sivertsen, Harvey et al. 2015). However, it is unclear how excessive daytime sleepiness and mood are temporally organized. Tracking the daily fluctuations would give much needed understanding of the topic.

However, feasible methods to measure and analyze complexity between sleepiness and mood or other psychological processes have been scarce. To address the temporal dynamics, a method called ecological momentary assessment (EMA), which uses repeated measurements of multiple state-like factors with relatively short follow-up intervals, is needed. Regarding EMA and sleep, previous studies have shown that experiences of fatigue in diseases such as multiple sclerosis (Kratz, Murphy et al. 2017, Powell, Liossi et al. 2017) vary dynamically across the day, and emotions are associated with these fluctuations (Powell, Liossi et al. 2017). Previous studies have also shown that the experiences of psychological problems fluctuate over time, such as suicidal ideation, even from hour to hour (Hallensleben, Spangenberg et al. 2017), and there are large intrapersonal differences in these fluctuations.

Recently, a psychological network approach and related tools to analyze dynamic relationships among multiple psychological variables have been developed (Epskamp, Cramer et al. 2012, Epskamp 2015). The basic idea behind the psychological network approach is that various psychological states and problems develop as a result of the interaction among individual symptoms or risk factors (Borsboom 2017). For example, troubles in sleeping may result in concentration problems, which may lead to more rumination and daytime sleepiness, which in turn may lead to negative emotional states. When the relations among these risk factors are sufficiently strong, they can be self-sustained via a negative feedback loop.

Network analysis has so far mostly been applied to cross-sectional data but can also be applied to EMA data using vector autoregression (VAR) techniques, in which a variable at a certain time point (t1) is predicted by the same variable at the previous time point (t–1) (autoregressive effects) and all other variables at t–1 (cross-lagged effects) (Epskamp, Waldorp et al. 2018). These autoregressive and cross-lagged effects can be quantified and visualized in a network. The network analyses with VAR techniques have extended more traditional multilevel analysis by estimating and visualizing the co-occurrence of multiple variables, allowing generation of hypotheses about the potential dynamic process among multiple variables. By allowing VAR coefficients to differ across individuals via multilevel modeling, it is possible to model and visualize temporal dynamics between sleepiness and mood at the group level. Thus, network analyses could guide researchers and clinicians toward more complex and dynamic thinking about psychological states (Fried, van Borkulo et al. 2017), such as sleepiness and emotional states. As far as we know, there are no published studies focusing on the dynamics of emotional states using longitudinal network approach, although some studies have modelled psychiatric problems, including suicidality (Rath, de Beurs et al. 2019) and auditory verbal hallucinations (Jongeneel, Aalbers et al. 2020)."

Network analysis extends standard time series analysis, such as hierarchal linear modeling, by offering a visual representation of the relations among all assessed variables. In our study, we applied the VAR method to examine the dynamic associations between daytime sleepiness and emotional states, including being depressed, anxious, content, irritated, and happy. To increase understanding of the effects of very late sleep rhythms on sleepiness and emotions, we compared the sleepiness-emotion networks between those with a concurrent DSP and those without classified based on actigraphy measurements.

METHODS

Sample and procedure

This research is part of the population-based cohort study SleepHelsinki!. Originally, the Finnish Population Registry was utilized to identify all Finnish adolescents born between January 1, 1999, and December 31, 2000 (n=10,476), who resided in Helsinki and whose native language was registered as Finnish (72% of the total sample). The register thus included 7,539 adolescents (3,789 born in 1999 and 3,750 born in 2000), of whom 50% were boys. We sent invitation letters to all registered adolescents to participate in the SleepHelsinki! study Phase 1, which consisted of an online survey primarily targeting sleep, health, and behavior. The estimated time for filling in the questionnaire was 30 minutes.

Altogether, 1,411 adolescents (19% of the initial cohort) responded to the online survey, with valid responses from 1,374 (18%) participants. The age of the respondents did not differ from the initial cohort mean age ($p = 0.34$), but the respondents were more often girls (66%, $p < 0.0001$). All respondents signed an electronic consent form for Phase 1. Ethical permission was obtained from The Hospital District of Helsinki and Uusimaa Ethics Committee for gynecology and obstetrics, pediatrics, and psychiatry (Decision number 50/13/03/03/2016). The study is registered under Clinical Trials (ID: 1287174).

