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Sleep and affect in older adults: using multilevel modeling to examine daily associations

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SUMMARY

The main objective of the present study was to examine daily associations (intraindividual variability or IIV) between sleep and affect in older adults. Greater understanding of these associations is important, because both sleep and affect represent modifiable behaviors that can have a major influence on older adults' health and well-being. We collected sleep diaries, actigraphy, and affect data concurrently for 14 days in 103 community-dwelling older adults. Multilevel modeling was used to assess the sleep–affect relationship at both the group (between-persons) and individual (within-person or IIV) levels. We hypothesized that nights characterized by better sleep would be associated with days characterized by higher positive affect and lower negative affect, and that the inverse would be true for poor sleep. Daily associations were found between affect and *subjective* sleep, only and were in the hypothesized direction. Specifically, nights with greater reported awake time or lower sleep quality ratings were associated with days characterized by less positive affect and more negative affect. Gender was not a significant main effect in the present study, despite previous research suggesting gender differences in the sleep–affect relationship. The fact that self-ratings of sleep emerged as the best predictors of affect may suggest that perceived sleep is a particularly important predictor. Finally, our results suggest exploration of affect as a potential intervention target in late-life insomnia is warranted.

Keywords

affect; daily variability; intraindividual variability; mood; older adults; sleep

INTRODUCTION

Multilevel modeling (MLM) was used to examine daily associations between sleep and affect in older adults. Although sleep and affect are frequently measured on a daily basis, traditional analytic approaches aggregate these data to reduce error. However, studies now show that transient fluctuations in an individual's responses over time [often referred to as within-person variation or intraindividual variability (IIV)] provide unique, meaningful information that can be reliably distinguished from error (Hultsch *et al.*, 2000; Li *et al.*, 2001). Using MLM, sleep researchers can examine the impact of daily fluctuations (IIV)

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within a data set and can gain a more precise understanding of the dynamic relationships among variables, particularly when compared with traditional mean level analyses.

Measuring sleep (objective and subjective)

Although IIV has received some attention in the sleep research literature (Totterdell *et al.*, 1994), the vast majority of studies have focused on characterizing differences in the sleep patterns of good versus poor sleepers. In this regard, the literature is consistent. Individuals with insomnia tend to exhibit highly variable sleep patterns (Coates *et al.*, 1981; Edinger *et al.*, 1991, 1997; Frankel *et al.*, 1976; Hauri and Wisbey, 1992; Vallieres *et al.*, 2005), while ‘normal’ sleepers tend to have less varied patterns (Edinger *et al.*, 1997; McCrae *et al.*, 2003, 2005). Despite the obvious contribution of these studies to the field, the drive to characterize group differences may have unintentionally inhibited our ability to fully understand/appreciate the dynamic relationship between sleep and affect.

An additional complication to understanding the sleep–affect relationship involves the method used to measure sleep. Sleep can be assessed subjectively (e.g. self-report sleep diaries) and objectively (e.g. actigraphy, polysomnography). Unfortunately, quite often these different modes of measurement are poorly correlated within individuals (Espie *et al.*, 1989; McCrae *et al.*, 2005; Means *et al.*, 2003). Consequently, the literature on the importance of sleep to various constructs may vary depending on how sleep was measured. Further, there may be unique temporal associations between (subjective and/or objective) measures of sleep and other constructs (e.g. affect) that are individually specific. These may be obscured by excluding one type of sleep measurement or through a comparison of mean level performance between groups.

Recently, researchers have begun to recognize the usefulness of studying the daily fluctuations in an individual’s sleep pattern (IIV) to broaden our understanding of sleep and its correlates (e.g. affect; Espie, 1991; Pallesen *et al.*, 1998). Furthermore, because MLM allows for the study of change over time (Aiken *et al.*, 1991; Collins and Sayer, 2001; Magnusson and European Network on Longitudinal Studies on Individual Development., 1991; Singer and Willett, 2003), as well as the separation of between- and within-person processes, and even the study of individual differences in within-person processes, this analytic approach appears both timely and appropriate for contemporary sleep research.

Affect

According to State-Trait theory (Cattell, 1963; Mischel and Shoda, 1995; Nesselroade, 1988), affect (frequently referred to as mood) is the temporal (state) portion of human emotional life, which fluctuates with present experiences (Kraemer *et al.*, 1994). Historically, the literature conceptualized affect as a unitary, bipolar construct, bracketed by high levels of either positive or negative scores (Meddis, 1972; Russell, 1979). By definition, a shift toward, or increase in one dimension (e.g. negative) necessitates a decrease and shift away from the other polar dimension (e.g. positive) (Russell, 1979). However, studies have shown that positive and negative affect scores are not mutually exclusive, and thus are relatively distinct constructs (Watson *et al.*, 1984, 1988). Moreover, studies have argued that positive and negative affective systems operate independently (Cacioppo and Bernston, 1994; Cacioppo *et al.*, 1999). Recent neuroimaging studies have effectively identified and manipulated disparate positive and negative affective neural networks (Canli *et al.*, 1998, 2001; Davidson *et al.*, 2000), lending credence to this view. Given the conceptual and biological support for distinct positive and negative affect constructs, the present study examined the relationship between sleep and positive–negative affect, independently.

Research has shown that variability in affect is associated with increased stress and daily conflict (Bolger *et al.*, 1989), self-reported health problems (Watson *et al.*, 1988), and depression (McConville and Cooper, 1996). However, despite the intuitive appeal of a strong daily affect–sleep link, only three studies have examined daily associations between these variables (Berry and Webb, 1983, 1985; Totterdell *et al.*, 1994), and only one has focused specifically on 'older adults' (Berry and Webb, 1985).

Sleep and affect

Berry and Webb (1983) examined correlations between sleep and affect using two nights of sleep recordings (18 variables) and one night of affect data [five mood scales from the Lorr Mood test (Lorr *et al.*, 1967) collected on the second night] from middle aged adults (aged 50–60). They analyzed their data separately for men and women and found a greater number of significant correlations for women compared with men (24 versus 3). They did not interpret the correlations for males (only three), attributing them to chance alone. For women, they concluded that positive affective states were related to increasing sleep efficiency and total sleep time, while negative affective states were positively correlated with waking after sleep onset.

