American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Wearable-Derived Sleep Patterns and Everyday Well-Being

Prof. Michael W. L. Chee

Professor, University: National University of Singapore, Singapore

Abstract

Wearable devices have expanded the possibility of studying sleep under everyday conditions by repeatedly estimating sleep duration, sleep timing, sleep efficiency, nocturnal wakefulness, and related physiological signals outside conventional sleep laboratories. This capability is particularly relevant to well-being research because a single retrospective sleep questionnaire may obscure night-to-night variability and temporal relationships between sleep and next-day functioning. Contemporary sleep-health theory also emphasizes that healthy sleep is multidimensional and cannot be reduced to duration alone. Buysse's sleep-health framework identifies duration, timing, efficiency, regularity, alertness, and satisfaction as complementary dimensions, while objective and wearable research has increasingly shown the value of examining consistency and timing alongside conventional measures of sleep quantity.

The present study develops a longitudinal framework connecting wearable-derived sleep patterns with everyday well-being. A synthetic dataset representing 360 hypothetical adults monitored across 21 consecutive days was generated, producing 7,560 participant-day observations. Nightly sleep duration, sleep efficiency, wake after sleep onset, and deviation from habitual sleep timing were modeled as predictors of next-day well-being. Cluster-robust standardized regression was used to account for repeated observations nested within individuals. Sleep duration was modeled nonlinearly around approximately 7.5 hours rather than assuming that progressively longer sleep always predicts superior outcomes.

The simulated analysis showed that deviation from the 7.5-hour sleep-duration reference was the strongest predictor of lower next-day well-being (standardized $\beta = -.429$). Greater night-to-night sleep-timing deviation was also negatively associated with well-being ($\beta = -.241$), whereas higher sleep efficiency was positively associated with well-being ($\beta = .150$). Greater wake after sleep onset showed a smaller negative relationship ($\beta = -.097$). The model explained 28.2% of variance in the simulated daily well-being outcome. Mean well-being declined from 80.36 among nights with less than 30 minutes of timing deviation to 75.71 among nights exceeding 60 minutes of deviation.

The findings illustrate the value of treating wearable sleep information as a pattern rather than a single nightly score. The manuscript further emphasizes that consumer wearables are not equivalent to polysomnography. Validation studies published through 2021 indicate promising performance for sleep–wake estimation in several devices, but device-specific error and inconsistent sleep-stage classification remain important limitations. Future empirical research should therefore prioritize transparent device validation, longitudinal modeling, multidimensional sleep metrics, and cautious interpretation of wearable-derived sleep stages.

Keywords: wearable technology; sleep patterns; everyday well-being; sleep regularity; sleep efficiency; sleep duration; actigraphy; consumer sleep trackers; digital health; longitudinal monitoring

1. Introduction

Sleep is a recurring biological and behavioral process that contributes to everyday functioning, health, cognition, affect regulation, and subjective well-being. Historically, sleep research often emphasized deficits such as insomnia, insufficient sleep, or excessive sleepiness, but contemporary sleep-health frameworks increasingly conceptualize healthy sleep positively and multidimensionally. Buysse proposed that sleep health involves multiple dimensions rather than a single metric, including regularity, satisfaction, alertness, timing, efficiency, and duration. Composite sleep-health studies subsequently demonstrated that combinations of these dimensions can contain information relevant to mental and physical functioning. This perspective is important for wearable research because modern devices can generate repeated estimates of several sleep characteristics rather than relying entirely on retrospective judgments.

Sleep duration nevertheless remains one of the most familiar indicators of healthy sleep. The American Academy of Sleep Medicine and Sleep Research Society concluded that adults should regularly obtain at least seven hours of sleep per night to support optimal health, while broader recommendations have commonly identified approximately seven to nine hours as an appropriate range for many adults. Duration alone, however, does not capture whether sleep is fragmented, irregularly timed, or inefficient. Two individuals may each average seven and a half hours per night while differing markedly in how consistent their bedtime is, how frequently they awaken, or how much time they remain awake while attempting to sleep.

Sleep regularity has therefore become an important dimension of sleep research. Phillips and colleagues used objective sleep–wake data to show that irregular schedules among college students were associated with delayed circadian timing and poorer academic performance. Fischer and colleagues later found that irregular and mistimed sleep schedules were associated with poorer average self-reported well-being in college students, although their analyses also indicated that relationships can differ when examined at daily versus longer-term timescales. Fischer, Klerman, and Phillips further demonstrated that different regularity metrics capture different characteristics of day-to-day sleep–wake variability, underscoring the need to define precisely how regularity is operationalized.