The SleepHelsinki! study (total N = 552) focused on late sleep rhythms. Based by online survey questionnaire two subsamples: (A) those without (N=188) and (B) those with late sleep rhythms (N=364) were identified and invited to participate in the EMA phase. The criteria for belonging to the late sleep phase group was reporting bedtime after 1 a.m. at least three times per week. Out of these 552 adolescents, 353 agreed to participate and 24 dropped out before completing the EMA phase, leaving us with a sample of 329 adolescents. The EMA period of the study was conducted between November 2016 and December 2017. The data for this study were thus from late adolescence (mean age 16.9 years, SD = 0.6) when the EMA measurements were done. A total of 315 participants provided usable EMA data and formed the final analyses sample.

The participants underwent a minimum 7-day EMA assessment with three signal-contingent assessments per day using the “Psymate” software, resulting in a maximum of 66 assessments per participant. The first EMA signal was scheduled in the morning (around 8–10 a.m.), the second in the afternoon (1–5 p.m.), and the final in the evening (around 8–10 p.m.). Participants could postpone a prompt for 30 minutes if they were not able to answer the questions immediately, and they had the possibility to reject a prompt. The data set consisted of 4,348 observations (315 persons).

Additionally, adolescents’ sleep timing was measured using accelerometers (GeneActiv Original, Kimbolton, UK) to determine and confirm possible DSP tendencies. Mean sleep duration in those with DSP was 7:23 hours (SD=1:01) and in those without 8:09 hours (SD=0:43). The sleep mid-point in those with DSP was 5:31 (SD=1:05) and in those without 3:50 (SD=0:36).

Measures

During the EMA assessment, participants rated their momentary sleepiness-perceived depressiveness, anxiousness, irritation, contentedness, and happiness by answering a structured 14-item questionnaire. At each measurement point, participants reported how alert vs. sleepy they felt during the last 10 minutes on a 9-point scale with 5 anchors (1 = very alert; 3 = alert; 5 = neither alert nor sleepy; 7 = sleepy but no trouble staying awake; and 9 = very sleepy, fighting to stay awake) (Karolinska Sleepiness Scale, KSS).

Additionally, participants reported how they felt using two positive effect and three negative effect items using 7-point scales from 1 (not at all) to 7 (very much). These specific emotions were chosen to include those most frequently appearing in several longer affect checklists (Diener and Emmons 1984, Watson, Clark et al. 1988). The constructs represented were depression, anxiety (worried), and hostility (irritated) on the negative affect side. Activation (energetic/ sleepiness) and positive feelings (happy, and content) were represented on the positive side. The list was required to be short to facilitate its use over multiple daily assessments.

The actigraphy measurements covered a minimum of 3 nights (range 3–12 nights) and yielded a binary classification of concurrent DSP tendency. This information was calculated based on going to sleep after 1 a.m. at least three times per week. The classification was used to compare the emotional responses of those with weaker circadian control to those without. Based on the actigraphy measurements 172 participants were classified as having a late circadian rhythm and having a concurrent delayed sleep phase (DSP) and 143 were classified as not having DSP (non-delayed sleep phase / non-DSM) circadian rhythm. Of those with DSM 63% were girls and of those with non-DSM 78% were girls ($X^2 = 8.22$, df = 1, p-value = 0.004 for sex difference). Parental education was used as a measure of parental socio-economic status (SES). Participants were asked to report the highest educational attainment of their parents, and the highest report was selected as the basis for classifying participants' SES as (1) lower (2) middle, or, (3) upper. Lower SES included minimum compulsory educational attainment. Education attained beyond this (i.e. vocational school, technical college) was classified as middle level SES. SES was classified as upper level if either parent had university level degree. Most of the parents of those in DSP (N= 119, 73%) and in those non-DSP (N = 105, 77%) belonged to the highest SES category. There were no differences in parental socioeconomic status measured as education (lower / middle/ upper) between the DSP and non -DSP group (X2(2) = 0.83, p = 0.66).