In a follow-up study, Berry *et al.* (1985) examined four nights of laboratory recorded sleep and three nights of affect information (collected on the second, third, and fourth nights) from 25 women aged 56–66. Results from this study found that sleep efficiency and the latency to the first rapid eye movement (REM) period were significantly related to affect. Combined, these two studies suggest that the relationship between sleep and affect might be stronger for women than men, and this relationship may be mediated by objective measures of sleep (i.e. sleep efficiency and latency to first REM period).

Using subjective measures of sleep, Totterdell *et al.* (1994) examined 14 concurrent days of sleep diaries and well-being measures (affect, physical and cognitive symptoms, and social interaction) from 30 healthy, employed adults (aged 20–59). Their results showed small, but significant correlations among most of the subjective sleep and well-being variables (including affect).

Unfortunately, the interpretation and contextualization of these findings is complicated by methodological differences between these studies (e.g. objective versus subjective sleep measures). Moreover, Totterdell and colleagues' sample was younger (mean age 31.6 versus 59.5 years) and of mixed gender (versus women only). These studies also used different tools to measure affect [items from the University of Wales Institute of Science and Technology Mood Adjective List (Matthews *et al.*, 1990) versus the Loor Mood Test (Lorr *et al.*, 1967)] and had different lengths of data collection (14 versus 4 days). Consequently, ambiguity remains in understanding the sleep–affect relationship.

However, these three studies suggest that sleep and affect may fluctuate on a daily basis, making them ideal constructs for MLM. This type of analysis offers an important next step in understanding the dynamic relationship between sleep and affect for at least two reasons. First, because sleep and affective disorders are amenable to behavioral modification, a more detailed understanding of the relationship between the two would lead to better intervention outcomes. Second, enhanced intervention efficacy would improve the quality of life in older adults as both sleep and affect are known to have a major influence on their health and well-being.

As discussed above, few studies have focused on the relationship between sleep and affect in older adults. Those that have are not conclusive, in part, because of methodological and/or analytic disparities. Increased clarity regarding the sleep–affect relationship has broad implications for our knowledge of sleep in later life and specific implications for the treatment of late-life insomnia.

This study addressed the aforementioned limitations by using a multifaceted approach to assess sleep and then analyzing its relationship with affect over time using MLM. We hypothesized that nights characterized by better sleep would be associated with days characterized by higher positive affect and lower negative affect, and that the inverse would be true for nights characterized by poor sleep. Additionally, we hypothesized that the nature of this relationship would be consistent for both objective and subjective sleep variables.

METHODS

Subjective sleep measures

Participants completed sleep diaries (Lichstein *et al.*, 1999) each morning for 14 days, providing subjective estimates of the following sleep–wake parameters: (i) total wake time (TWT_S)-total unwanted awake time in bed; and (ii) sleep quality rating (SQR), scaled from 1 (very poor) to 5 (excellent). Because TWT was also collected objectively using actigraphy (see below), an 's' subscript indicates the variable was measured subjectively, and an 'o' subscript indicates it was measured objectively. Compliance with diary completion was exceptionally high, and only minimal data were lost. Out of 5768 possible data cells (four sleep diary variables × 14 days × 103 participants), only 76 were missing (1.32%).

A mean was computed for each of these variables for the 2-week recording period. Centered variables, which give the daily deviation from the participant's mean, were also computed for each sleep-wake parameter (Kreft *et al.*, 1995; Singer, 1998). These centered variables were used to examine daily fluctuations or IIV (see Statistical analysis).

Objective sleep measures

Participants wore an actigraph, the Actiwatch-L, which has an integral ambient light sensor (Mini Mitter Co., 2001), on their non-dominant wrist for 14 consecutive days, concurrent with the sleep diary period. The Actiwatch-L monitors ambient light exposure and gross motor activity and contains an omnidirectional, piezoelectric accelerometer with a sensitivity of ≥0.01 ***g***-force and a light sensor with a recording range of 0.1–150 000 Lux.

The sensors of the Actiwatch-L are sampled 32 times/s and record the peak value for each second. These peak values are then summed into 30-s 'activity' counts. These activity counts are then downloaded to a PC and analyzed using Actiware-Sleep v. 3.3 (Mini Mitter Co., 2001), which uses a validated algorithm to identify each epoch as either sleep or wake (Oakley, 1997). The software provides three default sensitivity settings (high, medium, low). This study utilized medium sensitivity. On medium sensitivity, the threshold is set at 40 activity counts. If the total activity for an epoch was ≥40, it was scored as wake. If the total activity was ≤40, the final activity count for the epoch was based on the level of activity in the surrounding 2 min (Eq. 1).

Total activity—

$$\text{Epoch}A=E_{A-4}(0.04)+E_{A-3}(0.04)+E_{A-2}(0.20)+E_{A-1}(0.20)+E(2)+E_{A+1}(0.20)+E_{A+2}(0.20)+E_{A+3}(0.04)+E_{A+4}(0.04) \qquad (1)$$

where A = activity count for the epoch being scored and $E_{A\pm1–4}$ = activity count in adjacent epochs. If Epoch A total activity (i.e. weighted sum of activity counts) exceeded the threshold of 40, then Epoch A was scored as wake; otherwise, it was scored as sleep.

Bedtime and time out of bed in the morning were based on sleep diary entries as recommended in the software manual (Mini Mitter Co., 2001). Actiware-Sleep determined sleep start automatically by searching for the first 10 min during which no more than one epoch was scored as wake. Likewise, sleep end was the last 10 min during which no more than one epoch was scored as wake. As previously mentioned, Actiware-Sleep provides objective estimates for TWT, a variable also provided by the sleep diaries. When measured objectively by actigraphy TWT_o represents the sum of all wake epochs within the sleep period. Similar to the sleep diaries, TWT_o was averaged over the 14 days. Centered variables, which give the daily deviation from the participant's mean, were also computed for this objective sleep–wake parameter (Kreft *et al.*, 1995; Singer, 1998). This centered variable was used to examine daily fluctuations or IIV (see Statistical analysis).

