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The Influence of Sleep on Subjective Well-Being:

An Experience Sampling Study

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OSF repository can be found at <https://osf.io/tdh3x/> (Lenneis et al., 2023).

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Abstract

Previous research has associated sleep with subjective well-being (SWB), but less is known about the underlying within-person processes. In the current study, we investigated how self-reported and actigraphy-measured sleep parameters (sleep onset latency, sleep duration, sleep satisfaction, social jetlag, and sleep efficiency) influence SWB (positive and negative affect, life satisfaction) at the within- and between-person level. Multilevel analyses of data from 109 university students who completed a two-week experience sampling study revealed that higher within-person sleep satisfaction was a significant predictor of all three components of next day's SWB ($ps < .005$). Higher between-person sleep satisfaction was also related to higher levels of positive affect and life satisfaction ($ps < .005$) whereas shorter self-reported between-person sleep onset latency was associated with higher positive affect and life satisfaction, and lower negative affect ($ps < .05$). However, longer actigraphy-measured within-person sleep onset latency was associated with higher next day's life satisfaction ($p = .028$). When including within- and between-person sleep parameters into the same models predicting SWB, only within- and between-person sleep satisfaction remained a significant predictor of all components of SWB. Additionally, we found an effect of higher self-reported within-person sleep onset latency on positive affect and of shorter self-reported within-person sleep duration on life satisfaction ($ps < .05$). Our results indicate that the evaluative component of sleep—sleep satisfaction—is most consistently linked with SWB. Thus, sleep interventions that are successful in not only altering sleep patterns but also enhancing sleep satisfaction may stand a better chance at improving students' SWB.

Keywords: Sleep, experience sampling, subjective well-being, sleep satisfaction within- and between-person processes

The Influence of Sleep on Subjective Well-Being: An Experience Sampling Study

Sleep has been related to subjective well-being (SWB) in previous research (e.g., Lemola et al., 2013; Ong et al., 2017; Tang et al., 2017). It refers to how individuals evaluate or appraise their own lives and current situations (Diener et al., 2018). Higher SWB appears to be related to many good outcomes in life (Larsen & Eid, 2008), such as better health and longevity, better quality social relationships, and resilience (Diener et al., 2018). Thus, there are many reasons to believe that high SWB is very beneficial at both individual and societal levels (Larsen & Eid, 2008).

SWB is often conceptualized as consisting of three independent components: positive affect, negative affect, and life satisfaction (Diener, 1984). Positive affect (PA) refers to the extent to which an individual subjectively experiences positive moods (Miller, 2011), whereas negative affect (NA) involves feelings of emotional distress (Watson et al., 1988). The third component of SWB—life satisfaction (LS)—involves an evaluative judgment of one's life (Diener, 1984). Previous research has shown that the strength of relationships among the three components of SWB may depend on age, personality traits and cultural values (Kööts-Ausmees et al., 2013; Kuppens et al., 2008). The affective and cognitive constituents of SWB are influenced by different factors (Diener, 2013) and related to different outcomes (Realo et al., 2017). Therefore, it is important to consider all three variables independently from each other. In line with this, our study will measure the three components separately, as sleep might show a differential relationship with each component.

Sleep

Sleep can be measured across multiple levels, which can be further characterized along multiple dimensions (Buysse, 2014). Levels of analysis include for example self-reports of sleep and actigraphy-derived¹ measures of sleep (Buysse, 2014). Dimensions of sleep comprise sleep quantity (duration), continuity (ability to initiate and maintain sleep),

quality (subjective evaluation of one's sleep), and timing (Buysse, 2014; Hall, 2010; Hall et al., 2008). Sleep continuity can be measured in terms of how long it takes to fall asleep (sleep onset latency), frequency and length of awakenings (times and duration of wake after sleep onset), and/or as a percentage of time in bed spent asleep (sleep efficiency; Hall, 2010). An indicator of sleep timing is chronotype, which can be operationalized as midpoint of sleep (Terman et al., 2001), i.e., the midpoint between sleep onset in the evening and wake-up time in the morning. Chronotype is highly related to preferences for morningness or eveningness (Zavada et al., 2005), but the two are distinct constructs (Roenneberg, 2015). People may experience social jetlag when their social and biological schedules are not aligned with each other (Wittmann et al., 2006); for example later chronotypes might go to bed late but still need to wake-up early to go to work.

In the current study, we focus on self-reported sleep onset latency, sleep duration, social jetlag, sleep satisfaction, and actigraphy-derived sleep efficiency (see [pre-registration](#)). We followed up the pre-registered analyses with exploratory analyses investigating whether other frequently used actigraphy-derived variables (Konjarski et al., 2018) influenced SWB, namely actigraphic sleep onset latency and total sleep time.

Relationship Between Sleep and SWB

The relationship between sleep and SWB has been addressed in many studies (see for example Gaina et al., 2005; Lemola et al., 2013; Tang et al., 2017; Wrzus et al., 2014). Previous studies have conceptualized SWB in different ways, for example as one overarching factor, the mean score of several dimensions, or as three independent components. They have also investigated the relationship between sleep and SWB using different designs. However, most studies were cross-sectional and therefore investigated between-person effects. Fewer studies have examined the relationship using multiple measurements of the same participants, such as in experience sampling studies, which allow the investigation of the day-to-day

within-person influence of sleep on SWB and vice versa (Konjarski et al., 2018). We will review the literature on the relationship between SWB and the five dimensions of sleep (and some of their actigraphic counterparts) that are included in the current study. The reviewed studies have explored the relationship between sleep and SWB with participants of all age groups—from children to older participants. Studies have shown that sleep changes with age, for example self-reported sleep quality (Lemola & Richter, 2013), actigraphy-assessed sleep quantity and continuity (Evans et al., 2021), and self-reported sleep duration (Ancoli-Israel et al., 1997).

Studying Within-Person and Between-Person Effects

A pitfall of cross-sectional research is that it only allows the investigation of between-person variability at one time point, thereby not considering change over time or any within-person processes, which means that group-level effects cannot be applied to individuals within that group (Curran & Bauer, 2011). This discrepancy has often been illustrated with the following medical example: Even though people who exercise more tend to have a lower risk of heart attacks (i.e., between-person effect), heavy physical exertion can trigger a heart attack (i.e., within-person effect), particularly in individuals who usually exercise less (e.g., Curfman, 1993; Mittleman et al., 1993). Hence, greater emphasis must be placed on the study of within-person processes (Curran & Bauer, 2011), and this can only be accomplished through studying intraindividual differences in repeated measures data (for example Molenaar, 2004). Van Dongen et al. (2005) found interindividual variability in human sleep parameters, indicating that people differ among each other in the number of hours they sleep, in their sleep quality, or in their midpoint of sleep (chronotype). Furthermore, both the amount and quality of sleep also fluctuate within people; for example, there is a substantive amount of night-to-night variability in various sleep parameters (Buysse et al., 2009; Lenneis

et al., 2021) that might affect SWB. Components of SWB also show a substantive amount of intraindividual variability (Mill et al., 2016; Willroth et al., 2020).

