Daytime Alertness Quantification and Modeling: Results From a Large Observational Study

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INTRODUCTION

- Alertness is a subjective measure that varies throughout the day. It can be characterized using the two-process model (TPM) of sleep regulation, which combines sleep homeostasis and the circadian rhythm to derive a theoretical daytime alertness curve.[1–3]
- The TPM, along with other models based on the TPM, has been adopted in studies of insomnia disorders, memory, altered circadian patterns, and synaptic weight in the brain.[4–7]
- Despite its broad influence, evidence supporting the TPM-derived alertness curve comes largely from small-scale, controlled studies.[8]
- Here, we show that a similar, three-parameter alertness measure can scale to a large study sample under real-world conditions.

METHODS

- Subjective alertness was rated on a scale from 1 to 10 by Sleep Number smart bed users (N = 22 499) using the SleepIQ app.
  1. All responses were voluntary and could be made at any time throughout the day.
  2. The alertness ranking scale was similar in structure to the 9-point Karolinska Sleepiness Scale,[9] such that 1 designated the highest alertness possible and 10 the highest level of sleepiness (**Table 1**).

TABLE 1. ALERTNESS RATINGS.

To rate alertness, participants could choose from the following list.

Numeric Choice	Definition
1	Extremely alert
2	Very alert
3	Alert
4	Rather alert
5	Neither alert nor sleepy
6	Some signs of sleepiness
7	Sleepy, but no effort to stay awake
8	Sleepy, some effort to stay awake
9	Very sleepy, great effort to stay awake
10	Extremely sleepy, can't stay awake

- Alertness scores were averaged for each hour in a 24-hour time period, and analyzed two ways:
  1. using the full data set
  2. using the data set stratified by age group, with the follow three categories: 18–40, 41–65, and 66–90 years
- A 3-parameter version of the TPM-derived alertness curve was fit to the self-rated alertness responses using the nonlinear least-squares function in R.

RESULTS

- A total of 65 528 sleep sessions were gathered over 95 days. The number of sleep sessions by age group and other data set attributes are provided in **Table 2**.

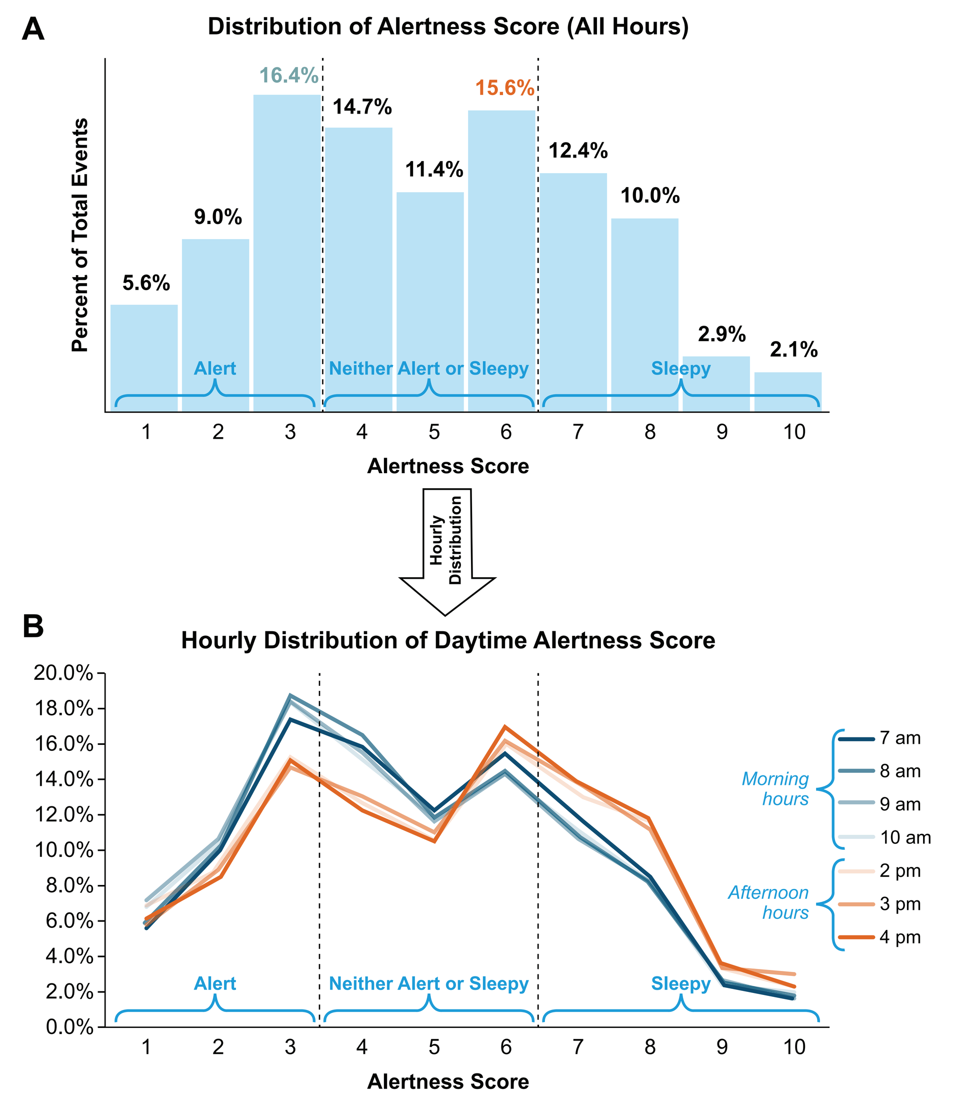
TABLE 2. DATA SET ATTRIBUTES.