Wearable technology offers a practical way to examine these processes repeatedly in ordinary environments. Research-grade actigraphy has long been used to estimate sleep–wake behavior outside the laboratory, and comparisons with polysomnography support its usefulness for field measurement while also identifying limitations in detecting wake during the sleep period. Consumer devices extend this principle by combining accelerometry with heart rate and other sensors. Mantua, Gravel, and Spencer found that several personal monitoring devices produced reasonably useful estimates for selected sleep measures, while de Zambotti and colleagues reported promising performance of Fitbit Charge 2 for several sleep parameters relative to polysomnography. More recent pre-2022 validations likewise showed that newer devices can perform well for sleep–wake detection, but sleep-stage classification and individual-night precision remain less consistent.

The present paper examines wearable-derived sleep patterns and everyday well-being through a simulation-based longitudinal design. The model focuses on nightly duration, efficiency, wake after sleep onset, and sleep-timing deviation because these variables are comparatively interpretable and can be repeatedly estimated using wearable or actigraphic systems. Sleep stages are intentionally excluded from the primary analytical model because validation studies show greater uncertainty in stage classification across consumer devices. By relating nightly sleep characteristics to next-day well-being across 21 simulated days, the study illustrates how wearable data can move sleep research beyond single-night summaries and toward temporal patterns of everyday functioning.

2. Objectives of the Study

2.1 To Examine Wearable-Derived Sleep Duration and Everyday Well-Being

The first objective is to examine whether nightly sleep duration is associated with next-day well-being when sleep is observed repeatedly rather than measured once. The analysis does not assume that progressively longer sleep is always better. Instead, deviation from an approximately 7.5-hour reference is modeled quadratically so that both substantial shortfall and substantial excess can correspond with lower simulated well-being.

This approach is consistent with the broader view that adequate sleep duration is necessary but not sufficient for healthy sleep. Adult sleep-duration recommendations provide population-level guidance, while multidimensional sleep-health frameworks emphasize the additional contribution of continuity, regularity, and timing. The study therefore assesses duration alongside complementary wearable-derived characteristics.

2.2 To Evaluate Sleep Efficiency, Nocturnal Wakefulness, and Timing Regularity

The second objective is to assess whether sleep efficiency, wake after sleep onset, and night-to-night timing deviation contribute independently to next-day well-being. Sleep efficiency represents the proportion of the sleep period spent asleep, while wake after sleep onset reflects sleep fragmentation after initial sleep onset.

Sleep timing regularity is operationalized as the nightly deviation of the observed sleep midpoint from an individual's habitual sleep timing. This choice treats regularity as an individual-centered temporal characteristic rather than imposing identical clock times across all participants. The sleep-regularity literature emphasizes that different metrics capture different dimensions of variability, making transparent operationalization essential.

2.3 To Demonstrate a Longitudinal Wearable Analytics Framework

The third objective is methodological: to demonstrate how wearable-derived nightly observations can be analyzed as repeated longitudinal data rather than as independent measurements. The study therefore uses participant-level clustering when estimating regression uncertainty.

This framework is relevant because mobile and wearable research permits repeated measurement of sleep, mood, energy, and activity in naturalistic environments. Merikangas and colleagues demonstrated the feasibility of real-time mobile monitoring for investigating dynamic associations among sleep, mood, energy, and activity, illustrating the analytical potential of intensive longitudinal monitoring.

3. Review of Literature

3.1 Sleep as a Multidimensional Health Pattern

A major conceptual development in sleep research has been the shift from examining individual sleep problems toward considering overall sleep health. Buysse proposed a multidimensional model in which healthy sleep incorporates regularity, satisfaction, alertness, timing, efficiency, and duration. This framework challenges studies that classify sleep exclusively according to total hours slept, because an individual can obtain an adequate quantity of sleep while still experiencing substantial fragmentation or instability.

Dong, Martinez, Buysse, and Harvey subsequently evaluated a composite sleep-health measure incorporating multiple dimensions and found that multidimensional sleep health predicted concurrent mental and physical health outcomes in adolescents prone to eveningness. DeSantis and colleagues similarly examined duration, satisfaction, efficiency, timing, and regularity within a composite sleep-health approach. These studies strengthen the rationale for treating sleep as a configuration of interrelated characteristics.