Statistical analysis

To estimate the different network structures over all participants, we applied multilevel vector autoregression (mlVAR) models on the data (Epskamp, Waldorp et al. 2018), as implemented within the mlVAR package in R. In conducting the analyses and presenting the results we mostly followed the procedure presented by Jongeneel and others (Jongeneel, Aalbers et al. 2020). Temporal dynamics within individuals are estimated by regressing scores of an emotion at time t on a previous (i.e., lagged) value of itself at t-1. VAR modeling indicates that all variables at time t are regressed on a t-1 version of themselves, resulting in a vector of lagged regression coefficients (fixed effects). The multilevel modeling allows the VAR coefficients to differ between individuals (random effects), and a temporal network was estimated. When visualizing the networks in a two-dimensional graph, we used the Fruchterman-Reingold (FR) algorithm, which places nodes that are highly connected in the center of the network. The estimates of between-subject effects, the sample means within subjects, were used as predictors. The contemporaneous network was estimated using the residuals of the multilevel model that were used to estimate the temporal and between-subject effects (Epskamp, Waldorp et al. 2018).

In the graphical representation of the network, variables are presented as nodes. These networks are called temporal networks because they can be indicative of potential causality given that one variable preceded the other in time. Epskamp et al. (2018) introduced an additional network for estimating EMA data (a contemporaneous network) that can be used in the partial association between the residuals of the temporal network that are the result of associations between the variables that are not explained by the current chosen time interval, the chosen lag, or anything else that is not explicitly measured and modeled. In the contemporaneous network, the edges between nodes represent the partial correlation obtained after controlling for both temporal effects and all other variables in the same window of measurement (Epskamp, Waldorp, Mõttus, & Borsboom, 2017; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). When data are collected from multiple subjects, between-person networks using EMA data may also be estimated. Between-subject predictors are calculated using the covariance structure of stationary means. In addition, we calculated the centrality measures of each symptom in each network (strength centrality identifies how well each emotion in a network is associated with the other emotions). We calculated the strength of the nodes for all networks, using the R package qgraph (Epskamp et al., 2012). In the temporal network centrality indicates both how well each emotion is predicted by others (in-strength) and how well it predicts others (out-strength).

Variables were standardized before estimation and scaled within persons via mlVAR. Networks were presented using the graph package in R.

RESULTS

Means and standard deviations for all emotions and sleepiness in those with and without DSP are presented in Table 1 and the distribution of the emotions in the high and low sleepiness group in Figure 1. Those with DSP more often experienced anxiety, depression, and irritation, and those without DSP more often were happy and content. There were no differences in sleepiness reporting between the groups. Only small differences were found in distributions of emotion reporting between those with and without DSP (Figure 1). Girls were slightly less happy (mean 4.34 vrs. 4.81, p-value 0.006), less content (mean 4.46 vrs. 5.04, p-value 0.002), and more anxious (mean 2.32 vrs. 1.88, p-value 0.025) than boys.

Temporal networks

The temporal network including the directed associations is based on time series EMA data that was analyzed with timelags. All variables at a certain measurement point is predicted by the same variable and all other variables at the previous measurement point providing information about the temporal multivariate relations. All coefficients are allowed to differ across individuals by using multilevel modeling, and thus time dynamics are possible to model and visualize at the group level. The left top panel in Figure 2 shows how emotions predicted themselves (autoregressions) and each other across time (adjusted predictions) in those without DSP and the left bottom panel in those with DSP. Green lines represent positive and red lines (dotted) represent negative associations. The thickness of the line corresponds to the strength of the association. The panels in the right-hand side show the centrality measures.

In individuals without DSP, there were no significant patterns observable in the fluctuation of emotions except a bidirectional loop between depression and irritation (0.12, p = 0.002/0.06, p = 0.17) and a continuous loop within depression and anxiety. In individuals with DSP, there were several significant patterns in the temporal fluctuations of emotions. Feelings of depression led to a decrease of positive emotions (depressed -> happy, -0.074, p = 0.032 and depressed -> content -0.100, p = 0.004) and increase of irritation (0.09, p = 0.006) and anxiety (0.08, p =0.005) in the next measurement point. Irritation led both to a more positive mood (irritated -> happy, 0.088, p = 0.001, irritated -> content 0.057, p = 0.030) and less sleepiness (-0.080, p = 0.009) and also to a less anxious state of mind (-0.07, p = 0.003). None of the emotional states were predicted by sleepiness (p-values of fixed effects coefficient from sleepiness to emotional states all non-significant. Being anxious predicted sleepiness (0.08, p = 0.04) and happiness (-0.09, p = 0.005). Only depressiveness and anxiousness predicted themselves in the consecutive measurement points.