	18–40 years	41–65 years	66–90 years	All participants
Number of participants	3308	13 386	5805	22 499
Gender (M/F), %	40/60	44/56	49/51	45/55
Total number of alertness reports	8358	35 745	21 425	65 528
Mean number of alertness reports per participant	2.5	2.7	3.7	2.9
Mean time of day alertness was reported	11:59 am	10:57 am	10:05 am	10:53 am
Fitted parameters				
a	4.32	3.66	3.15	3.68
b	0.013	0.028	0.08	0.02
w	1.396	1.03	1.02	1.08

- Analysis of mean scores across all hours (**Figure 1A**), and on an hourly basis (**Figure 1B**), revealed that the most commonly reported scores were 3 ("Alert") and 6 ("Some signs of sleepiness").
  - Low scores, indicating higher alertness, were most often reported in the morning hours of 7–10 am (**Figure 1B**).
  - High scores, indicating lower alertness, were most often reported in the afternoon between 2:00 pm and 4:00 pm.

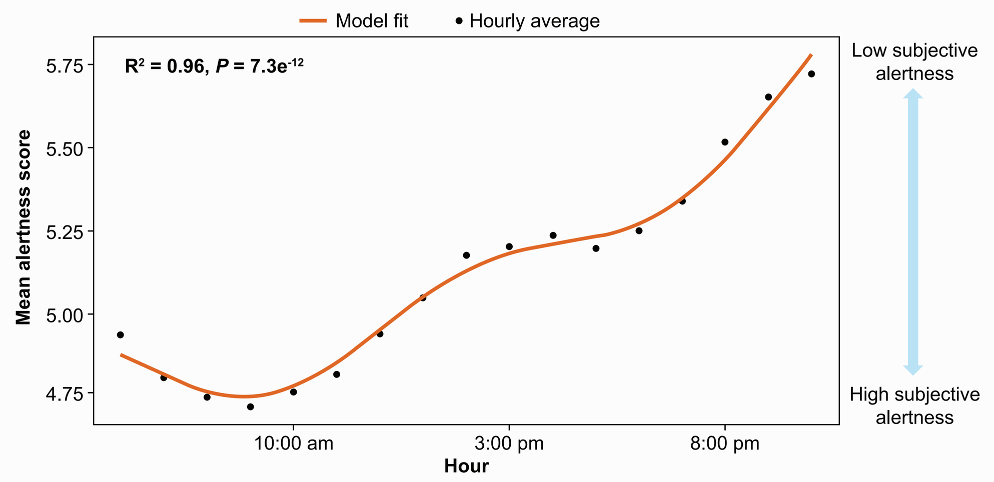
FIGURE 1. DISTRIBUTION OF ALERTNESS SCORES.

Score distributions for all hours (A) and for morning and afternoon hours (B).



- Alertness scores, averaged for each hour, were regressed on time (hours) for daytime hours only to model the wakeful portion of the 24-hour cycle.
  - The results showed a positive but nonlinear trend in alertness scores over daytime hours (**Figure 2**), indicating decreasing alertness as the day progresses.
  - From this analysis, a 3-term model was derived to predict alertness based on the hour (**Equation 1**).

FIGURE 2. MODEL FIT TO MEAN ALERTNESS SCORE ACROSS ENTIRE DATASET.