Duration nevertheless remains fundamental. Watson and colleagues' consensus recommendation concluded that adults should regularly sleep seven or more hours per night to promote optimal health. The purpose of including duration in a multidimensional framework is therefore not to diminish its importance but to avoid assuming that duration alone exhausts the meaning of good sleep.

Okano and colleagues provided an example of the value of multiple objective sleep dimensions. In college students, better sleep quality, longer duration, and greater consistency were associated with stronger academic performance, while the sleep obtained on the single night immediately preceding an examination was less informative than sleep patterns accumulated over preceding days and weeks. Their findings support a pattern-based rather than event-based interpretation of sleep.

3.2 Sleep Regularity, Variability, and Daily Functioning

Day-to-day variability is especially suited to wearable measurement because irregularity cannot be quantified accurately from a single night. Phillips and colleagues used sleep–wake data across multiple days to demonstrate associations between irregular sleep patterns, delayed circadian timing, and poorer academic performance. Their work contributed to greater interest in sleep regularity as a dimension that may contain information distinct from average duration.

Fischer and colleagues extended this perspective directly to well-being. Their study of US college students found that irregular sleep and event schedules were associated with poorer average self-reported well-being. Importantly, their detailed analysis indicated that average sleep irregularity across approximately one month was more informative for average well-being than the corresponding day-level relationship, suggesting that some effects of sleep regularity may accumulate rather than manifest identically from one night to the next.

The measurement of regularity is itself methodologically important. Fischer, Klerman, and Phillips compared metrics including standard deviation, interdaily stability, social jet lag, composite phase deviation, and the Sleep Regularity Index. They showed that different measures respond differently to naps, awakenings, changes between consecutive days, weekly shifts, and study duration. Consequently, researchers should avoid using the generic term “sleep regularity” without explaining the precise calculation.

Dzierzewski, Donovan, and Sabet further demonstrated that sleep regularity can be assessed as a construct distinct from conventional sleep-quality and insomnia measures. Their 2021 Sleep Regularity Questionnaire showed promising reliability and validity and distinguished circadian regularity from continuity-related regularity during scale development. Although the present study uses wearable-derived timing deviation rather than retrospective questionnaire measurement, this evidence supports the theoretical importance of regularity beyond average sleep quantity.

3.3 Wearable Sleep Measurement and Interpretive Limitations

Wearable sleep measurement offers an important practical advantage: repeated sleep estimation can occur with relatively low participant burden in everyday environments. Actigraphy has long provided a validated approach for estimating sleep duration and wakefulness outside laboratory polysomnography, although accuracy is not uniform across sleep and wake classification. Consumer wearable devices attempt to extend this approach through combinations of accelerometers, photoplethysmography, temperature, and proprietary algorithms.

Mantua, Gravel, and Spencer compared several personal health monitoring devices with research actigraphy and polysomnography and found that total sleep time could be estimated reasonably well by several devices, although performance differed across parameters and devices. De Zambotti and colleagues' Fitbit Charge 2 validation similarly reported promising agreement for several conventional sleep measures relative to polysomnography.

The field nevertheless requires cautious interpretation. De Zambotti and colleagues' review of wearable sleep technology emphasized both the potential and methodological challenges of integrating consumer devices into research and clinical settings. Chinoy and colleagues compared seven consumer devices with polysomnography and concluded that sleep–wake detection was generally promising, whereas sleep-stage estimates were inconsistent across devices.

Stucky and colleagues' naturalistic validation among shift workers similarly found that Fitbit Charge 2 could provide reasonably accurate mean sleep estimates under carefully processed conditions, while wide limits of agreement constrained precision for individual sleep episodes. This distinction is essential for everyday well-being studies. Wearables may provide useful longitudinal patterns at the group or repeated-measure level, but individual nightly values should not automatically be interpreted as clinical diagnoses.

4. Research Methodology

4.1 Research Design and Longitudinal Simulation

The study employs a simulation-based longitudinal repeated-measures design. A synthetic cohort of 360 hypothetical adults was observed across 21 consecutive days, generating 7,560 participant-day observations.