Sleep Onset Latency

Studies investigating the relationship between sleep onset latency (both self-reported and actigraphy-derived) and SWB have reported mixed results with either shorter sleep onset latency being related to better SWB or no relationship between sleep onset latency and SWB (Konjarski et al., 2018). A cross-sectional study that assessed actigraphic sleep onset latency over seven days found that it was not related to SWB conceptualized as positive well-being and symptoms of distress (Lemola et al., 2013). An experience sampling study by Kouros and El-Sheikh (2015) found between-person effects of longer actigraphy-derived sleep onset latency on worse mood in children, but no within-person effects. Within-person relationships were reported by de Wild-Hartmann et al. (2013) in women and Cousins et al. (2011) in youth with major depressive disorder—shorter self-reported and actigraphy-derived sleep onset latency were related to higher PA and lower NA on the next day. Another cross-sectional study reported no relationship between self-reported sleep onset latency and life satisfaction (Gaina et al., 2005). However, difficulties in initiating sleep is also a symptom of insomnia (Roth, 2007), which has been negatively related to PA and LS, and positively related to NA (Hamilton et al., 2007).

In the current study, we hypothesized that longer than average sleep onset latency is related to worse SWB on the next day (Hypothesis 1).

Sleep Duration

The importance of sleep duration for SWB has been identified in sleep deprivation studies. The findings of experimental studies show that sleep-deprived adolescents and young adults report less PA (Dagys et al., 2012; Rossa et al., 2014) but no change in NA (Rossa et al., 2014). When looking into how relative sleep loss affects well-being, an experience

sampling study by Wrzus et al. (2014) found that in adolescents, shorter than average sleep duration led to worse affective well-being on the next day, whereas in adults over 20 years of age, both shorter and longer sleep duration than average led to worse affective well-being. Affective well-being was conceptualized as affect balance, i.e., the difference between PA and NA. Only self-reported but not actigraphy-derived total sleep time was associated with next day's PA and NA in older adults (McCrae et al., 2008). An experience sampling study using actigraphy by Cousins et al. (2011) found that longer total sleep time was associated with higher PA the next day in youth with major depressive disorder and anxiety, but not in the healthy control group. The results of an experience sampling study in medical residents showed that sleep loss increased one's levels of PA the next day (Zohar et al., 2005). This is consistent with findings in depression literature reporting that short-term sleep deprivation results in a transient improvement of mood (Giedke & Schwärzler, 2002; Ioannou et al., 2021). In a panel study, Piper (2016) observed that LS was the highest when participants slept eight hours on a typical weekday. A cross-sectional actigraphy study of the general population aged 35 to 85 years by Lemola and colleagues (2013) did not find an association between sleep duration and SWB, but found that the variability in sleep duration was related to SWB.

Based on the results of the earlier studies, we hypothesized that either shorter or longer sleep duration is related to worse SWB on the next day (Hypothesis 2).

Mid-Sleep/Social Jetlag

A cross-sectional study by Diaz-Morales and Escribano (2015) examined the relationships between chronotype and mood in a sample of high school students and found that evening-oriented students showed worse mood compared to other chronotypes. In a comprehensive review, Adan et al. (2012) also reported a few cross-sectional studies that linked morningness with greater SWB. The association between low psychological well-

being, i.e., depressed mood, and later chronotypes has been explained by social jetlag (Wittmann et al., 2006). To our knowledge, there are no experience sampling studies that have investigated the relationship between social jetlag and SWB.

We hypothesized that greater daily social jetlag is related to worse SWB on the next day (Hypothesis 3).

Sleep Quality/Satisfaction

A systematic review by Ong et al. (2017) reported consistent evidence of an association between PA and self-reported sleep quality in healthy populations. Findings of the review of cross-sectional and longitudinal studies indicate that higher levels of both trait and state PA are independently associated with better sleep quality in non-clinical samples of children, adolescents, and adults. A cross-sectional study found that in adolescents, the relationship between positive and negative affect seems to be stronger associated with sleep quality than with sleep duration (Shen et al., 2018). A recent experience sampling study of university students supports these findings (Hachenberger et al., 2022).

Thus, we hypothesized that greater sleep satisfaction is related to greater next day's SWB (Hypothesis 4).

Sleep Efficiency

Mixed results have been found regarding the relationship between sleep efficiency and SWB. A validation study by Jackowska et al. (2016) using both cross-sectional and longitudinal methods found that higher actigraphy-derived sleep efficiency was negatively related to PA, positively to NA, and not related to LS. Yet, a three-day long actigraphy study by Girardin et al. (2000) reported no relationship between sleep efficiency and quality of well-being in an adult population. In a systematic review, Konjarski et al. (2018) reported that one out of six studies found a significant positive association between sleep efficiency and next day's PA.

We still hypothesized that greater sleep efficiency is related higher SWB on the next day (Hypothesis 5).

The Aims of the Present Study

The review of previous studies indicates mixed results regarding the relationship between sleep and well-being. The most consistent link has been reported between self-reported sleep quality/satisfaction and measures of PA. As most studies were cross-sectional in nature, we address limitations of previous research in the present study by applying experience sampling methodology in examining how daily fluctuations from one's average sleep indicators relate to next day's SWB (i.e., PA, NA, and LS), hence exploring within-person processes. To supplement the pre-registration, we will study between-person effects at the same time, i.e., how differences from the mean of the study sample relate to changes in SWB. Including the between-person effects in the models is necessary to statistically isolate the within-person effects. Otherwise, the observed within-person effects confound between- and within-person effects (Bolger & Laurenceau, 2013).

In a systematic review, Konjarski et al. (2018) found that over short periods of time there is a reciprocal relationship between self-reported sleep variables and daytime affective states. However, both experience sampling and longitudinal studies have shown that it is predominantly sleep that affects SWB (Kalak et al., 2014; Newman et al., 2022; Simor et al., 2015; Triantafillou et al., 2019). This directionality has also been supported by experimental studies linking acute partial sleep deprivation on one night to lower PA the following day (see for example Rossa et al., 2014). Therefore, in our study we examined the influence of sleep on SWB.

We chose university students as our participants as they are a homogenous group, which minimized the effect of age and comorbid health conditions. Differently from a study by Wrzus and colleagues (2014), we did not focus on a single sleep indicator (i.e., sleep

duration) as this does not grasp sleep as a multidimensional experience (Buysse, 2014). Instead, we measured several self-reported and actigraphy-derived sleep indicators in our study, including sleep duration, sleep onset latency, social jetlag, sleep satisfaction (a component of sleep quality), and sleep efficiency.

Thus, our study addressed two other gaps in the literature that, to our knowledge, have not been examined before. First, we examined daily fluctuations of (absolute) social jetlag (i.e., the absolute difference between midpoint of sleep on free days and daily midpoint of sleep). Second, we examined joint models that consist of five sleep indicators to explain one component of SWB at a time, simulating the complexity of sleep in real life as the components of sleep occur together throughout the night.

We pre-registered all our within-person hypotheses before the analyses of the data, which can be found [here](#).² However, as already explained above, we also explored the between-person effects. We also used absolute values of within-person sleep duration and total sleep time as there is a curvilinear relationship between sleep and SWB in over 20-year-olds (Wrzus et al., 2014). Therefore, the magnitude of the deviation from one's personal mean value is interesting to explore for these variables.