In the temporal network, irritation had the highest on in-strength in those without DSP and happiness in those with DSP, which shows that these emotions were most strongly predicted by other emotions in these groups. In those without depressiveness and in those with DSP irritation and depressiveness had high out-strength, meaning that their outgoing temporal associations were relatively high (compared to other emotions in the network). However, considering the small number of associations (edge weights) in those without DSP, it appears that none of the emotions are strong predictors of other emotions.

Contemporaneous networks

The contemporaneous network, including all separate measurement points of each variable, investigates concurrent relations between emotions. These relations are controlled for temporal effects and all other emotions the same timepoint to compute a partial (independent of other associations) correlations network and thus takes the temporal relationship into account. The relationships within a measurement point can be separately analyzed from relationships between timepoints in temporal models. In other words, it shows how emotions tend to co-occur at the same moment, controlling for all other emotions at the same moment and for all temporal relations among emotions.

Figure 3 shows the contemporaneous network between sleepiness and emotions in individuals with and without DSP. The contemporaneous networks showed a clustering of positive and negative emotions in both groups. Specifically, both sleepiness and irritation decreased the experience of positive emotions concurrently. The contemporaneous networks were strikingly similar in both groups. However, there were also subtle differences. In individuals with DSP, sleepiness was associated only with decreased positive emotions, whereas in individuals without DSP, sleepiness was in inverted association with irritation and in positive association with depression. In both groups, positive emotions and depressiveness had the highest strength centrality.

Between subject network

Similarly, the between-individual networks (Figure 4) shows the pair-wise associations among the mean levels of emotions over all measurement points, when adjusting for the mean levels of all other emotions in the network. The between-subjects model is comparable to cross-sectional analyses. In general, a positive connection between depressiveness, irritation and anxiety in this analysis indicate that people with higher scores on depressiveness during a week tend to have higher scores on anxiety/irritation during the same period and vice versa. In both DSP groups, positive and negative emotions were again associated with each other and in that sense the results presented in Figure 4 were relatively similar to those of the contemporaneous networks. In those without DSP, happiness was negatively associated with irritation but in those with DSP, happiness was negatively associated with depressiveness. Sleepiness was negatively associated sleepiness in DSP whereas in non-DSP group sleepiness was associated with irritation. In those without DSP the most central emotion was irritation, but in those with DSP it was happiness.

DISCUSSION

Poor sleep patterns, sleepiness, and related emotional states form a complex network of associations that fluctuate over time. As far we know, no studies thus far have focused on delayed sleep phase and investigated how it affects everyday emotions. In our study, we applied mlVAR models to analyze the temporal and contemporaneous associations between sleepiness and multiple emotional states and analyzed whether these networks were different between those suffering from very late sleep rhythm (DSP) and others. Previous research suggests that DSP is associated with elevated anxiety and depression scores (Saxvig, Pallesen et al. 2012) and other problems relating to emotion regulation as well as mental health problems (Sivertsen, Harvey et al. 2015). The causes behind DSP are multiple: biological mechanisms and those relating to psychological wellbeing are prominent in delaying sleep phase, especially during adolescence (Micic, Lovato et al. 2016). The same pathways that might lead to DSP are likely to result in poorer emotional welfare because anxiety and rumination tend to result in later sleep onset times—these phenomena may also occur reciprocally with late sleep timing (Hiller, Lovato et al. 2014, Stewart, Gibb et al. 2018). On the other hand, a lack of self-regulating skills is likely to be associated with later sleep timing or delayed sleep phase (Owens, Dearth-Wesley et al. 2016). These overall associations have been reported in several studies (Gradisar and Crowley 2013). However, it is not known how these general challenges are related to dynamic fluctuations of emotions during the day.