The simulated structure was designed to approximate the type of data that could be obtained from a wrist-worn consumer wearable or research actigraph linked to a brief daily well-being assessment. No actual device brand was assigned to participants because proprietary algorithms differ substantially between manufacturers, models, and software versions. This avoids implying that the simulated measurement performance belongs to a specific commercial product.

Each hypothetical participant was assigned an individual habitual sleep-duration tendency, habitual efficiency, typical wake after sleep onset, baseline sleep-timing variability, and baseline well-being level. Daily variation was then generated around those individual tendencies.

Table 1: Operationalization of Wearable-Derived Sleep and Well-Being Variables

Variable	Operational Definition	Illustrative Measurement	Analytical Role
Sleep Duration	Estimated hours of nightly sleep	Wearable-derived hours per night	Primary predictor
Sleep Efficiency	Percentage of the sleep period estimated as asleep	0–100%	Positive sleep-continuity predictor
Wake After Sleep Onset	Total minutes estimated awake after initial sleep onset	Minutes per night	Sleep-fragmentation predictor
Sleep Timing Deviation	Absolute deviation of nightly sleep midpoint from the participant's habitual timing	Minutes	Regularity predictor
Duration Deviation^2	Squared distance from a 7.5-hour reference duration	Derived quadratic term	Nonlinear duration predictor
Everyday Well-Being	Next-day perceived emotional and functional well-being	Synthetic 0–100 score	Dependent variable

4.2 Synthetic Data Generation and Analytical Model

Nightly sleep duration was generated around participant-specific habitual duration with additional day-level variation. Sleep efficiency and wake after sleep onset were generated with both between-person and within-person variation, allowing participants to experience nights that differed from their usual pattern.

Sleep-timing deviation was defined as the absolute difference between that night's sleep midpoint and the participant's habitual midpoint. Higher values therefore represent greater irregularity. This approach is conceptually similar to individual-centered regularity measures that quantify deviations from habitual timing, although it should not be confused with the formally defined Sleep Regularity Index or Composite Phase Deviation. Fischer, Klerman, and Phillips emphasize that these metrics have different theoretical properties and should not be treated interchangeably.

The squared duration term was used to model departure from an intermediate sleep-duration reference rather than imposing a purely linear relationship. The 7.5-hour value is an analytical reference for this simulation and should not be interpreted as an individually optimal clinical prescription.

4.3 Statistical Procedures, Device Limitations, and Ethics

Descriptive statistics were calculated for all principal variables. Predictor variables and the well-being outcome were standardized prior to regression so that coefficient magnitudes could be compared directly.

Cluster-robust standard errors were calculated at the participant level because repeated nights from one individual are statistically dependent. This design is preferable to treating all 7,560 participant-day observations as completely independent.

For graphical analysis, nightly sleep-timing deviations were categorized as consistent (<30 minutes), moderate (30–60 minutes), or irregular (>60 minutes). Mean next-day well-being and approximate 95% confidence intervals were calculated for each group.

Wearable-derived sleep measurements should be interpreted as behavioral estimates rather than clinical sleep diagnoses. Consumer devices can show acceptable performance for selected sleep–wake parameters, but individual-night disagreement and sleep-stage uncertainty remain material limitations. A real study should record the exact device model, firmware or algorithm version where available, wear protocol, nonwear rules, data-cleaning procedure, and validation evidence relevant to the population being studied.

5. Analysis

5.1 Descriptive Pattern of Wearable-Derived Sleep

Across 7,560 simulated nights, mean sleep duration was 7.19 hours with a standard deviation of 0.94 hours. Mean sleep efficiency was 87.47% (SD = 5.55), while wake after sleep onset averaged 39.34 minutes (SD = 15.27).

Average nightly deviation from habitual sleep timing was 34.02 minutes, with a standard deviation of 30.68 minutes. The substantial dispersion illustrates why sleep timing should be analyzed longitudinally. Two individuals with nearly identical average bedtimes can differ considerably in how consistently that timing is maintained across nights.

Mean next-day well-being was 79.00 on the synthetic 0–100 scale, with a standard deviation of 8.02. This value has no epidemiological interpretation because the scale and observations were generated for methodological illustration.