Data loss was minimal. There were no equipment failures. Three participants reported taking their watch off *during the day* for several hours (<3 h). However, in each case, the participant reported putting the watch back on several hours before bedtime. Another three participants reported leaving their watches off for an entire day (24 h). To make up for this lost day, these participants wore their watches and completed their sleep diaries for an additional day immediately following the study period. One participant forgot to wear the watch during week 2 and was excluded for the present study. Thus, concurrent sleep diary and actigraphy data are available for 14 days for 103 participants.

Affect measure

Participants completed the Positive and Negative Affect Schedule (PANAS; Watson *et al.*, 1988) following completion of the sleep diary each morning for 14 days. The PANAS consists of 20 self-report items; 10 items measure positive affect (PA), and 10 items measure negative affect (NA). Participants rated the degree to which each mood was experienced at that time using a 1 (*very slightly or not at all*) to 5 (*extremely*) Likert scale. Daily PA and NA scores were calculated by summing the scores of the 10 PA and 10 NA items, respectively.

Participants and procedure

A convenience sample of 116 adults aged 60 years and over (*M* = 72.81 years; SD = 7.12) who resided in North Central Florida were recruited through media advertisements, community groups, and flyers to participate in a study of sleep patterns in the elderly. Interested individuals were screened in two phases: a brief telephone interview (15–20 min) that was followed by a 1–1½ hour in-person interview conducted either in the individual's home (76%) or at a local continuing care retirement center (24%). Exclusionary criteria included: (i) age-younger than 60 years; (ii) presence of sleep disorders other than insomnia (e.g. sleep apnea, narcolepsy); (iii) severe psychiatric disorders (e.g. thought disorders, depression); (iv) cognitive impairment [scoring in the impaired range on three or more subtests of the Cognistat (Mueller *et al.*, 2001)]; and (v) psychotropic or other medications (e.g. beta-blockers) known to alter sleep. Twelve individuals were ineligible following the initial telephone screening for reasons including age, cognitive impairment, and sleep apnea diagnosis; no individuals were ineligible following the in-person interview; one individual was excluded for failure to wear the actigraph during week 2. Thus, the final sample consisted of 103 participants. All were living in their own homes during the study. The majority of participants were Caucasian (96%) and had some college coursework or a college degree (75%; *M* = 16.34 years, *SD* = 2.92).

During the 1–1½ interview session, participants read and signed an informed consent form approved by the University of Florida's Institutional Review Board, and a member of the research team administered the Cognistat (Mueller *et al.*, 2001), conducted a sleep history interview, and explained how to complete the sleep diaries and PANAS. The research team member also gave the participant an actigraph and explained how it works and how it should be worn. Participants were asked to complete the sleep diaries and PANAS every morning and to wear the actigraph continuously for 2 weeks. After the first week, a research team member visited the participants again to determine how the study was going, answer any questions, and download the first week's data from the actigraph. At the end of the 2 weeks, a research team member visited the participants a third time to collect the actigraph and daily measures (sleep diaries and PANAS). All participants received $30 compensation.

Statistical analysis

Analytical framework-general—The current study used daily data from the objective and subjective sleep measures (TWT) along with the subjective sleep quality rating (SQR) to predict both positive and negative affect applying a MLM approach. MLM, also referred to as hierarchical linear modeling (HLM, Bryk and Raudenbush, 1992), is an extension of the general linear model, and does not require observations to be independent. Thus, MLM is very flexible and especially suited for daily data because of its autoregressive nature and hierarchical structure with daily observations nested within each participant (Singer *et al.*, 1998a,b; Willett *et al.*, 1998; Zautra *et al.*, 2005).

Fixed and random effects can be estimated with MLM. Fixed effects refer to 'average effects', or effects that hold over all persons. In our models, fixed effects are examined at two levels. Level 2 fixed effects assess the *between-person* association, across all participants, of individual differences in predictor and criterion variables. Level 1 fixed effects assess the daily association, across all participants and occasions, between day-level variation in a predictor (i.e. SQR) and day-level variation in an outcome (i.e. PA). Random effects test whether there are significant individual differences in obtained fixed effects. For example, if there is a generally small positive within-person relationship between SQR and PA, a significant random variance term would indicate that the magnitude of that within-person relationship may differ substantially across individuals. Fig. 1 illustrates these three levels/types of effects schematically.

Because of the hierarchical nature of our data (14 consecutive days nested within 103 participants) and in order to increase the precision of predicting fluctuations in PA and NA with changes in sleep patterns, we modeled the data with an MLM approach. This provided the opportunity to examine how well sleep predicted affect both within- (level 1) and between- (level 2) persons. Level 1 analyses addressed questions such as: 'On days in which a person reports above-average sleep quality, does s/he also experience higher levels of positive affect?'. Level 2 analyses examined questions like: 'Do people who are generally better sleepers report higher levels of positive affect?'.

Analytical framework-MLM analysis—Both objective and subjective sleep measures were used to predict affect (positive and negative, tested separately) using a multistep MLM approach, using the MIXED procedure in SPSS 14.0. All models were estimated using the Maximum Likelihood (ML) method. The ability of a model to predict affect better than a baseline (null) model was used as an index of Goodness of Fit. Improvements in predictability were determined by the proportional reduction of within- and between-person residual variances compared with this baseline model (Bryk and Raudenbush, 1992). Decreases in residual variances represent a proportional reduction of the prediction error, which is analogous to R^2, and used as an estimate of effect size. One issue that has received substantial attention in work on longitudinal MLM is the issue of optimal modeling of repeated measures error structures (e.g. Singer and Willett, 2003); issues such as homoscedasticity and autocorrelation of errors over time warrant consideration. While these issues go beyond the scope of the current paper, we examined the effect of different error structure specifications on model fit. The different error structures tested had little effect on the fixed and random parameter estimates or their pattern of significance (Singer and Willett, 2003).

Several features of the modeling are briefly described here. First, level 2 effects were estimated using predictors, which varied between persons, and for which there was only one value per person. Thus, for the variables of TWT_o, TWT_s, and SQR, the level 2 predictor was each person's *mean*. Second, level 1 effects were estimated using predictors which varied within persons, and for which there was a new value at each occasion of measurement. For the variables of TWT_o, TWT_s, and SQR, the level 1 predictor was each person's *centered daily score* (i.e. daily score–person's mean). Thus, the level 1 predictors represented each person's daily deviation from his or her average value on the predictor.