Method

Participants

We recruited 129 undergraduate students from a University in the United Kingdom (UK) to take part in the study. Of these, 13 were not able to participate since they experienced difficulties in downloading the mobile phone application that was used for the experience sampling. One participant dropped out at the beginning of the study. We excluded 22 daily sleep data entries due to several reasons,³ which resulted in excluding all instances of one participant. We also excluded one participant who was 32 years old as chronotype is dependent on age (Adan et al., 2012) and will likely change throughout young adulthood (see

pre-registration). Finally, our model excluded four participants because there was insufficient data available (i.e., valid sleep data for only one day and only one valid momentary survey).

The final sample consisted of 109 participants. Their average age was 19.60 ($SD = 1.06$) years, ranging from 18 to 22 years. Seventy (64.22%) identified themselves as female and 39 (35.78%) as male. Sixty (55.05%) were from the UK, 28 (25.69%) were international students, and 21 (19.27%) were from a country within the European Union. Sixty-one (55.96%) identified themselves as White/Caucasian, 37 (33.39%) as Asian/Asian British, and nine (8.26%) as Black/African/Caribbean/Black British. Two (1.83%) of them identified as “other”. They were enrolled in a variety of courses, with 27 in Psychology (24.77%) and 20 in Economics (18.35%), to name the two most frequent ones. Of these, 104 (95.41%) had actigraphy data available. The dataset has been used in other studies (Das-Friebel et al., 2020; Lenneis et al., 2021) but it has not been used for the present purpose. The sample size was determined by other experience sampling studies that used similar number of participants, as well as time and resources available for data collection (Dimotakis et al., 2013). We overrecruited from our original target of 100 participants.

Procedure

The study was approved by the Ethics Committee of the Department of Psychology at a UK University. Students were invited to participate in a two-week experience sampling study between October 2017 and March 2018. They received information about the study either through their participation in a prior SMaRT (Student Mental Health and Resilience in Transition) study or through SONA, a system used at the UK University to book in research participants. Due to the number of actigraphs available, only 25 participants could partake in the study at a time, which is why we ran the study in five stages.

Those who indicated interest were asked to sign up for a one-hour introductory session in groups of four to six. During this session, participants were informed about the

study procedure and actigraphy and then asked to give their written consent. Afterwards they filled out a 30-minute baseline questionnaire and downloaded the app used for the experience sampling part of the study. All participants received £5 for attending the first session.

Participants' sleep was recorded with actigraphy the same night following the introductory session; the experience sampling part of the study started on the following day. The data collection lasted for two weeks. At the end, participants were invited back for a debrief session where they filled in a short feedback questionnaire, handed back their actigraphs and collected their outstanding reward for participation of up to £35 (depending on their compliance rate; one survey was equivalent to approximately £0.63). We used a unique identification code for each participant to link their questionnaire data with the experience sampling data and actigraphy. Participants were advised to contact the experimenters if they had any questions during the study.

For the experience sampling part of the study, we used Iulumivu's mobile ecological momentary assessment app (mEMA) since it was compatible with both major mobile operating systems (i.e., Android OS and iOS). Participants received two types of surveys a day—open and momentary surveys. Participants were prompted to fill in the open survey every day at 8 am, and although they could respond to it any time over the next 24 hours, they were asked to fill it in as soon as possible to avoid memory biases. It consisted mainly of retrospective questions about the previous day and night, such as physical activity, social media usage, and sleep. Nevertheless, it also included a few questions about the current day, such as whether it was a free day or a workday. Over the course of the study, participants were asked to fill in fourteen open surveys (one survey a day). However, due to technical problems with the app, six participants received only thirteen prompts; hence the total number of prompts was 1,520 ($103 \times 14 + 6 \times 13$). Altogether, participants responded to

1,374 prompts, yielding a response rate of 90.04%. The valid answers per participant ranged from four to fourteen open surveys ($M = 12.61$, $SD = 2.04$).

For the momentary survey, participants were prompted at five varying time points in a day to fill it in. The prompt arrived either between 8 am and 8 pm (Mondays to Fridays) or between 10 am and 10 pm (Saturday and Sunday), with a minimum of one hour between the prompts. Participants were instructed to complete each survey as soon as possible, although they had a maximum of 20 minutes to respond before the survey closed. The momentary surveys asked participants about their current mood, well-being, what they were doing, their social media usage, etc. The complete list of questions asked in the open and momentary surveys can be found at the [Open Science Framework \(OSF\)](#). In theory, participants were able to fill in 70 (14 x 5) momentary surveys throughout the study. However, due to technical issues, some of the momentary prompts were not released, leading to an average number of prompts of 68.72 ($SD = 17.71$), ranging from 30 to 70 prompts. Overall, participants responded to 4,523 momentary prompts, yielding a response rate of 60.39%.

Participants were asked to wear a waterproof actigraph for the entire study duration. We advised them to wear it as much as possible, but that they should take it off in situations when they could harm themselves, others, or the device (e.g., when practicing martial arts).

Measures

Self-Reported and Actigraphic Daily Sleep Measures

Participants were asked to keep an electronic sleep diary. Through the open survey, participants were asked to report each day about the previous night's sleep times (i.e., time they went to bed, time they got ready to fall asleep, time it took them to fall asleep, wake-up time, getting up time), which was based on the Munich Chronotype Questionnaire (MCTQ; Roenneberg et al., 2003). Using these sleep times, we were able to calculate sleep parameters. Participants also had to indicate how satisfied they were with their sleep the previous night.

Since participants wore an actigraph when sleeping, we could calculate sleep parameters, such as sleep efficiency, total sleep time, and sleep onset latency. We used ActiGraph wGT3X-BT devices manufactured by ActiGraph to obtain actigraphic estimates of sleep. The actigraph recorded information about participants' movements and activities using a 3-axis accelerometer. As reported in the pre-registration at <https://osf.io/rzd5>, we only included those sleep indicators in the study that correlated at less than $r = .30$ with each other in order to ensure only low to moderate multicollinearity (Baguley, 2012). At the stage of pre-registration, we only included one measure of actigraphy in our study as we were most interested in actigraphic measurements of sleep quality, hence sleep efficiency. However, we added two actigraphic variables to our exploratory single models: sleep onset latency and total sleep time. The following variables were used in the current study.

Sleep Onset Latency. We asked participants to indicate how long it took them in minutes to fall asleep after they had switched off the lights and got ready to sleep. We also added an actigraphic measure of sleep onset latency to our exploratory analyses.

Sleep Duration. Sleep duration was calculated as the time difference between sleep-onset and wake-up time. We also added a measure of actigraphic total sleep time, which is defined as the total number of minutes scored as "asleep" (ActiGraph Software Department, 2012), hence including time spent awake since falling asleep.

Absolute Social Jetlag. Absolute social jetlag is usually calculated as the absolute value of the difference between i on free days (MSF) and workdays (MSW; Wittmann et al., 2006). It can be interpreted as the amount of time people's social and biological clocks differ from each other. The score is also given in hours, and the higher the score is, the more the two clocks differ from each other. A score of 0 indicates that people are not experiencing a misalignment of their social and biological clocks. Mid-sleep is defined in the MCTQ as the

midpoint between sleep onset and wake-up time (Roenneberg et al., 2003), i.e.

$$\text{mid-sleep} = \text{sleep onset} + \frac{\text{sleep duration}}{2} .$$

As we were interested in daily ratings of absolute social jetlag, we calculated daily absolute social jetlag (within-person) as the absolute value of the difference between mid-sleep on free days from the MCTQ (MSF_{MCTQ}) and daily mid-sleep scores (MS_{daily}), i.e.,

$$\text{daily absolute social jetlag} = \left| MSF_{MCTQ} - MS_{\text{daily}} \right| .$$

MSF_{MCTQ} can be seen as an indicator of chronotype (Roenneberg et al., 2003). Participants in our study filled out the MCTQ during the introductory session the day before the experience sampling study started. The between-person score of social jetlag was calculated as the absolute value of the difference between the average MSF and MSW scores extracted from the sleep diaries.