5.2 Multivariable Prediction of Everyday Well-Being

Table 2: Cluster-Robust Standardized Regression Predicting Next-Day Well-Being

Predictor	Standardized β	p-value	Direction	Interpretation
Deviation From 7.5-Hour Sleep Duration²	−0.429	< .001	Negative	Larger departure from the reference duration predicts lower next-day well-being
Sleep Efficiency	0.150	< .001	Positive	More efficient sleep predicts higher next-day well-being
Sleep Timing Deviation	−0.241	< .001	Negative	More irregular nightly timing predicts poorer well-being
Wake After Sleep Onset	−0.097	< .001	Negative	Greater nocturnal wakefulness predicts modestly lower well-being
Model (R^2)	0.282	—	—	28.2% of simulated variance explained

Note: N = 360 hypothetical participants and 7,560 participant-day observations. Standard errors were clustered by synthetic participant identifier. These coefficients are simulation outputs rather than estimates from a real wearable cohort.

The strongest predictor was squared deviation from the 7.5-hour reference, β = −.429. Because this term is quadratic, it does not imply that every additional hour of sleep decreases well-being. Instead, well-being is modeled as becoming lower as nightly duration moves substantially away from an intermediate reference in either direction.

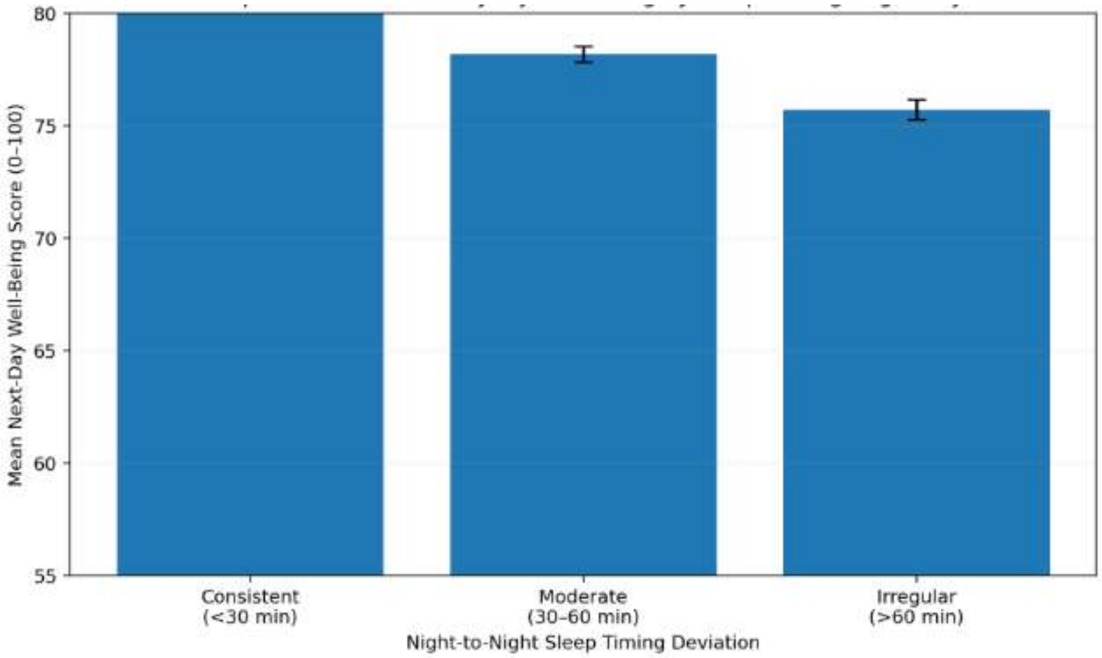
Sleep-timing deviation produced the second-largest coefficient in absolute magnitude, β = −.241. This indicates that the simulation assigns meaningful importance to regularity independent of sleep duration. The conceptual decision is supported by pre-2022 research showing that irregular sleep schedules are associated with poorer well-being and functional outcomes even when average duration alone does not fully explain the pattern.

Sleep efficiency was positively related to well-being, β = .150, whereas wake after sleep onset was negatively related, β = −.097. Their simultaneous inclusion illustrates that wearable analysis can distinguish sleep quantity from continuity.

The model explained 28.2% of simulated daily well-being variance. The unexplained majority is theoretically appropriate because everyday well-being is influenced by many factors beyond sleep, including social experiences, physical health, work demands, stress, activity, nutrition, and individual disposition.