We built our models in a series of seven steps. Details of these steps, including specific parameters estimated, and the corresponding MLM equations, can be found in the statistical Appendix. Briefly, the seven steps estimated were as follows: step 1: null model (no predictors), which defined the variance to be explained, and which served as the baseline against which subsequent models would be used to calculate (i) variance explained, and (ii) improvement in fit; step 2: fixed (overall effect, averaged across all subjects) and random (estimation of the size of individual differences in the strength of the effect) effects of Day (Occasion, coded 0–13) were estimated. Introducing Day as a fixed effect into the models anchored all subsequently added fixed level 2 effects at the first occasion of measurement (i.e. day 1, coded as 0). This step controlled for any overall temporal trends in the data which might spuriously create time-varying relationships between predictors and the affect outcome; step 3: fixed effect of gender estimated; steps 4–6: effects of three sleep variables (objective, accelerometer-measured total wake time; subjective, sleep-diary measured total wake time; subjective sleep quality rating) were estimated, respectively. For each of these sleep variables, we estimated a fixed level 2 effect (i.e. the association between a participant's mean level of sleep and their level of affect at the beginning of the assessment period), a fixed level 1 effect (i.e. the association between participants' day-to-day deviations from their mean level of sleep and their day-to-day variation in affect), and a random level 1 effect (i.e. whether there were significant between-person differences in the strength of the day-to-day sleep and affect relationship); step 7: a reduced form equation including only Occasion, TWT_s and SQR was conducted (because only these predictors were significant at all levels in both equations). This test was conducted to verify that the significant predictors in the preceding model were not conditional on the inclusion of the other, non-significant predictors.

RESULTS

Sleep characteristics

Table 1 shows the means and standard deviations for the objective and subjective sleep variables. Nineteen participants reported insomnia consistent with the American Academy of Sleep Medicine Work Group's published Research Diagnositic Criteria for insomnia (Edinger *et al.*, 2004). Average duration of insomnia was 8.41 years (*SD* = 11.33; range .5–50).

Multicollinearity

Multicollinearity is a situation in which the data from two or more variables are perfectly or near perfectly correlated (Pedhazur, 1997). In the presence of multicollinearity, slight fluctuations in the data may lead to substantial fluctuations in the sizes of such estimates and may even change their signs. Consequently, ‘multicollinearity may have devastating effects on regression statistics to the extent of rendering them useless or highly misleading (Pedhazur, 1997).’

Because this study assessed sleep repeatedly, and used two different methods (sleep diaries and actigraphy), issues of multicollinearity were a concern. Table 2 shows the bivariate correlations of the predictor variables at both the between- and within-person levels. These values were obtained by estimating a multivariate mixed-effects null model in SPSS 14.0. This procedure produced both ‘G’ (between-persons) and ‘R’ (within-persons) covariance matrices, which were subsequently rescaled into correlations.

Between-person multicollinearity—In terms of absolute values, significant between-person bivariate correlations among predictor variables ranged from 0.20 to 0.50. TWT_o was significantly, negatively correlated with SQR ($r = -0.25$, $P < 0.05$) only. In contrast, TWT_s was significantly, negatively correlated to SQR and PA and positively correlated with NA (see Table 2). Both objective and subjective TWT were significantly, positively correlated.

Within-person multicollinearity—Again, in terms of absolute values, significant within-person bivariate correlations among predictor variables ranged from 0.07 to 0.55. Consistent with the between-person analyses, there was evidence for convergent validity (though somewhat weaker) for subjective and objective TWT (see Table 2, upper o.-diagonal). Likewise, there was a significant negative correlation between TWT (both objective and subjective) and SQR. TWT_s was significantly, positively correlated with positive affect and negatively with negative affect, while TWT_o was significantly, positively correlated with negative affect only. Collectively, these results suggest that some of the predictor variables shared up to 30% of their variance. Consequently, we orthogonalized SQR in the later models based on a regression model, effectively isolating the unique component of SQR that is independent of TWT_s. The orthogonalized SQR represents the day-to-day variations in sleep quality that are not explained by day-to-day variations in total wake time. As with all regressions, regression parameter effects represent partial effects, and should be interpreted as the *unique* effects of the predictors, controlling for all other predictors.

MLM analysis and results

An initial step in MLM is determining how much variance can be accounted for by improving upon the null (baseline) model of predicting affect with sleep variables; which includes estimates of level 1 and level 2 variability. Intraclass correlation coefficients (ICC) serve as an index of these variability estimates (Bryk and Raudenbush, 1992). For positive affect, 27% of the overall variability was within-person and 73% was between-person. For negative affect, 48% was within-person and 52% was between-person. Therefore, our initial analyses revealed that there was a significant amount of variability in both level 1 and level 2 estimates which could be explained by our models.

Sleep and positive affect

Table 3 shows the model fit results for each added predictor block. The left side of the figure shows results for positive affect. Each modeling step resulted in a reduction in −2LL for the model, indicating better fit. However, in step 2 (fixed level 2 effect of gender), step 3 (fixed level 2 effect of mean TWT_o; fixed and random level 1 effect of centered daily TWT_o), and step 7 (reduced-form equation), changes in −2LL were negligible (when a nested χ^2-test was used), and did not represent a significant change in fit.

The final model, the reduced-form step 7, which retained only the variables which were significant (generally at all levels) in the preceding step 6, is summarized in Table 4 (left panel). The level 1 (within person) results suggested that only TWT_s and SQR had significant within-person associations with positive affect. On those days where perceived TWT was above-average, or the residualized SQR was below-average, positive affect was also lower. The level 1 residualized SQR effect was qualified by a random effect, suggesting that there were significant individual differences in the strength of the residualized SQR-positive affect relationship. In addition, while there was no overall linear temporal trend in positive affect, a significant random effect for occasion (day) suggested that there were individual differences in the 14-day affect trend.

With regard to the level 2 effects, there was a single significant effect of TWT_s, suggesting that persons with higher average self-reported wake times experienced lower positive affect. The level 2 model explained about 28% of the between person variation in positive affect, and the level 1 model explained about 18% of the within person (daily) variation in positive affect. Finally, different repeated measures error structures were tested, but had little effect on fixed and random parameter estimates or their pattern of significance (Singer and Willett, 2003).[1]

Sleep and negative affect

Model fit results for negative affect are shown on the right side of Table 3. As for positive affect, each modeling step resulted in a reduction in −2LL for the model, indicating better fit. However, in step 2 (fixed level 2 effect of gender), step 3 (fixed level 2 effect of mean TWT_o; fixed and random level 1 effect of centered daily TWT_o), and step 7 (reduced-form equation), changes in −2LL were negligible (when a nested χ^2 test was used), and did not represent a significant change in fit.