Sleep Satisfaction. Participants were asked to indicate on a four-point scale (from 1 = “very dissatisfied” to 4 = “very satisfied”) how satisfied they were with their previous night’s sleep. Self-reported sleep satisfaction is a component of self-reported sleep quality (Lemola et al., 2013) but the terms sleep satisfaction and sleep quality are often used interchangeably (Harvey et al., 2008). Sleep quality judgments seem to be determined by not only what happens during sleep, but also what happens after the sleep period (Ramlee et al., 2017) and therefore include an evaluative component (Ramlee et al., 2017).

Actigraphy-Based Sleep Efficiency. We calculated sleep efficiency via the ActiLife 6 software using the Sadeh scoring algorithm. We measured sleep efficiency as the percentage of time spent asleep in bed since attempting to fall asleep (Reed & Sacco, 2016). Participants were not able to indicate on their actigraph at what time they tried to fall asleep and got out of bed. Therefore, we used the information extracted from the sleep diaries as anchoring points.

Subjective Well-Being (Assessed With Momentary Surveys)

Positive and Negative Affect. We measured PA and NA using five positive (happy, enthusiastic, content, relaxed, attentive) and five negative (upset, annoyed, bored, sad, worried) mood items. We selected items from the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) and James Russell's (1980) Circumplex Model of Affect, including items that were low and high on arousal as well as unpleasant and pleasant feelings. Participants were asked to indicate on a five-point scale (from 1 = "not at all" to 5 = "to a large extent") how they felt at the moment. The items were presented in randomized order.

Exploratory Factor Analysis of Positive and Negative Affect Items. To investigate the underlying structure of the ten emotional items that were included in the study, we first ran a principal component analysis with varimax rotation across all participants and instances. The scree plot clearly indicated a two-factor solution that explained 55.78% of the total variance. The factor loadings of the first factor, which we identified as PA, ranged from .63 (relaxed) to .77 (happy), whereas the factor loadings of the second factor (NA) ranged from .48 (bored) to .81 (upset). The secondary loadings of all ten emotion items were smaller in size than their primary loadings and ranged from -.36 (sad) to .08 (attentive).

Based on the exploratory factor analysis, the mean scores of the five positive and five negative items as measures of PA and NA were computed, respectively, with higher scores indicating greater levels of respective mood. Since participants filled out these items up to five times a day, we calculated a daily mean score of PA and NA. Higher scores indicate higher levels of PA and NA, respectively. The Cronbach's α of PA and NA across all participants and measurement instances were .81 and .75, respectively.

Life Satisfaction. We measured LS using a single item, namely, "All things considered, how satisfied are you with your life at the moment?". Participants were asked to rate this item on a 10-point scale from 1 = "extremely dissatisfied" to 10 = "extremely

satisfied” using a continuous slider. Participants were asked to indicate their satisfaction with life five times a day, and a daily mean score of LS was used in further analyses.

Time of Day. Daily average scores of SWB have also been calculated in other experience sampling studies (see for example Steptoe et al., 2008). To complement our findings, we conducted three-level models considering the prompt number, hence time of day. These can be found in Supplement 2 (Tables S2.1 to S2.7; Figures S2.1 and S2.2). We also explain the slight differences between the two- and three-level models there.

Statistical Analysis

The data analysis plan was pre-registered on the OSF on September 17th, 2019 (<https://osf.io/rzdvt5>). However, the review process resulted in differences between the pre-registration and the actual analyses. The differences are described in Supplement 1.

We used linear mixed models (see below) in our analyses. All models included both within- and between-person effects as well as previous day’s SWB (PA, NA, and LS respectively) to control for the possibility that previous day’s SWB was affecting both the night’s sleep and next day’s SWB. Thus, theoretically we investigated the change of SWB from one day to another.

Within-Person Effects

To investigate within-person effects, we first person-mean centered (Wang & Maxwell, 2015) the following independent variables: self-reported and actigraphic sleep onset latency, self-reported sleep duration and actigraphic total sleep time, sleep satisfaction and sleep efficiency over the personal two week-average. This means that for each self-reported sleep indicator, we subtracted the average two-week scores of each participant from their daily scores. For example, if a person slept eight hours on average during the two-week period but slept 9 hours on the first and 7.5 hours on the second day of the study, their person-mean centered scores for Day 1 and Day 2 were 1 and -0.5, respectively. In the first

example, a hypothetical slope estimate for sleep duration of 0.1 for the dependent variable LS would indicate that, if a person reports a sleep duration that is 1 hour higher than their average sleep duration, it is associated with a LS that is on average 0.1 higher than their average mean life satisfaction on the LS scale from 0 to 10. As explained above, for daily absolute social jetlag, we centered the scores on mid-sleep on free days (absolute value) that we extracted from the MCTQ (Roenneberg et al., 2003), which was assessed at the beginning of the study. As there is a curvilinear relationship between sleep and SWB in over 20-year-olds (Wrzus et al., 2014), we also included the absolute value of self-reported person-centered sleep duration and actigraphic person-centered total sleep time in the models.

Between-Person Effects

To investigate the between-person effects, we grand-mean centered the independent variables (Wang & Maxwell, 2015) from above, i.e. we subtracted the average score per person and time point from the overall mean across all persons and time points. For social jetlag, we subtracted the average biweekly mid-sleep on workday scores from the average mid-sleep on free day scores for each person. We used absolute values.

We did not person-mean and grand-mean center absolute social jetlag since we wanted to get more interpretable variables for social jetlag. However, to isolate the within-person effect and be consistent with the other analyses, we report the findings of person-mean and grand-mean centered absolute daily social jetlag in Supplement 4 (Tables S4.1 to S4.3).

Linear Mixed Models

We analyzed the data using linear mixed models and the Satterthwaite method for testing model terms using the package afex (Singmann et al., 2020) in R 4.0.5. All initial mixed models included by-participant random intercepts and by-participant random slopes for all independent variables that varied within- and between-participants. This constituted the maximal random effect structure justified by design (Barr et al., 2013). The initial models

also included correlations among random slopes, which we removed first in case of convergence problems. When the model showed further convergence problems (e.g., a singular fit), we iteratively reduced the random-effects structure, beginning with removing the highest-order random slopes, until the model converged successfully (Singmann & Kellen, 2019).

Transparency and Openness

Our data, analysis code, and research materials are available at <https://osf.io/tdh3x/>. We pre-registered our analysis prior to the analyses of the data at <https://osf.io/rzdv5>. Hence, we collected the data before the pre-registration. Changes from the pre-registration are reported in Supplement 1.