5.3 Everyday Well-Being Across Sleep-Timing Regularity

Graph 1: Simulated Everyday Well-Being by Sleep Timing Regularity



The graph displays a progressive decline in average next-day well-being as nightly sleep timing becomes more irregular. Nights classified as consistent, with less than 30 minutes of deviation from habitual sleep timing, produced a mean well-being score of approximately 80.36. The moderate-deviation group averaged approximately 78.17, while nights with more than 60 minutes of deviation averaged approximately 75.71.

The pattern is particularly useful because the three groups do not represent differences in total sleep duration alone. They represent timing stability. This reinforces the conceptual argument that sleep regularity provides information not captured by a simple count of hours slept.

Key Finding: Within the simulation, increasingly irregular sleep timing is associated with progressively lower next-day well-being, supporting a multidimensional interpretation of wearable-derived sleep patterns.

6. Discussion

6.1 Why Wearable Sleep Research Should Move Beyond Total Sleep Time

The principal implication of the study is that sleep duration should remain important without becoming the sole definition of healthy sleep. Duration guidelines provide useful population-level anchors, and insufficient sleep has well-established consequences for functioning. However, the present model illustrates why two people obtaining similar sleep duration can experience different next-day outcomes when continuity and timing differ.

Buysse's sleep-health framework provides a strong theoretical foundation for this interpretation because it defines sleep through multiple dimensions rather than one average quantity. Dong and colleagues' composite sleep-health work likewise indicates that combinations of dimensions can be meaningfully related to mental and physical outcomes. Wearable devices are particularly suitable for implementing this perspective because they repeatedly observe behavior across many nights.

The quadratic duration relationship in the simulation should also be interpreted carefully. It does not establish that 7.5 hours is universally optimal. Individual sleep need differs, and population guidelines provide ranges rather than exact prescriptions for each person. A more rigorous empirical model could estimate person-specific or age-specific nonlinear relationships rather than imposing one common optimum.

The stronger implication is methodological: wearable researchers should avoid converting sleep into a single proprietary "sleep score" without preserving the underlying dimensions. Duration, efficiency, regularity, wakefulness, and timing may relate differently to well-being and may respond differently to intervention.

6.2 Sleep Regularity as a Distinct Component of Everyday Well-Being

The second major implication concerns timing consistency. The simulated well-being gradient across regularity categories reflects the growing pre-2022 evidence that variability in sleep schedules deserves independent consideration. Phillips and colleagues linked irregular schedules with delayed circadian timing and poorer academic performance, while Fischer and colleagues directly linked irregular and mistimed schedules with lower average well-being.

Regularity may matter through several pathways. Consistent sleep–wake timing can align behavioral schedules more closely with circadian processes, whereas large shifts can create repeated misalignment between internal biological rhythms and external obligations. The present study does not test a biological mechanism, and its synthetic data should not be interpreted as evidence for a particular circadian pathway. Nevertheless, regularity offers a plausible behavioral marker of whether an individual's sleep system is stable across days.

Fischer, Klerman, and Phillips' 2021 methodological work adds an important caution: regularity metrics are not interchangeable. Standard deviation of sleep midpoint, social jet lag, composite phase deviation, interdaily stability, and the Sleep Regularity Index each quantify different temporal properties. Future wearable studies should therefore specify the chosen metric and explain why it matches the research question.

For studies concerned with everyday well-being, multiday metrics may be especially valuable because Fischer and colleagues observed that associations between sleep irregularity and well-being differed across daily and longer-term timescales. This suggests that researchers should test both immediate next-day effects and accumulated patterns rather than assuming that the same relationship operates identically at every temporal scale.

6.3 Interpreting Consumer Wearables Responsibly

The third implication concerns measurement validity. Consumer sleep devices can collect large quantities of naturalistic data, but high volume does not guarantee clinical accuracy. Validation studies generally show stronger performance for distinguishing sleep from wake than for reconstructing detailed sleep architecture. Chinoy and colleagues explicitly reported inconsistent sleep-stage performance across seven consumer sleep trackers despite promising sleep–wake detection.

This distinction should shape study design. Research questions centered on longitudinal duration, timing, efficiency, or general sleep–wake patterns may be better aligned with the strengths of validated wearables than questions requiring precise measurement of rapid-eye-movement, deep-sleep, or other stage-specific physiology. De Zambotti and colleagues' review similarly emphasized that wearable sleep technology has substantial research potential but requires validation-aware interpretation.