The right side of Table 4 shows the final model, step 7. The level 1 (within person) results suggested that there was a significant negative linear temporal trend in negative affect (such that persons became more negative over time). This time effect was qualified by a significant random effect, suggesting that there were individual differences in negative affect change over time. As with positive affect, both the level 1 effects of TWT_s and residualized SQR were significant; on days where persons had above-average TWT_s or below-average residualized SQR, negative affect was higher. There were significant individual differences in this TWT_s-negative affect relationship, as qualified by a significant random effect. The level 2 model suggested that persons with higher TWT_s, and lower residualized SQR reported higher negative affect at the beginning of the study. It should be noted that in step 6 there was also a significant negative effect of TWT_o, such that persons with lower mean TWT_o had higher negative affect. The step 7 model shows, however, that this term could be removed without a significant loss of model fit; it probably represented a statistical artifact (i.e. suppressor effect). In this final reduced-form model, the level 2 model explained about 26% of the between person variation in negative affect, and the level 1 model explained about 3% of the within person (daily) variation in negative affect. As with positive affect, different error structures were tested, but had little effect on fixed and random parameter estimates or their pattern of significance (Singer and Willett, 2003).[2]

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[1] The initial sequence of seven steps was estimated under the simplest assumptions about the error structure over time (i.e. homoscedasticity and independence of errors). As Table 3 shows for positive affect, the fit (−2LL) of this model was 7800.90. We re-estimated this model under alternative error structure assumptions, including *diagonal* (heteroscedasticity and independence of observations; −2LL = 7778.17), *compound symmetry* (homoscedasticity and fixed correlation between all occasions; model would not converge), and *autoregressive error* (*AR(1);* homoscedasticity and interoccasion correlations that are reduced, exponentially, by the temporal lag between them; −2LL = 7761.30). Thus, homoscedasticity and independence of errors are not tenable assumptions in these data, and AR(1) provided the best specification of the repeated measures error of the three approaches tested. It is important to note, however, that all fixed and random parameter estimates remained essentially unchanged under different error structure assumptions, and the pattern of significance was not altered.

DISCUSSION

Only the subjective measures of sleep exhibited daily associations with positive affect. Specifically, on days on which individuals reported above average sleep quality (shared variance with total wake time controlled) or below average wake time, they also reported experiencing higher levels of positive affect. For sleep quality, this was qualified by a significant random effect, suggesting that the average daily association between positive affect and residualized sleep quality rating varied between individuals. At the between persons level, individuals who reported greater wake time during the night also experienced lower positive affect.

Similar to positive affect, only the subjective measures of sleep exhibited daily associations with negative affect. On days on which individuals reported below average sleep quality (shared variance with total wake time controlled) or above average wake time, they also reported experiencing higher levels of negative affect. For total wake time, this relationship was qualified by a significant random effect, suggesting the average daily association between negative affect and reported wake time varied between individuals. At the between persons level, both the objective and subjective measures of sleep were associated with negative affect. Thus, on average, persons with greater subjective wake time during the night and lower sleep quality experienced greater negative affect already at the beginning of the study.

Overall, our results support *daily* associations between affect and *subjective* sleep only. These associations were in the hypothesized direction, indicating that nights with lower residualized quality ratings or greater reported wake time were associated with days characterized by less positive affect and greater negative affect. Interestingly, despite previous research suggesting gender differences in the sleep–affect relationship, gender was not associated with either positive or negative affect. Additional analyses (not shown here) further confirmed that gender did not moderate any of the effects of sleep on affect in the present study.

Our results extend the existing literature in this area in several important ways. First, we examined both *subjective* and *objective* sleep over a relatively long time period; whereas previous researchers examined affect in relation to either subjective (Totterdell *et al.*, 1994) or objective (Berry and Webb, 1983, 1985) sleep alone. Because subjective and objective sleep measures are poorly correlated for some individuals (Espie *et al.*, 1989; McCrae *et al.*, 2005; Means *et al.*, 2003), daily associations between subjective sleep and affect apparently differ significantly from those between objective sleep and affect. Second, we included a broader range of older adults (60–89 years) than did Berry and Webb, increasing the generalizability of our results. Third, the inclusion of both men and women allowed for further exploration of the interesting gender differences found in Berry and Webb’s (1983) initial study. This study failed to support the importance of gender in predicting affect or moderating sleep’s effects on affect.

The subjective sleep–affect relationships identified in this study are generally consistent with those identified by Totterdell *et al.* (1994). Our failure to find daily associations between objective sleep and affect is inconsistent with the earlier study of Berry and Webb

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[2] As a concluding step, for negative affect, we again examined the tenability of the homoscedasticity and errors independence assumptions for the repeated measures, for which the −2LL (Table 3) was 6660.12. As with Positive Affect, alternative error structures provided better fits to the data: *diagonal*, −2LL = 6598.45; *compound symmetry*, model again would not converge; and *autoregressive error*, −2LL = 6628.23. Thus, for Negative Affect, of the three specifications of repeated measures error tested, a diagonal structure provided the best fit to the data. Again, as with Positive Affect, different error structure specifications had little effect on fixed and random parameter estimates or their pattern of significance.

(1983). However, they are generally consistent with their follow up work (Berry and Webb, 1985) which found associations between affect and only two out of 18 polysomnographic sleep variables studied (sleep efficiency and latency to first REM period). They reported total sleep time (but not total wake time), and it was not significantly associated with their measure of affect. It is important to note that direct comparison of the Berry and Webb's studies with the present study is complicated by several important methodological differences. Specifically, sleep and affect were measured concurrently using 14 days of actigraphy and affect data in the present study compared with only 1 and 3 days of polysomnography and affect data, respectively (Berry and Webb, 1983, 1985).