Results

Descriptive Statistics

The descriptive statistics presented here are based on the mean scores of each participant during the 14-day period. During the 14 days, participants on average needed 19.60 ($SD = 13.30$) minutes to fall asleep. Actigraphy-measured sleep onset latency on average was 9.00 ($SD = 8.09$) minutes. Their mean self-reported sleep duration was 7.43 ($SD = 1.01$) hours. Actigraphy-derived total sleep time averaged at 8.27 ($SD = 1.12$) hours. The average mid-sleep across all days was 5.05 ($SD = 1.25$; i.e., 5:03 am). The average score of mid-sleep on free days ($M = 5.54$; $SD = 1.47$, i.e. 5:32 am) was significantly higher than on workdays ($M = 4.75$; $SD = 1.18$, i.e. 4:45 am), $t(107) = 8.95$, $p < .001$. The average absolute social jetlag score over the 14 days was 0.91 ($SD = 0.78$), whereas the mean absolute social jetlag score extracted from the MCTQ at the beginning of the study was 1.24 ($SD = 0.76$). The two scores differed significantly, $t(107) = -3.64$, $p < .001$. Participants were quite satisfied with their sleep, indicated by an average score of 2.85 ($SD = 0.41$) out of a 4-point scale. Their average actigraphy-based sleep efficiency was 80.80% ($SD = 6.79$).

The mean score of PA over the two-week period was $M = 2.74$ ($SD = 0.52$), with average daily scores ranging from 1.60 to 4.46, and the mean score of NA was $M = 1.64$ ($SD = 0.44$), with average daily scores ranging from 1.01 to 2.93, both on a scale from 1 to 5. Participants rated their LS as 6.04 ($SD = 1.71$) on a scale from 1 to 10 over the two-week period, with average daily scores ranging from 1.41 to 9.85.

Table 1 depicts the correlations among the sleep indicators and the components of SWB. For the correlations, we used average scores of the two-week period for each person. Among the sleep indicators, we found the highest correlation between sleep onset latency and sleep satisfaction, $r = -.30$ ($p < .002$) and the lowest correlation between sleep efficiency and MSF_{MCTQ} , $r = .01$ ($p = .922$). In SWB, PA correlated with NA at $r = -.51$ and with LS at $r = .83$, whereas NA and LS correlated at $r = -.63$ with each other, all correlations were significant with $p < .001$.

Insert Table 1 here.

Mixed Models Predicting PA, NA, and LS From Sleep Variables

Our primary aim was to examine how individual fluctuations in sleep (i.e., sleep onset latency, sleep duration, absolute social jetlag, sleep satisfaction, and sleep efficiency) are related to next day's SWB. We also were interested in seeing how interindividual differences in sleep influence average SWB. We ran separate models for each independent and dependent variable at a time, resulting in fifteen different models. In addition to our pre-registration, we added two more commonly analyzed actigraphic variables to our single models (Konjarski et al., 2018). We also came up with three joint models that included all five sleep variables predicting one component of SWB (i.e., PA, NA, and LS) at a time.

Intraclass Correlation Coefficients (ICCs). To calculate ICCs, we used models which had PA, NA, and LS as dependent variables and only included by-subject random intercepts and no further fixed effects. Results showed that in PA, NA, and LS, 54.68%, 51.39%, and

69.29% of the variances were explained by between-participant effects, respectively.

However, as the ICC is only defined for random-intercept models, but not for more complex models (e.g., those involving random slopes; Lenneis et al., 2021), we did not calculate it for the other models.

Single Models.

Tables S3.1 to S3.7 in Supplement 3 give an overview of the model estimates b , confidence intervals, standard errors, and t -values of all predictors of the single models. Previous day's SWB was a significant predictor of next day's SWB in all models.

Within (also its absolute value)- and between-person sleep duration, within- and between-person absolute social jetlag, actigraphy-measured within-and between-person sleep efficiency, and actigraphy-measured within (also its absolute value)- and between-person total sleep time did not significantly predict PA, NA, or LS ($ps > .093$).

Between-person self-reported sleep onset latency was a significant predictor of PA, $b = -0.01$, $t(80.47) = -3.08$, $p = .003$, NA, $b = 0.01$, $t(79.32) = 2.29$, $p = .025$, and LS, $b = -0.02$, $t(72.61) = -2.96$, $p = .004$. The results show that those who reported falling asleep more quickly than others experienced more PA, less NA, and more LS. However, within-person self-reported sleep onset latency did not predict any component of next day's SWB at $p < .05$. When investigating actigraphic sleep onset latency, the results showed that within-person sleep onset latency was a significant predictor of LS, $b = .00$, $t(820.70) = 2.20$, $p = .028$, indicating that if it takes participants longer than their personal average to fall asleep, they experience more LS on the next day. There was no significant effect of within-person actigraphic sleep onset latency on PA and NA. Figure 1 depicts the associations of within-person actigraphic sleep onset latency and between-person self-reported sleep onset latency with the three components of SWB.

Insert Figure 1 here.

Self-reported within-person sleep satisfaction was a significant positive predictor of PA, $b = 0.12$, $t(57.20) = 4.70$, $p < .001$ and LS, $b = 0.21$, $t(76.34) = 3.72$, $p < .001$, and a negative predictor of NA, $b = -0.05$, $t(123.17) = -2.34$, $p = .021$. The results suggest that if one is more satisfied with one's previous night's sleep than on average across the 14-day period, one experiences an increase in their levels of PA and LS well as a decrease of NA on the next day. Further, between-person sleep satisfaction was a significant predictor of PA, $b = 0.48$, $t(91.28) = 5.03$, $p < .001$ and LS, $b = 0.90$, $t(29.95) = 3.35$, $p = .002$ —but not of NA—indicating that those who were more satisfied with their sleep than others experienced more PA and LS. Figure 2 depicts all six models.

Insert Figure 2 here.

Joint Models

Finally, in the joint models, we predicted each of the three components of SWB from the pre-registration's sleep variables (at both the within-and between-person level) and previous day's SWB. The model estimates b , t -values, degrees of freedom, and p -values models can be found in Table 2. Previous day's SWB was a significant predictor of SWB in all three models.

Insert Table 2 here.

When predicting PA simultaneously from five sleep indicators at both the between- and within-person level, we found higher within-person self-reported sleep onset latency, $b = 0.00$, $t(854.20) = 2.19$, $p = .029$, within-person sleep satisfaction, $b = 0.11$, $t(847.34) = 4.50$, $p < .001$, and between-person sleep satisfaction, $b = 0.46$, $t(77.74) = 4.03$, $p < .001$, to be statistically significant predictors of increased PA. The results indicate that those who took longer than their personal average to fall asleep, who were more satisfied with their sleep than normally, and who experienced more sleep satisfaction than others, experienced more PA on the next day.

When investigating the relationship between sleep and NA, both within- and between-person higher sleep satisfaction significantly predicted lower levels of NA, $b = -0.07$, $t(840.70) = -3.07$, $p = .002$ and $b = -0.19$, $t(70.75) = -2.02$, $p = .048$, respectively. In other words, people who were more satisfied with their previous night's sleep than on average across the fourteen-day period, and who in general were more satisfied with their sleep than others had lower levels of NA on the next day. Shorter within-person sleep duration, $b = -0.05$, $t(828.61) = -2.12$, $p = .034$, greater within-person sleep satisfaction, $b = 0.23$, $t(829.71) = 4.01$, $p < .001$, and greater between-person sleep satisfaction, $b = 1.20$, $t(70.02) = 3.70$, $p < .001$ were significant predictors of LS. That is, those who slept less than their personal average, were more satisfied with their previous night's sleep compared to their 14-day average, and who were more satisfied with their sleep than others, were more satisfied with their lives the next day. We only found the effect of shorter sleep duration on life satisfaction in the joint, but not the single model.