Device performance can also differ by population. Stucky and colleagues' naturalistic study among shift workers found reasonably accurate average sleep estimates under careful processing but wide individual limits of agreement. Therefore, a device validated in healthy young adults should not automatically be assumed to perform identically in older adults, patients with sleep disorders, rotating shift workers, or people with atypical movement patterns.

Researchers should report missing-device nights, wear adherence, exclusion rules, firmware or algorithm changes where known, and whether the device provides raw sensor data or only proprietary summary measures. Such transparency is essential for reproducibility, particularly because commercial algorithms may change during a longitudinal research program.

7. Conclusion

Wearable technology has created an important opportunity to study sleep as it unfolds across ordinary life. Rather than relying exclusively on a participant's retrospective estimate of a typical night, researchers can observe repeated patterns of duration, timing, efficiency, and nocturnal wakefulness. This methodological change aligns closely with multidimensional sleep-health theory, which emphasizes that healthy sleep involves more than the number of hours spent asleep.

The present simulation demonstrates how such information can be connected with everyday well-being through a longitudinal analytical framework. Departure from an intermediate sleep-duration reference was the strongest predictor of lower simulated next-day well-being, while greater sleep-timing deviation and nocturnal wakefulness were also negatively associated with the outcome. Sleep efficiency provided an independent positive contribution. The regularity graph further demonstrated a progressive decline in average well-being across consistent, moderately irregular, and highly irregular sleep-timing categories.

These findings are methodological demonstrations rather than empirical health estimates. Their principal value lies in illustrating that wearable sleep information should be interpreted as a multiday behavioral pattern. Researchers should examine duration, continuity, and regularity simultaneously and should distinguish immediate next-day relationships from accumulated sleep patterns across longer periods. Existing pre-2022 research on sleep regularity, multidimensional sleep health, and objective sleep monitoring provides a strong theoretical basis for such designs.

At the same time, wearable-derived sleep data require disciplined interpretation. Consumer devices may provide useful longitudinal estimates, but they are not interchangeable with polysomnography and should not automatically be treated as diagnostic tools. Sleep-stage outputs are particularly sensitive to device and algorithm limitations. Future research should therefore combine validated wearable metrics, transparent preprocessing, repeated well-being measurement, appropriate longitudinal statistics, and explicit acknowledgement of device uncertainty. Used in this way, wearable sleep data can contribute to a more ecologically valid understanding of how nightly behavioral rhythms relate to the quality of everyday life.

References

1. Massar, S. A. A., Ng, A. S. C., Soon, C. S., Chua, X. Y., Ong, J. L., Chee, N. I. Y. N., Lee, T. S., Ghosh, A., & Chee, M. W. L. (2021). Reopening after lockdown: The influence of working-from-home and digital device use on sleep, physical activity, and wellbeing following COVID-19 lockdown and reopening. *Sleep*, *45*(1), zsab250. https://doi.org/10.1093/sleep/zsab250
2. Massar, S. A. A., Chua, X. Y., Soon, C. S., Ng, A. S. C., Ong, J. L., Chee, N. I. Y. N., Lee, T. S., Ghosh, A., & Chee, M. W. L. (2021). Trait-like nocturnal sleep behavior identified by combining wearable, phone-use, and self-report data. *npj Digital Medicine*, *4*, 90. https://doi.org/10.1038/s41746-021-00466-9
3. Smagula, S. F., Stahl, S. T., Krafty, R. T., & Buysse, D. J. (2021). Initial proof of concept that a consumer wearable can be used for real-time rest-activity rhythm monitoring. *Sleep*, *45*(3), zsab288. https://doi.org/10.1093/sleep/zsab288
4. Rezaei, N., & Grandner, M. A. (2021). Changes in sleep duration, timing, and variability during the COVID-19 pandemic: Large-scale Fitbit data from 6 major US cities. *Sleep Health*, *7*(3), 303–313. https://doi.org/10.1016/j.sleh.2021.02.008
5. Thota, D., et al. (2020). Evaluating the relationship between Fitbit sleep data and self-reported mood, sleep, and environmental contextual factors in healthy adults: Pilot observational cohort study. *JMIR Formative Research*, *4*(9), e18086. https://doi.org/10.2196/18086
6. Grossi, N. R., Batinic, B., & Moharitsch, S. (2021). Sleep and health: Examining the relation of sleep to burnout and well-being using a consumer fitness tracker. *Health and Technology*, *11*, 1247–1257.
7. Berryhill, S., Morton, C. J., Dean, A., Berryhill, A., et al. (2020). Effect of wearables on sleep in healthy individuals: A randomized crossover trial and validation study. *Journal of Clinical Sleep Medicine*, *16*(5), 775–783. https://doi.org/10.5664/jcsm.8356
8. Asgari Mehrabadi, M., Azimi, I., Sarhaddi, F., Axelin, A., Niela-Vilén, H., Myllyntausta, S., Stenholm, S., Dutt, N., Liljeberg, P., & Rahmani, A. M. (2020). Sleep tracking of a commercially available smart ring and smartwatch against medical-grade actigraphy in everyday settings: Instrument validation study. *JMIR mHealth and uHealth*, *8*(11), e20465. https://doi.org/10.2196/20465
9. de Zambotti, M., Cellini, N., Goldstone, A., Colrain, I. M., & Baker, F. C. (2019). Wearable sleep technology in clinical and research settings. *Medicine & Science in Sports & Exercise*, *51*(7), 1538–1557.
10. Haghayegh, S., Khoshnevis, S., Smolensky, M. H., Diller, K. R., & Castriotta, R. J. (2019). Accuracy of wristband Fitbit models in assessing sleep: Systematic review and meta-analysis. *Journal of Medical Internet Research*, *21*(11), e16273. https://doi.org/10.2196/16273
11. Ong, J. L., Tandi, J., Patanaik, A., Lo, J. C., & Chee, M. W. L. (2019). Large-scale data from wearables reveal regional disparities in sleep patterns that persist across age and sex. *Scientific Reports*, *9*, 3415. https://doi.org/10.1038/s41598-019-40156-x