In our study, individuals with DSP reported higher average levels of irritation, depressiveness, and anxiousness and lower levels of contentedness and happiness than those without. This observation is in line with findings from a large American study investigating over 10,000 adolescents aged 13–18 years. They reported increased risks of mental problems, suicidality, and mood disorders in relation to greater bedtime delay, and they also found that adolescent sleep behavior deviated substantially from recommended optimal standards, which was also the case in our current study (Zhang, Paksarian et al. 2017). We found that, specifically in individuals with

DSP, there were several significant patterns in the temporal fluctuations of emotions, whereas in individuals without DSP, the only temporal associations were seen in the bidirectional loop between depression and irritation and in the continuity of anxiety. In the DSP group, feeling depressed led equally to irritation and anxiety but also to feeling less happy and content at the following measurement point. Interestingly, in the DSP group, feelings of irritation seemed to be a driving node that led to feeling less sleepy, happier, and more content and equally less anxious. While depression preceded irritation, it could show how irritation may function as a catalyst emotion to feel better.

Without negative feedback loops between emotions unbalanced states that are never able to recover or reach any positive state of mind would result. Thus, at some point, there need to be a recovery from negative emotion and in DSP adolescents, and feeling irritated was such as node. Irritation is not only a negative emotion, but the arousal associated with this emotion may also potentiate self-directed action to solve the situation causing irritation and then lead to recovery of the emotion. For adolescents, the irritation maybe also a more frequent emotional response compared to adults, and, according to the current findings, an important trigger to get out of the negative emotion loop.

Unexpectedly, sleepiness was not a driving state of mind for specific emotions in the next time point in either the DSP or non-DSP group; thus, none of the emotional states were predicted by sleepiness in the previous time point. The DSP group did not report more daytime sleepiness than the non-DSP group. In objective measurements, they had a later sleep rhythm of 1 hour and 40 minutes, but the difference in sleep duration was only 45 minutes. The mean sleep duration in the DSP group was over 7 hours during the measurement period, suggesting a sub-optimal but still reasonable amount of sleep. Previous studies have shown that partial daily sleep restriction of 2–4 hours increases subjective sleepiness (Lo, Groeger et al. 2012, Slobodanka, Basta et al. 2013). It was recently reported that restricting sleep for 1 hour over 6 days caused increased sleepiness (Santisteban, Brown et al. 2019). In that study, however, a similar impact was observed in the control group with a placebo treatment (sham restriction), which suggests subjective sleepiness to be affected by the individual's conception of obtained sleep. Accordingly, the DSP group in our study may regard their conventional sleep amount sufficient.

Nevertheless, while sleepiness had no association with any of the emotions in temporal networks, it was positioned as expected in the contemporaneous network. It showed how feeling sleepy associated with being less happy and content; thus, sleepiness was associated with reduced positive emotion. Only in the non-DSP group, sleepiness associated also with increased depression. In both the DSP and non-DSP groups, the different negative and positive feelings appeared as separate clusters that were inversely correlated.

Although a large body of evidence suggests that poor sleep increases the experience of negative emotions, reduces the occurrence of positive emotions, and changes the ways in which individuals experience, understand, express, and regulate these emotions (Walker and van der Helm 2009, Kahn, Sheppes et al. 2013), only a few studies have been able to model and analyze the dynamic, ongoing process of emotion generation. The strength of the network analyses and specifically the mlVAR models is the ability to model such complex and potentially causal relationships. The finding that irritation, rather than depression or anxiety, is the key emotion in long-term emotional generation and regulation is to be replicated in future studies. This result would be in line with a body of research showing an association between sleep deprivation and increased anger and aggression, which was found in men and women and across various age groups (Saghir, Syeda et al. 2018).

Similar findings were obtained by the previous study using EMA in those with and without psychiatric disorders. Cousins and co-workers (2011) found that although the relationships between individual emotions and sleep duration were strongly dependent on present psychiatric disorders, more time asleep was associated with more positive affect for all diagnostic groups the following day. However, in adolescents with diagnosed depression disorders, positive emotions were associated with longer sleep duration in the following night. Higher daytime positive affect in those with anxiety disorders was associated with less time in bed (Cousins, Whalen et al. 2011).

The findings from the contemporaneous network models as compared to the ones from the temporal network models suggest that the emotions that we normally think follow each other, in fact, does that very rapidly or basically are present simultaneously. That means that positive emotions co-occur with other positive emotions and negative with other negative emotions. These rapid predictions or co-occurrences followed very similar patterns in both DSP groups. Fluctuations from positive to negative and from negative to positive happens with a time lag and that fluctuation seems to be more apparent in those with DSP.