The observed differences between affect and actigraphic versus self-reported sleep data in the present study are not surprising. The importance of utilizing different types of measurement to fully understand and explain sleep has been well-documented, and discrepancies between self-report and polysomnographic measures of sleep have been identified. Such discrepancies are typically greater for individuals with insomnia than they are for normal sleepers (Espie *et al.*, 1989; Means *et al.*, 2003). For many individuals, sleep perceptions are more important in terms of sleep satisfaction than are objective sleep parameters. For individuals with insomnia, cognitive-behavioral therapy for insomnia (CBTi) often improves their perceptions of specific sleep–wake parameters, including total wake time, as well as their overall satisfaction with sleep despite the fact that improvements in objective sleep parameters are generally much smaller or in some cases, not significant (Morin *et al.*, 1999; Murtagh and Greenwood, 1995). Harvey's cognitive model (Harvey, 2002) of insomnia captures the importance of perceptions for sleep. According to this model, insomnia is maintained by excessively negatively toned cognitive processes (attention and perception). One implication of the daily subjective sleep–affect associations identified in this study is that treatment of insomnia should not focus solely on improving sleep perceptions *per se*, but should also focus on reducing negative affect and increasing positive affect. Because the present study utilized a community-based sample, future research examining the sleep–affect link in the context of insomnia is warranted. In particular, whether insomnia explains the residual variance between people in the relationship between self-reported sleep and affective outcomes would be an important hypothesis to test. Additionally, exploration of a potential causal connection between sleep and affect would be of particular interest.

Sleep and emotional inhibition

Mood regulation refers to a basic drive to feel more pleasant than unpleasant affect (Erber and Erber, 2001; Larsen, 2000). Our finding of an association between poorer sleep and greater emotional disregulation (e.g. less positive and more negative affect) is consistent with Totterdell *et al.* (1994) and Berry and Webb (1983, 1985). Interestingly, our results contradict evidence suggesting that poorer sleep (e.g. decreased stages 3 and 4 and increased stage 1) is associated with alexithymia (a condition for which a key symptom is the inability to identify emotions; Bazydlo *et al.*, 2001). However, it is important to note that these contradictory findings have not always been replicated (De Gennaro *et al.*, 2002, 2004). Thus, questions about the relationships between quality of sleep, affective regulation, and emotional inhibition remain.

Limitations

Potential limitations of the current study deserve mention. For example, participants were generally healthy, community-dwelling older adults who volunteered to participate. Therefore, the generalizability of these results to a clinical population of older adults may not be straightforward. Affect was measured only once per day (in the morning). Thus, it is possible that the relationship between sleep and affect may differ with multiple measurements and/or measurement later in the diurnal cycle. Because affect and subjective sleep were assessed using ‘paper and pencil’, it is possible that shared method variance contributed to their association. Additionally, only one measure of affect was used in the present study. While the PANAS is both highly reliable and valid (Watson *et al.*, 1988), the inclusion of multiple measures of affect may have provided additional information. Furthermore, because mood is highly correlated with other subjective measures, such as alertness, sleepiness, and fatigue, it is unclear whether the results of the present study could be interpreted solely in the terms of general subjective well-being rather than specifically in terms of affect. Thus, future research employing a broader range of subjective daytime functioning measures is needed. Also, the current study lacks in the measurement of possible covariates of the sleep–affect relationship. Variables such as physical activity (Montgomery and Dennis, 2004; Pretty *et al.*, 2005) and daily stress (Morin *et al.*, 2003) that are known to be associated with both sleep and affect could prove useful in interpretation of the results. Consequently, future studies might assess a broader range of daytime functioning such as physical activity (Montgomery and Dennis, 2004; Pretty *et al.*, 2005) and daily stress (Morin *et al.*, 2003). Finally, the design of the study prohibits any causal conclusions.

CONCLUSION

Our results highlight the need for greater focus on intraindividual variability in sleep research and reinforce the importance of perceptions–not only in terms of sleep–wake parameters, but also in terms of affect and other daytime functioning factors. Finally, our results suggest exploration of affect as a potential intervention target in late-life insomnia is warranted.

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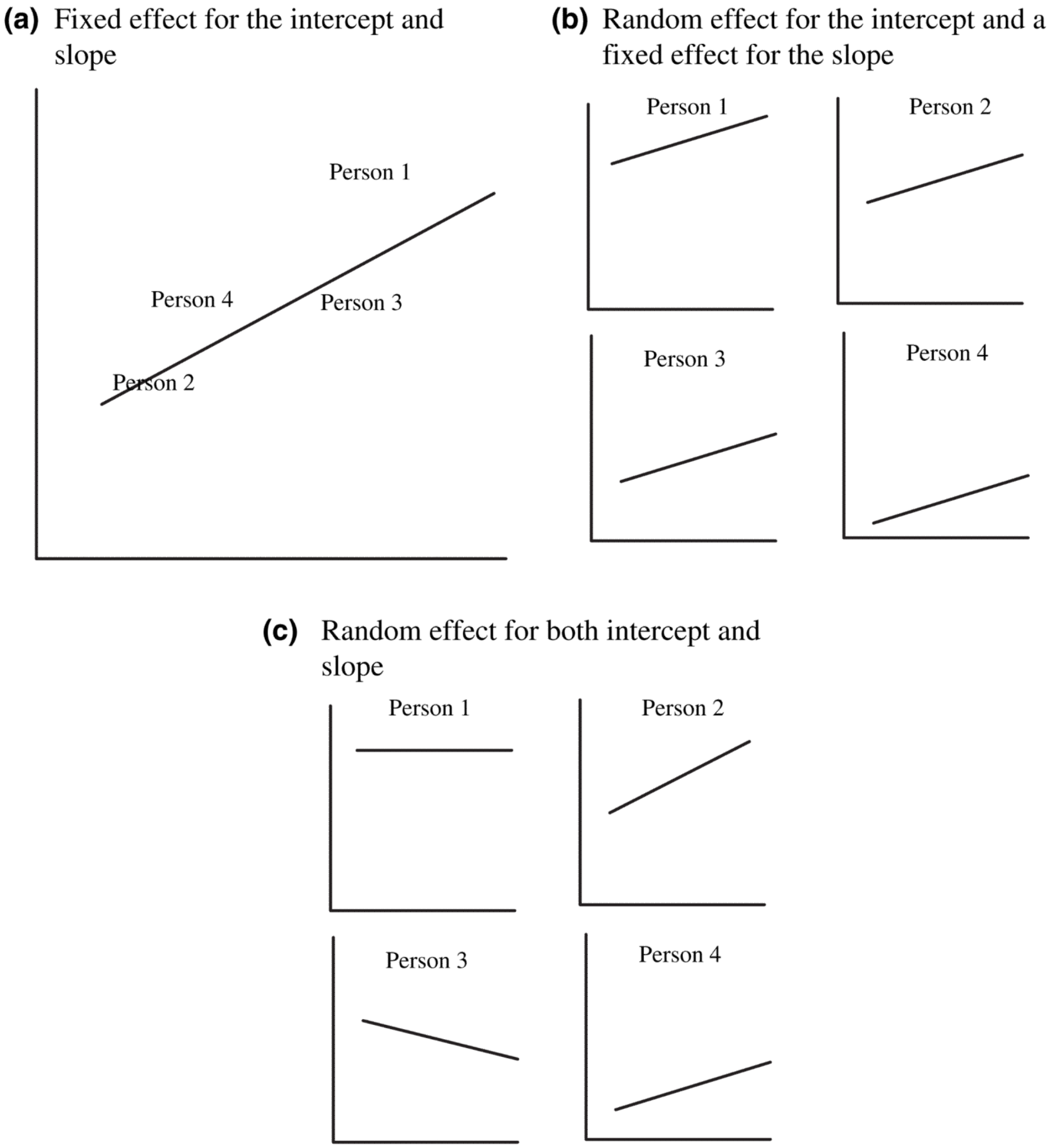