12. Chinoy, E. D., Cuellar, J. A., Jameson, J. T., & Markwald, R. R. (2021). Performance of seven consumer sleep-tracking devices compared with polysomnography. *Sleep, 44*(5), zsaa291.
13. Liang, Z., & Chapa-Martell, M. A. (2019). Accuracy of Fitbit wristbands in measuring sleep stage transitions and the effect of user-specific factors. *JMIR mHealth and uHealth, 7*(6), e13384.
14. Koo, H. K., et al. (2020). Mood prediction of patients with mood disorders by machine learning using passive digital phenotypes based on the circadian rhythm: Prospective observational cohort study. *Journal of Medical Internet Research, 21*(4), e11029.
15. Kim, J., et al. (2021). Relationship between major depression symptom severity and sleep collected using a wristband wearable device: Multicenter longitudinal observational study. *JMIR mHealth and uHealth, 9*(4), e24604. https://doi.org/10.2196/24604
16. NeCamp, T., Sen, S., Frank, E., Walton, M. A., Ionides, E. L., Fang, Y., Tewari, A., & Wu, Z. (2020). Assessing real-time moderation for developing adaptive mobile health interventions for medical interns: Micro-randomized trial. *Journal of Medical Internet Research, 22*(3), e15033. https://doi.org/10.2196/15033
17. Lai, J., Rahmani, A., Yunusova, A., Rivera, A. P., Labbaf, S., Hu, S., Dutt, N., Jain, R., & Borelli, J. L. (2021). Using multimodal assessments to capture personalized contexts of college student well-being in 2020: Case study. *JMIR Formative Research, 5*(5), e26186.
18. Ringeval, M., Wagner, G., Denford, J., Paré, G., & Kitsiou, S. (2020). Fitbit-based interventions for healthy lifestyle outcomes: Systematic review and meta-analysis. *Journal of Medical Internet Research, 22*(10), e23954.
19. Godino, J. G., Wing, D., de Zambotti, M., Baker, F. C., Bagot, K., Inkelis, S., Pautz, C., Higgins, M., Nichols, J., & Brumback, T. (2020). Performance of a commercial multi-sensor wearable (Fitbit Charge HR) in measuring physical activity and sleep in healthy children. *PLOS ONE, 15*(9), e0237719. https://doi.org/10.1371/journal.pone.0237719
20. Scott, H., Biello, S. M., & Woods, H. C. (2019). Social media use and adolescent sleep patterns: Cross-sectional findings from the UK Millennium Cohort Study. *BMJ Open, 9*, e031161.