Limitations

There are some limitations that need to be considered. First, the definition of DSP in our current study was based only on one out of three diagnostic criteria of the full disorder (DSM-5). The very late sleep rhythm was also assessed only once, without knowing whether it referred to persistently late or transiently late sleep rhythm. False classifications are possible regarding subclinical DSP. Nevertheless, the sleep rhythm was defined with actigraphy, which increases reliability of the assessment. Although EMA has multiple strengths compared to surveys and other measurement techniques, the intensive nature of EMA studies makes it very difficult to scale up the number of participants. The participants also must be trained in the use of devices and programs. However, the target population of this study was probably very familiar with both phones and the types of devices used. Given the considerable respondent burden involved, there was a risk of selective drop out (those with DSP sleepiness, depression, or anxiety would not respond). In our study, the mean number of responses was larger in those with DSP than those without. However, in general, it would have been preferable to be able to gather more observations per participant from the mlVAR modeling. One clear advantage of the temporal network over conventional statistical models is that associations are bidirectional meaning that all variables are simultaneously predictors and outcomes which provides information about the temporal multivariate relations in the data.

There were more girls than boys in our sample but larger share of boys belonged to the DSP group. Thus, although the potential effects of gender differences on the association between emotions is probably small, that needs to be confirmed in the future studies. Our data were mostly collected during the school year, and data collection was paused for the summer holidays. The actigraphy measurement period was aimed to represent typical sleep behavior, and we found no differences between DSP groups across the representativeness of all seven weekdays. We can't rule out bias due to residual confounding as this was an observational study. One factor potentially causing such bias, is socioeconomic status of the family, that may associate with both DSP and emotions. However, there were no differences in parental socioeconomic status between DSP and non-DSP groups in our sample and thus that could have technically not been a confounder in the models.

Conclusions

A delayed sleep phase is extremely common in adolescents but rarely studied beyond sleep behavior or sporadic health effects. Our study explores practical implications that emerge in everyday life. The findings in our study highlight that DSP is related to higher levels of irritation, depressiveness, and anxiousness and lower levels of contentedness and happiness than those with earlier sleep phases. This suggests that DSP may play a part in every reaction and every emotion a teenager experiences and thus further emphasizes the need for support for those with DSP.

REFERENCES

Borsboom, D. (2017). "A network theory of mental disorders." World Psychiatry **16**: 5-13.
Caldwell, J. A., J. L. Caldwell, J. K. Smith and D. L. Brown (2004). "Modafinil's effects on simulator performance and mood in pilots during 37 h without sleep." Aviat Space Environ Med **75**(9): 777-784.
Cousins, J. C., D. J. Whalen, R. E. Dahl, E. E. Forbes, T. M. Olino, N. D. Ryan and J. S. Silk (2011). "The bidirectional association between daytime affect and nighttime sleep in youth with anxiety and depression." J Pediatr Psychol **36**(9): 969-979.
Danielsson, K., A. Markstrom, J. E. Broman, L. von Knorring and M. Jansson-Frojmark (2016). "Delayed sleep phase disorder in a Swedish cohort of adolescents and young adults: Prevalence and associated factors." Chronobiol Int **33**(10): 1331-1339.
Diener, E. and R. A. Emmons (1984). "The independence of positive and negative affect." Journal of Personality and Social Psychology **47**: 1105-1117.
Epskamp, S. (2015). "bootnet: Bootstrap methods for various network estimation routines." R-package.
Epskamp, S., A. O. Cramer, L. J. Waldorp and e. al. (2012). "qgraph: network visualizations of relationships in psychometric data. ." J Stat Softw **12**: 1-18.
Epskamp, S., L. J. Waldorp, R. Mottus and D. Borsboom (2018). "The Gaussian Graphical Model in Cross-Sectional and Time-Series Data." Multivariate Behav Res: 1-28.
Fried, E. I., C. D. van Borkulo, A. O. Cramer, L. Boschloo, R. A. Schoevers and D. Borsboom (2017). "Mental disorders as networks of problems: a review of recent insights." Soc Psychiatry Psychiatr Epidemiol **52**(1): 1-10.
Gradisar, M. and S. J. Crowley (2013). "Delayed sleep phase disorder in youth." Curr Opin Psychiatry **26**(6): 580-585.
Hallensleben, N., L. Spangenberg, T. Forkmann, D. Rath, U. Hegerl, A. Kersting, T. W. Kallert and H. Glaesmer (2017). "Temporal Dynamics of Suicide Thoughts. First Results of an Ecological Momentary Assessment Study in Inpatients with depressive Disorders." Zeitschrift Fur Psychosomatische Medizin Und Psychotherapie **63**(1): 60-61.
Hiller, R. M., N. Lovato, M. Gradisar, M. Oliver and A. Slater (2014). "Trying to fall asleep while catastrophising: what sleep-disordered adolescents think and feel." Sleep Med **15**(1): 96-103.
Jongeneel, A., G. Aalbers, I. Bell, E. I. Fried, P. Delespaul, H. Riper, M. van der Gaag and D. van den Berg (2020). "A time-series network approach to auditory verbal hallucinations: Examining dynamic interactions using experience sampling methodology." Schizophr Res **215**: 148-156.
Kahn, M., G. Sheppes and A. Sadeh (2013). "Sleep and emotions: bidirectional links and underlying mechanisms." Int J Psychophysiol **89**(2): 218-228.
Kahn-Greene, E. T., D. B. Killgore, G. H. Kamimori, T. J. Balkin and W. D. Killgore (2007). "The effects of sleep deprivation on symptoms of psychopathology in healthy adults." Sleep Med **8**(3): 215-221.
Kolla, B. P., J. P. He, M. P. Mansukhani, S. Kotagal, M. A. Frye and K. R. Merikangas (2019). "Prevalence and Correlates of Hypersomnolence Symptoms in US Teens." J Am Acad Child Adolesc Psychiatry **58**(7): 712-720.
Kratz, A. L., S. L. Murphy and T. J. Braley (2017). "Ecological Momentary Assessment of Pain, Fatigue, Depressive, and Cognitive Symptoms Reveals Significant Daily Variability in Multiple Sclerosis." Arch Phys Med Rehabil **98**(11): 2142-2150.