Discussion

Interested in investigating how multiple dimensions of sleep at the within- and between-person level are related to the three components of SWB, we examined how intraindividual changes in sleep influence SWB on the following day and how interindividual differences in sleep relate to SWB. We used an experience sampling methodology. We found both within- and between-person effects, most consistently in how sleep satisfaction affects SWB.

We hypothesized that in the single models, longer than average sleep onset latency (Hypothesis 1), shorter or longer than average sleep duration (Hypothesis 2), and greater daily social jetlag (Hypothesis 3) were related to worse SWB whereas greater sleep satisfaction (Hypothesis 4) and greater sleep efficiency (Hypothesis 5) were related to better SWB on the next day.

Our study provides evidence that it is primarily the evaluative component of sleep that is associated with SWB. The direction of this relationship aligns with previous studies (Ong et al., 2017; Shen et al., 2018) and also the hypotheses proposed in our pre-registration (Hypothesis 4). The subjective perception of one's sleep satisfaction appears to be the best predictor of SWB and more important than actigraphy-measured sleep indicators, such as sleep efficiency. This supports previous research that showed that only self-reported and not actigraphy-defined measures of sleep were able to (better) predict next day's fatigue or pain (Russell et al., 2016; Tang et al., 2012). A study by K  ots-Ausmees and colleagues (2016) found that it is the component of satisfaction or evaluation that is common to subjective health and well-being ratings. This seems to be also true for the evaluative component of sleep—for example, sleep satisfaction—as it was related to all three components of SWB at the within-person level in our study.

Our findings regarding the effect of sleep onset latency depended on the use of self-reported or actigraphy-derived measures. On the one hand we found that people who report that it takes them a shorter time to fall asleep than others experience better SWB. On the other hand, we reported that longer within-person actigraphic sleep onset latency was related to higher LS on the next day. It may not be surprising that the results of the self-reported and actigraphy-derived models do not match as discrepancies between the two have been reported (Girschik et al., 2012). However, they do point in the same direction in the joint models at the within-person level (see below). Unlike hypothesized, we did not find an effect of self-reported within-person sleep onset latency on SWB (Hypothesis 1). Previous studies described mixed results regarding the effect of sleep onset latency on sleep (see Konjarski et al., 2018 for a review)—either that short sleep onset latency was associated with better well-being at both the within- (see for example Cousins et al., 2011; de Wild-Hartmann et al., 2013), and between-person level (Kouros & El-Sheikh, 2015) or that no effect was found (see

for example Hachenberger et al., 2022; Kalmbach et al., 2014). These findings have been reported for both self-reported and actigraphy-derived measures of sleep. To our knowledge, no study has found a relationship between longer sleep onset latency and higher LS.

However, a possible explanation for our findings might be that people are excited about what is happening the following day, which is why it takes them longer than usual to fall asleep.

For example, a study by Tavernier et al. (2016) has shown an effect in the opposite direction, that adolescents who experience high-arousal positive affect (i.e. excitement) during the day, take longer than usual to fall asleep the following night.

Even though many studies have reported a link between sleep duration and SWB (Konjarski et al., 2018), we did not find an effect of sleep duration on SWB in the single models (Hypothesis 2). As Wrzus et al. (2014) described a curvilinear relationship between sleep and SWB, we also used absolute scores of within-person sleep duration in our analyses. At the between-person level, our participants on average slept 7.41 ($SD = 1.01$) hours per night, which was close to the National Sleep Foundation recommended seven to nine hours of sleep per night for young adults (Hirshkowitz et al., 2015). Therefore, sleeping shorter or longer than others may not have made a big enough impact on participants' SWB.

We also did not find an effect of daily social jetlag (Hypothesis 3) and sleep efficiency (Hypothesis 5) on next day's SWB.

To reflect the complexity of sleep in real life, we developed joint models that included both within-and between-person sleep variables. In the joint models, higher within- and between-person sleep satisfaction predicted lower levels of NA. Additional to within-and between-person sleep satisfaction, longer within-person self-reported sleep onset latency or shorter self-reported within-person sleep duration predicted higher levels of PA and LS, respectively. The joint models support our proposition that sleep satisfaction is the most reliable indicator of SWB. Only when adjusting for the values of all other covariates (i.e.,

holding them constant), we found that longer within-person sleep onset latency is associated with greater PA and that shorter within-person sleep duration is associated with greater LS. In other words, if one's sleep satisfaction is the same on two days, then taking longer to fall asleep is additionally associated with higher greater PA, and that sleeping shorter than usual is additionally associated with higher LS. The within-person effect of self-reported sleep onset latency on PA is consistent with the within-person effect of actigraphic sleep onset latency on LS in the single models indicating that the actigraphy- and self-reported measures of sleep onset latency point in the same direction when using different components of SWB. Again, we can speculate that excitement about the next day might lead to a longer sleep onset latency. This might also be true for a shorter sleep duration. Interestingly, we found an effect for within-person self-reported sleep duration only in the joint model. We did not hypothesize that shorter than average sleep duration leads to improvements in mood, but it is consistent with some research, such as in people with depression or first-year medical residents working in nightshifts (Giedke & Schwärzler, 2002; Ioannou et al., 2021; Zohar et al., 2005).

Strengths, Limitations, Future Research, and Conclusions

We used an experience sampling approach, which allowed us to capture more true life experiences in a natural setting (Scollon et al., 2003). This is different from many previous studies that used cross-sectional designs to examine the relationships between sleep and SWB (see for example Diaz-Morales & Escibano, 2015; Gaina et al., 2005; Rossa et al., 2014). Even though there are individual differences in human sleep indicators, meaning that humans differ among each other in the amount of daily sleep they require or their sleep quality (van Dongen et al., 2005), sleep parameters also vary within humans, i.e., from night to night (Buysse et al., 2009; Lenneis et al., 2021). By assessing multiple observations in the same participants over a period of two weeks, we were able to examine a) if and to what extent deviations from one's personal average levels are related to SWB and b) how interindividual

differences in sleep parameters influence SWB. We added previous day's SWB to all our models to ensure that it was sleep and not previous day's SWB which influenced next day's SWB ratings. There was an impact of previous day's SWB on next day's SWB in all models, but sleep satisfaction, sleep duration, and sleep onset latency also influenced it.

In our study, we investigated within- and between- person effects only since the inclusion of interaction terms might have affected the estimation of main effects (Smith & Sasaki, 1979). However, the typical medical example of between- and within-person effects also includes an interactive term as heavy physical exertion can trigger heart attacks especially in those who exercise less (Mittleman et al., 1993). Therefore, future studies could investigate whether interactions between within-and between-person effects in sleep influence SWB. Daily fluctuations in sleep might be dependent on one's typical sleep patterns.