Figure 1.

Graphical representation of the three levels of effects. In panel a, a fixed effect for the intercept and slope is shown. This effect holds across all persons, and shows the *between-person* association between a predictor and an outcome (level 2). In panel b, random intercepts and a fixed slope are shown. The final effect reported will reflect the average *within-person* day-to-day association between an IV and a DV, and is estimated invariantly across all persons. In panel c, a random effect for both intercept and slope are shown. As the figure shows, this allows for individual differences in the association between the IV and the DV.

Table 1

Means and standard deviations of objective and subjective sleep variables

	Mean	Standard deviation
TWT_o	53.42	23.75
TWT_s	70.20	42.65
SQR	3.58	0.57

TWT, total wake time; SQR, sleep quality rating. A subscript ‘s’ indicates the variable was measured subjectively (Sleep Diary); a subscript ‘o’ indicates it was measured objectively (Actigraphy).

Table 2

Correlations among predictor variables and positive and negative affect between-persons (below diagonal) and within-persons (above diagonal)

	1	2	3	4	5	6
1. TWT_o	–	0.26^{**}	-0.26^{**}	−0.02	0.07^{*}	–
2. TWT_s	0.38^{**}	–	-0.55^{**}	-0.16^{**}	0.18^{**}	–
3. SQR	-0.25^{*}	-0.50^{**}	–	0.21^{**}	-0.18^{**}	–
4. Positive Affect	−0.07	-0.20^{*}	0.22^{*}	–	-0.24^{**}	–
5. Negative Affect	−0.07	0.32^{**}	-0.30^{**}	−0.07	–	–
6. Gender	−0.10	0.05	−0.02	0.10	0.07	–

TWT, total wake time; SQR, sleep quality rating. A subscript ‘s’ indicates the variable was measured subjectively (Sleep Diary); a subscript ‘o’ indicates it was measured objectively (Actigraphy).

[*] Correlation is significant at the 0.05 level (2-tailed).

[**] Correlation is significant at the 0.001 level (2-tailed).

Table 3

Model construction procedure

	Positive affect						Negative affect					
Models	**−2LL**	**Δ−2LL**	s_b^2	s_w^2	r_b^2	r_w^2	**−2LL**	**Δ−2LL**	s_b^2	s_w^2	r_b^2	r_w^2
(1) Null	8354.22	–	42.41	15.98	–	–	7181.44	–	8.03	7.46	–	–
(2) Time added	8276.93	77.29	38.76	13.97	0.09	0.13	7147.43	34.01	8.75	6.90	−0.09	0.08
(3) Gender added	8276.14	0.79	38.46	13.97	0.09	0.13	7146.93	0.5	8.68	6.90	−0.08	0.08
(4) TWT_o added	8273.29	2.85	38.47	13.72	0.09	0.14	7140.20	6.73	8.63	6.88	−0.08	0.08
(5) TWT_S added	7849.23	424.06	34.78	12.37	0.18	0.23	6694.07	446.13	7.92	5.74	0.01	0.23
(6) SQR added	7798.57	50.66	34.64	11.54	0.18	0.28	6654.33	39.74	7.34	5.52	0.09	0.26
(7) Reduced form*	7800.90	−2.33	35.00	11.64	0.18	0.27	6660.12	−5.79	7.79	5.50	0.03	0.26

*Reduced model retained Time, TWT_S, and SQR only.

−2LL, −2 log likelihood; Δ−2LL, change in −2LL relative to preceding model; s_b^2, unexplained intercept-related (between subjects) variance; s_w^2, unexplained residual-related (within subjects) variance; r_b^2, between-subjects pseudo *R*-squared, an estimate of the amount of between subjects variance (estimated from null model) explained by fixed and random predictors; r_w^2, within-subjects pseudo *R*-squared, an estimate of the amount of within subjects variance (estimated from null model) explained by fixed and random predictors.

Table 4

Sleep variables predicting positive and negative affect

	Positive affect					**Negative affect**				
	B	**SE**	**df**	***t***	***P*-value**	**B**	**SE**	**df**	***t***	***P*-value**
Fixed effects – predictor variable										
Within-person										
Occasion	−0.04	0.04	102.19	−0.99	0.320	−0.07	0.02	104.21	−3.52	<0.001
TWT_S	−0.01	0.004	68.38	−2.08	0.040	0.01	0.003	68.24	2.85	0.010
SQR	0.86	0.22	94.12	3.85	<0.001	−0.33	0.14	90.31	−2.30	0.020
Between-person										
TWT_S	−0.04	0.02	104.10	−2.26	0.030	0.03	0.01	97.81	3.28	<0.001
SQR	1.52	1.23	102.99	1.24	0.220	−1.24	0.59	97.14	−2.10	0.040
Random effects – Covariance parameter estimate										
Within-person										
Occasion	0.08	0.02		4.17	<0.001	0.01	0.01		2.35	0.020
TWT_S	0.0004	0.0002		2.94	0.003	0.0003	0.0001		3.37	<0.001
SQR	1.86	0.62		2.98	0.003	0.60	0.25		2.41	0.02
Within pseudo R^2					0.27	Within pseudo R^2				0.26
Between pseudo R^2					0.18	Between pseudo R^2				0.03

APPENDIX

Level 1 and level 2 equations for each model.