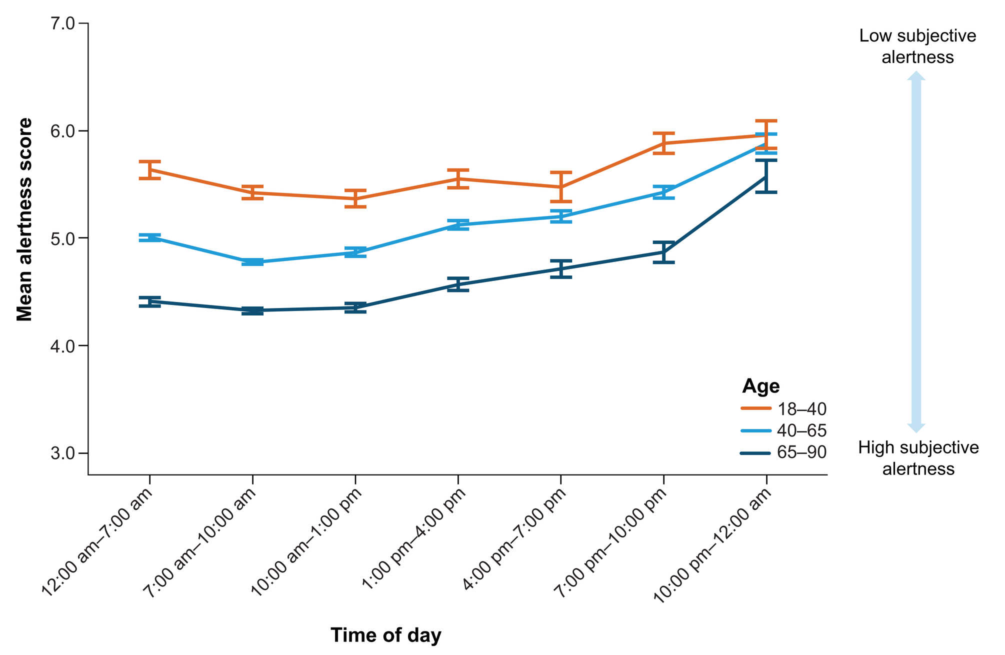
EQUATION 1.

$$\text{Alertness score} \sim a + \exp(b \times t_{hr}) + A \times \left(0.97 - \sin\left(\left(s \times \frac{t_{hr}}{\pi}\right) - w\right)\right) + 0.1 \times \sin\left(\left(3s \times \frac{t_{hr}}{\pi}\right) - w\right)$$

Fixed parameters: $A = 0.2$, $s = 2/3$; *Fitted parameters*: $a = 3.68$, $b = 0.02$, $w = 1.08$

- A high coefficient of determination ($R^2 = 0.96$, $P < 0.001$) showed that the model fit the experimental data well.
- The trend in mean alertness scores over a 24-hour cycle was similar to published results.[10]
  - Mean alertness scores were highest in late evening and low throughout the day, with a slight increase in the afternoon (**Figure 3**).

FIGURE 3. HOURLY TRENDS IN MEAN ALERTNESS SCORES BY AGE GROUP.



- However, the scale and magnitude of the results observed in this study differed from previous results (**Figure 3**).
- Analysis of mean alertness scores by age group showed that the youngest participants had the most stable alertness scores of the three age groups, and that these scores were consistently higher throughout the day compared to other age groups, indicating lower alertness in the youngest group (**Figure 3**).
- In contrast, middle-aged and older participants had lower alertness scores, and therefore higher subjective alertness, than the youngest participants, but their scores varied more widely throughout the day compared to the youngest participants.
- The study had a few limitations.
  - The timing for subjective alertness was not controlled, and an alertness rating was requested only once a day. Most users reported subjective alertness at approximately the same time every day.
  - The number of alertness reports per participant was low (approximately 2–4; **Table 2**).
  - The alertness scale was not validated; however it is similar to the Karolinska Sleepiness Scale.[9]
  - Due to insufficient variability in time at the participant level, individualized models could not be developed.

CONCLUSIONS

- Our results were similar to previous reports, with the exception of a small absolute change over the course of the day (approximately 1 unit) and an evening peak in alertness that was more pronounced in our data.
- These results show that the TPM-derived alertness can effectively predict daily alertness trends in a large sample under real-world conditions.

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DISCLOSURES

SB and **GGM**: Employees of Sleep Number Corporation.

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