Due to the design of the study, participants had only 20 minutes to respond to the momentary surveys assessing SWB. This is in line with other experience sampling studies that typically use an arguably arbitrary cut-off of below 30 minutes to avoid memory biases and the use of heuristics (Scollon et al., 2003). The cut-off point might have lowered the response rate in momentary prompts. Even though we compensated our participants with up to £35, this still might not have been enough to achieve a higher compliance rate. However, as the final analysis is based on over 1,000 observations for each statistical model, we feel that some confidence in our results is justified. For the open survey, participants had 24 hours to complete the survey. This might have resulted in a memory bias. A recent study by Tang et al. (2022), for example, has shown that sleep quality judgements change throughout the day. Unfortunately, it was not recorded at what time our participants filled in their sleep data. Therefore, we do not know how close to their wake-up time participants filled in the survey. Nevertheless, we did recommend the participants to fill it in as soon as they woke up.

Another limitation of our study is that we only used a homogenous sample of 18-22 years old university students. Even though our participants had different ethnic and cultural backgrounds, they were similarly aged and were part of the same generation (hence all of them owning smart phones). Therefore, our results cannot be generalized without caution to the general public due to age, ethnicity, and sociodemographic background. Future studies could investigate how sleep influences SWB on the next day using participants of all ages and from different sociodemographic groups. It would also be interesting to study persons who experience severe daily social jetlag and examine how it affects their next day's SWB. This desynchrony between biological and social clocks might be especially relevant for people who work in shifts since social jetlag is a smaller version of shift work (Roenneberg et al., 2012).

Overall, our study has provided valuable insights that the evaluative component of sleep—satisfaction with last night's sleep—is the factor most related to the SWB on the following day. Sleep satisfaction, but not actigraph-measured sleep efficiency, was a significant predictor of SWB in all models. This highlights the importance of studying both how sleep is *measured with actigraphy* and how humans *perceive* their sleep, as the different measures of sleep seem to work differently in predicting SWB. However, in large surveys, it might be much easier to implement an item of sleep satisfaction only as the value gained by actigraphy appears to be minimal compared to its costs. Our study implies that sleep interventions altering sleep patterns *and* enhancing sleep satisfaction may prove effective in improving young adults' SWB and, thus, also student mental health. Using experience sampling methodology allowed us to better understand the relationship between sleep and SWB in a sample of undergraduate students; future research should investigate whether these results can be generalized to other populations and settings of interest.

Author Notes

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A.L., A.D.F., S.L., and A.R. designed the study. A.L. and A.D.F. carried out the study. H.S. and A.N.S. together with A.L. performed the statistical analyses. A.L. and A.R. took the lead in writing the manuscript. All authors provided critical feedback and helped shape the manuscript.

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The study was approved by the Ethics Committee of the Department of Psychology at the University of Warwick on 16th October 2017.

This study's analysis plan was pre-registered at <https://osf.io/rzdv5>. The dataset, analysis code, and research materials are available at <https://osf.io/tdh3x/>.

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Footnotes

¹Actigraphs are wrist-worn devices that record movements that can be used to estimate sleep parameters (Martin & Hakim, 2011).

²Please note that Hypothesis 7 was accidentally duplicated - therefore positive affect in Hypothesis 9 should be replaced with life satisfaction. There is also a problem with the numbering from Hypothesis 9 onwards, but the contents of the hypotheses remain the same.

³We excluded 22 instances due to several reasons in the following order: Six instances because participants had indicated the same wake-up and going-to-bed times, one because they went to bed before trying to fall asleep, one because they needed more than five hours to fall asleep, six because their sleep duration was less than or equal one hour, one because their sleep duration was more than 15 hours, three because their mid-sleep score was more than 15, and lastly four because there was no information available on whether it was a work or free day. The instances were also excluded in a previous paper using the same dataset (Lenneis et al., 2021).

Tables

Table 1*Correlation Matrix of the Sleep Variables and Components of SWB*

	Sleep onset latency	Sleep duration	Mid-sleep on free days (MCTQ)	Absolute social jetlag (ES)	Absolute social jetlag (MCTQ)	Sleep satisfaction	Sleep efficiency	Positive affect (PA)	Negative affect (NA)	Life satisfaction (LS)
Sleep onset latency (SR)	1									
Sleep duration (SR)	-.10	1								
Mid-sleep on free days (MCTQ)	.16	-.18	1							
Absolute social jetlag (ES)	-.24*	-0.04	.17	1						
Absolute social jetlag (MCTQ)	-0.04	-0.12	.58	.22	1					
Sleep satisfaction	-.30**	.27**	-.14	.14	-.09	1				
Actigraphic sleep efficiency	.03	-0.14	.01	.03	.17	.05	1			
Positive affect (PA)	-.32***	.12	-.04	.07	-.04	.45***	-.03	1		
Negative affect (NA)	.24*	-.11	.21*	-.06	.19	-.26*	.01	-.51***	1	
Life satisfaction (LS)	-.30**	.06	-.17	.05	-.11	.39***	.00	.83***	-.63***	1

Note. *** $p < .001$, ** $p < .01$, * $p < .05$. ES = Experience Sampling (14-day average); SR = self-reported; MCTQ = Munich Chronotype Questionnaire. Scores are based on mean scores of each participant during the 14-day-period (except for scores from the MCTQ). SWB = Subjective well-being.

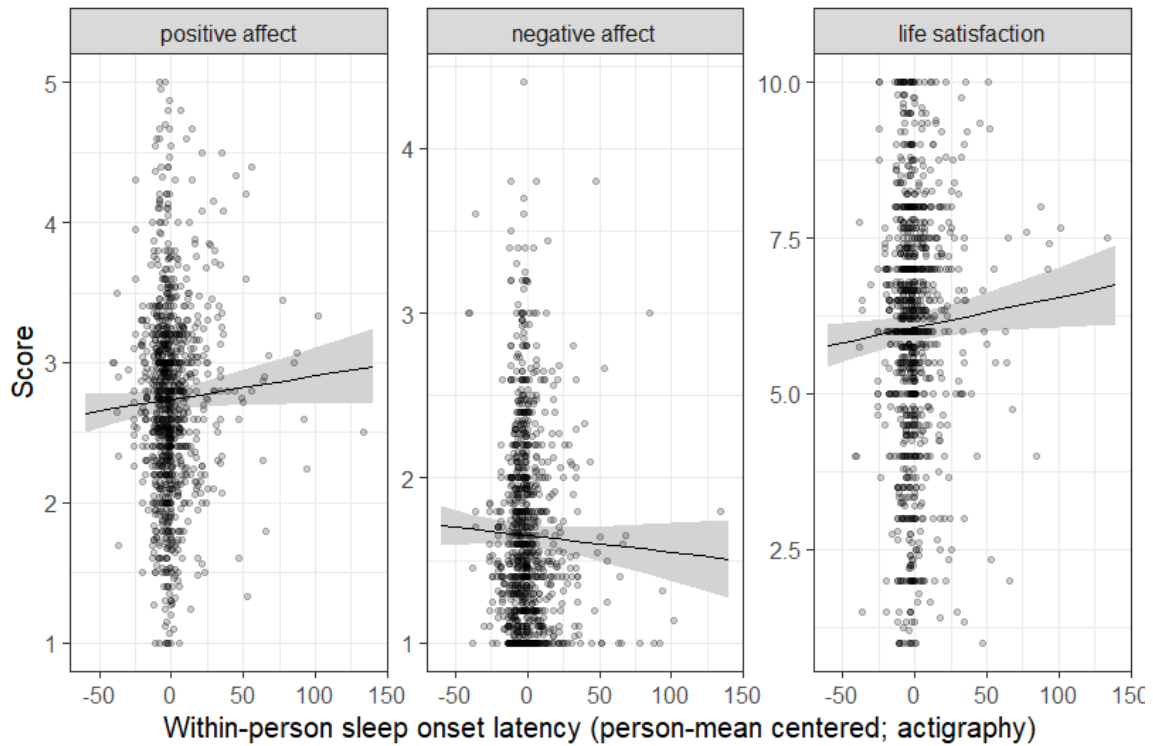
Table 2*Mixed Models Predicting Positive Affect, Negative Affect, and Life Satisfaction From Within-And Between-Person Sleep Parameters*