Step	Level 1 equation	Level 2 equation
1	$\text{Affect}_{ij}=\beta_{0j}+e_{ij}$	$\beta_{0j}=\gamma_{00}+u_{0j}$
2	$\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+e_{ij}$	$\beta_{0j}=\gamma_{00}+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$
3	$\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+e_{ij}$	$\beta_{0j}=\gamma_{00}+\gamma_{01}\text{Gender}_j+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$
4	$\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+\beta_{2j}(\text{TWT}_{\text{o}ij}-\overline{\text{TWT}_{\text{o}j}})+e_{ij}$	$\beta_{0j}=\gamma_{00}+\gamma_{01}\text{Gender}_j+\gamma_{02}\overline{\text{TWT}_{\text{o}j}}+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$ $\beta_{2j}=\gamma_{20}+u_{2j}$
5	$\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+\beta_{2j}(\text{TWT}_{\text{o}ij}-\overline{\text{TWT}_{\text{o}j}})+\beta_{3j}(\text{TWT}_{\text{s}ij}-\overline{\text{TWT}_{\text{s}j}})+e_{ij}$	$\beta_{0j}=\gamma_{00}+\gamma_{01}\text{Gender}_j+\gamma_{02}\overline{\text{TWT}_{\text{o}j}}+\gamma_{03}\overline{\text{TWT}_{\text{s}j}}+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$ $\beta_{2j}=\gamma_{20}+u_{2j}$ $\beta_{3j}=\gamma_{30}+u_{3j}$
6	$\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+\beta_{2j}(\text{TWT}_{\text{o}ij}-\overline{\text{TWT}_{\text{o}j}})+\beta_{3j}(\text{TWT}_{\text{s}ij}-\overline{\text{TWT}_{\text{s}j}})+\beta_{4j}(\text{SQR}_{ij}-\overline{\text{SQR}_j})+e_{ij}$	$\beta_{0j}=\gamma_{00}+\gamma_{01}\text{Gender}_j+\gamma_{02}\overline{\text{TWT}_{\text{o}j}}+\gamma_{03}\overline{\text{TWT}_{\text{s}j}}+\gamma_{04}\overline{\text{SQR}_j}+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$ $\beta_{2j}=\gamma_{20}+u_{2j}$ $\beta_{3j}=\gamma_{30}+u_{3j}$ $\beta_{4j}=\gamma_{40}+u_{4j}$
7	Reduced form equation: retain only significant terms from the model above: $\text{Affect}_{ij}=\beta_{0j}+\beta_{1j}\text{Occ}+\beta_{2j}(\text{TWT}_{\text{s}ij}-\overline{\text{TWT}_{\text{s}j}})+\beta_{3j}(\text{SQR}_{ij}-\overline{\text{SQR}_j})+e_{ij}$	Reduced form equations: retain only significant terms from the model above: $\beta_{0j}=\gamma_{00}+\gamma_{01}\overline{\text{TWT}_{\text{s}j}}+\gamma_{02}\overline{\text{SQR}_j}+u_{0j}$ $\beta_{1j}=\gamma_{10}+u_{1j}$ $\beta_{2j}=\gamma_{20}+u_{2j}$ $\beta_{3j}=\gamma_{30}+u_{3j}$

For each model step, following the conventions of hierarchical linear modeling (Bryk and Raudenbush, 1992) a level 1 (prediction of within-person processes) and a level 2 (prediction of between-person differences) equation were estimated. In SPSS MIXED, level 1 and level 2 equations not separately specified, but we have retained this convention in presenting the models to allow comparability with other MLM research. In *step 1*, we specified an initial level 1 null model, specifying that affect for person *j* on day *I* is a function of his or her mean level of affect (β_{0j}) and a random residual component (e_{ij}). The level 2 null model specifies that individuals' level 1 coefficients (β_{0j}) or average affect levels) reflect an overall grand mean (γ_{00}) and a between-persons error term (u_{0j}). In *step 2*, we estimated the unconditional growth model (to control for any general linear temporal trends in affect), allowing both fixed and random effects of time. In the level 1 model, the estimation of each person's daily affect now included the effect of the day of measurement (β_{1j}), and the level 2 model specified that each person's day effect reflected an overall relationship (γ_{10}) and between-person variation in the effect of day (u_{1j}). In step 3, a fixed level 2 effect of Gender was added, such that each person's mean affect (β_{0j}) was estimated to be a partial function (γ_{01}) of that person's gender. In *steps 4, 5 and 6*, the fixed level 2 effect, and fixed and random level 1 effects of three sleep related variables ($\mathrm{TWT_O}$, $\mathrm{TWT_S}$, SQR, respectively) were added. In the level 1 model, each person's daily variation in affect was now also modeled as a partial function of that day's person-centered effect of $\mathrm{TWT_O}$ (β_{2j}), $\mathrm{TWT_S}$ (β_{3j}), and SQR (β_{4j}). In the corresponding level 2 models, we specified that individuals' level 1 coefficients (β_{2j}, β_{3j}, β_{4j}, representing the person-level relationship between daily variation in affect and sleep) reflected an overall slope (γ_{20}, γ_{30}, γ_{40}) and random between-person variation in that slope (u_{2j}, u_{3j}, u_{4j}). Prior to running these models, to reduce multicollinearity between $\mathrm{TWT_S}$ and SQR, a residualized SQR term was produced (with the corresponding day's $\mathrm{TWT_S}$ regressed out); this residualized SQR term is used in all models that follow. In the final *step 7*, we investigated reduced-form equations based on the step 6 model; only Occasion, $\mathrm{TWT_S}$ and SQR were retained, because they were significant (generally at all levels) in the preceding models.