Lo, J. C., J. A. Groeger, N. Santhi, E. L. Arbon, A. S. Lazar, S. Hasan, M. von Schantz, S. N. Archer and D. J. Dijk (2012). "Effects of partial and acute total sleep deprivation on performance across cognitive domains, individuals and circadian phase." PLoS One **7**(9): e45987.
Mauss, I. B., A. S. Troy and M. K. LeBourgeois (2013). "Poorer sleep quality is associated with lower emotion-regulation ability in a laboratory paradigm." Cogn Emot **27**(3): 567-576.
Meyer, C., G. J. Ferrari Junior, R. D. Andrade, D. G. Barbosa, R. C. da Silva, A. Pelegrini and E. P. Gomes Felden (2019). "Factors associated with excessive daytime sleepiness among Brazilian adolescents." Chronobiol Int **36**(9): 1240-1248.
Micic, G., N. Lovato, M. Gradisar, S. A. Ferguson, H. J. Burgess and L. C. Lack (2016). "The etiology of delayed sleep phase disorder." Sleep Med Rev **27**: 29-38.
Owens, J., G. Adolescent Sleep Working and A. Committee on (2014). "Insufficient sleep in adolescents and young adults: an update on causes and consequences." Pediatrics **134**(3): e921-932.
Owens, J. A., T. Dearth-Wesley, D. Lewin, G. Gioia and R. C. Whitaker (2016). "Self-Regulation and Sleep Duration, Sleepiness, and Chronotype in Adolescents." Pediatrics **138**(6).
Paterson, J. L., J. Dorrian, S. A. Ferguson, S. M. Jay, N. Lamond, P. J. Murphy, S. S. Campbell and D. Dawson (2011). "Changes in structural aspects of mood during 39-66 h of sleep loss using matched controls." Appl Ergon **42**(2): 196-201.
Powell, D. J. H., C. Liossi, W. Schlotz and R. Moss-Morris (2017). "Tracking daily fatigue fluctuations in multiple sclerosis: ecological momentary assessment provides unique insights." J Behav Med **40**(5): 772-783.
Rath, D., D. de Beurs, N. Hallensleben, L. Spangenberg, H. Glaesmer and T. Forkmann (2019). "Modelling suicide ideation from beep to beep: Application of network analysis to ecological momentary assessment data." Internet Interv **18**: 100292.
Saghir, Z., J. N. Syeda, A. S. Muhammad and T. H. Balla Abdalla (2018). "The Amygdala, Sleep Debt, Sleep Deprivation, and the Emotion of Anger: A Possible Connection?" Cureus **10**(7): e2912.
Santisteban, J. A., T. G. Brown, M. C. Ouimet and R. Gruber (2019). "Cumulative mild partial sleep deprivation negatively impacts working memory capacity but not sustained attention, response inhibition, or decision making: a randomized controlled trial." Sleep Health **5**(1): 101-108.
Saxvig, I. W., S. Pallesen, A. Wilhelmsen-Langeland, H. Molde and B. Bjorvatn (2012). "Prevalence and correlates of delayed sleep phase in high school students." Sleep Med **13**(2): 193-199.
Shochat, T., M. Cohen-Zion and O. Tzischinsky (2014). "Functional consequences of inadequate sleep in adolescents: a systematic review." Sleep Med Rev **18**(1): 75-87.
Sivertsen, B., A. G. Harvey, S. Pallesen and M. Hysing (2015). "Mental health problems in adolescents with delayed sleep phase: results from a large population-based study in Norway." J Sleep Res **24**(1): 11-18.
Slobodanka, P., M. Basta, A. Vgontzas, I. Kritikou, M. Shaffer, M. Tsaoussoglou, D. Stiffler, Z. Stefanakis, E. Bixler and G. P. Chrousos (2013). "Effects of recovery sleep after one work week of mild sleep restriction on interleukin-6 and cortisol secretion and daytime sleepiness and performance." Am J Physiol Endocrinol Metab(305): E890–E896,.
Stewart, E., B. Gibb, G. Strauss and M. Coles (2018). "Disruptions in the Amount and Timing of Sleep and Repetitive Negative Thinking in Adolescents." Behav Sleep Med: 1-9.
Walker, M. P. and E. van der Helm (2009). "Overnight therapy? The role of sleep in emotional brain processing." Psychol Bull **135**(5): 731-748.
Wang, Z. Y., Z. Z. Liu, C. X. Jia and X. Liu (2019). "Age at menarche, menstrual problems, and daytime sleepiness in Chinese adolescent girls." Sleep **42**(6).