<i>Predictors</i>	Positive Affect				Negative Affect				Life Satisfaction			
	<i>b</i>	CI	<i>SE</i>	<i>t</i>	<i>b</i>	CI	<i>SE</i>	<i>t</i>	<i>b</i>	CI	<i>SE</i>	<i>t</i>
(Intercept)	2.12	1.91 – 2.32	0.11	20.12***	1.16	1.01 – 1.30	0.08	15.36***	4.10	3.60 – 4.61	0.26	15.91***
Sleep onset person-mean centered (SR)	0.00	0.00 – 0.00	0.00	2.19*	-0.00	-0.00 – 0.00	0.00	-0.70	0.00	-0.00 – 0.01	0.00	1.37
Sleep onset grand-mean centered (SR)	-0.00	-0.01 – 0.00	0.00	-1.52	0.00	-0.00 – 0.01	0.00	0.80	-0.01	-0.03 – 0.01	0.01	-1.39
Sleep duration person-mean centered (SR)	-0.01	-0.03 – 0.01	0.01	-0.71	0.00	-0.01 – 0.02	0.01	0.51	-0.05	-0.10 – -0.00	0.02	-2.12*
Sleep duration person-mean centered (absolute value; SR)	0.01	-0.02 – 0.04	0.02	0.62	-0.00	-0.03 – 0.03	0.01	-0.04	0.01	-0.07 – 0.08	0.04	0.16
Sleep duration grand-mean centered (SR)	-0.02	-0.10 – 0.06	0.04	-0.45	-0.02	-0.08 – 0.05	0.03	-0.50	-0.11	-0.34 – 0.12	0.12	-0.95
Sleep satisfaction person-mean centered	0.11	0.06 – 0.16	0.02	4.50***	-0.07	-0.11 – -0.02	0.02	-3.07**	0.23	0.12 – 0.34	0.06	4.01***
Sleep satisfaction grand-mean centered	0.46	0.24 – 0.68	0.11	4.03***	-0.19	-0.38 – -0.01	0.10	-2.02*	1.20	0.57 – 1.84	0.32	3.70***
Daily social jetlag	-0.02	-0.05 – 0.02	0.02	-0.98	0.02	-0.01 – 0.05	0.02	1.34	-0.03	-0.11 – 0.06	0.04	-0.58
Biweekly social jetlag	0.00	-0.10 – 0.11	0.05	0.04	-0.01	-0.10 – 0.08	0.05	-0.31	-0.01	-0.31 – 0.29	0.15	-0.09
Sleep efficiency person mean-centered	0.00	-0.00 – 0.01	0.00	0.55	0.00	-0.00 – 0.00	0.00	0.47	-0.00	-0.01 – 0.01	0.00	-0.54
Sleep efficiency grand mean-centered	-0.00	-0.02 – 0.01	0.01	-0.60	0.00	-0.00 – 0.01	0.01	0.98	-0.01	-0.04 – 0.02	0.02	-0.58
Previous day's positive affect	0.23	0.17 – 0.29	0.03	7.65***								
Previous day's negative affect					0.29	0.23 – 0.35	0.03	9.32***				
Previous day's life satisfaction									0.33	0.27 – 0.39	0.03	11.10***

Note: *** $p < .001$, ** $p < .01$, * $p < .05$; b = unstandardized model estimates, CI = 95% confidence interval; SR = self-reported; daily social jetlag was centered on the Munich Chronotype Questionnaire; biweekly social jetlag was calculated as the absolute difference between average mid-sleep on workdays and free days

Figure 1

Graphs Depicting the Relationship Between Actigraphic Within-Person Sleep Onset Latency (Person-Mean Centered) and Between-Person Self-Reported Sleep Onset Latency (Grand-Mean Centered) in Minutes with Subjective Well-Being (Positive Affect, Negative Affect, Life Satisfaction)



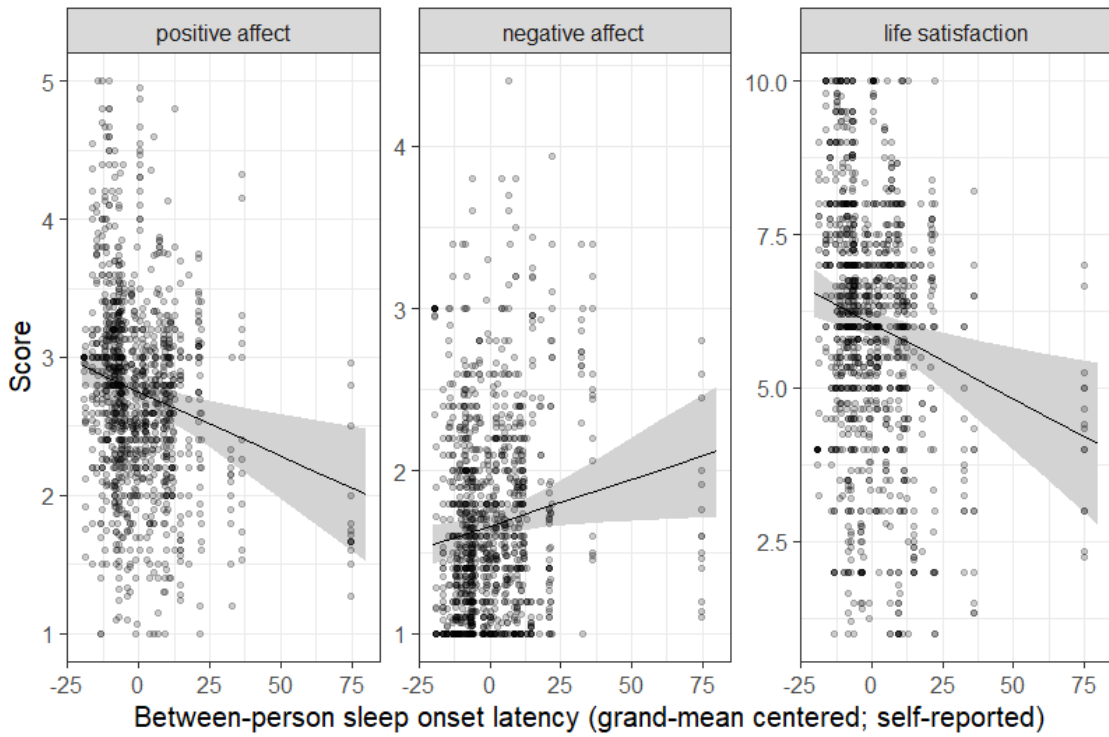


Figure 2

Graphs Depicting the Relationship Between Within-Person Sleep Satisfaction (Person-Mean Centered) and Between-Person Sleep Satisfaction Latency (Grand-Mean Centered) with Subjective Well-Being (Positive Affect, Negative Affect, Life Satisfaction)