Watling, J., B. Pawlik, K. Scott, S. Booth and M. A. Short (2017). "Sleep Loss and Affective Functioning: More Than Just Mood." Behav Sleep Med **15**(5): 394-409.
Watson, D., L. A. Clark and A. Tellegen (1988). "Development and validation of brief measures of positive and negative affect: The PANAS scales." Journal of Personality and Social Psychology **54**: 1063-1070.
Zhang, J., D. Paksarian, F. Lamers, I. B. Hickie, J. He and K. R. Merikangas (2017). "Sleep Patterns and Mental Health Correlates in US Adolescents." J Pediatr **182**: 137-143.

Figure 1. The distributions of sleepiness and emotional states in those with and without DSP

Figure 2. Temporal networks of sleepiness and emotional states according to DSP status. The green lines represent positive and red negative partial correlations. Strength centrality represent the extent how well a node is connected to other nodes. A high in-strength means the node is strongly predicted by other nodes and high out-strength means that the node is a strong predictor of other nodes.

Figure 3. Contemporaneous networks of sleepiness and emotional states according to DSP status. The green lines represent positive and red negative partial correlations. Strength centrality represent the extent how well a node is connected to other nodes.

Figure 4. Between – subject networks of sleepiness and emotional states according to DSP status. The green lines represent positive and red negative partial correlations. Strength centrality represent the extent how well a node is connected to other nodes.

Table 1. Emotional states and number of measurements by groups of DSP

Means and (SD)

	No N=1,833	Yes N=2,293	p-value
Sleepiness during the day (range 1–8)	4.52 (1.99)	4.56 (1.91)	0.505
Feeling happy (range 1–7)	4.59 (1.37)	4.43 (1.42)	0.001
Feeling content (range 1–7)	4.62 (1.48)	4.40 (1.48)	<0.001
Feeling depressed (range 1–7)	1.92 (1.29)	2.19 (1.56)	<0.001
Feeling irritated (range 1–7)	2.29 (1.56)	2.42 (1.59)	0.012
Feeling anxious (range 1–7)	2.19 (1.52)	2.39 (1.70)	<0.001
Number of measurement times	11.3 (9.55)	11.9 (10.0)	0.030