Dual Architecture of Consciousness Transitions: Evidence from Sleep EEG Analysis

Emma Dobbin

Consciousness Gradient Theory Group Ltd, United Kingdom

Abstract

The neural mechanisms underlying consciousness transitions have remained contentious, with Integrated Information Theory (IIT) predicting gradual changes and Global Workspace Theory (GWT) predicting discrete threshold events. Using an adaptive consciousness measurement framework applied to 622 sleep stage transitions across 12 subjects from the Sleep-EDF database, we demonstrate that both theories are correct within distinct transition types. Our Consciousness Gradient Index (CGI) framework reveals that three of four transition types (75%: Wake→N1, N2→N3, REM→Wake) follow gradual dynamics consistent with IIT predictions (mean slopes: -0.736, -0.532, +0.614), while one transition type (25%: N1→N2) exhibits threshold behavior via thalamic spindle gating mechanisms (mean slope: -2.188). The N1→N2 transition showed significantly steeper CGI decline compared to Wake→N1 (paired t-test: $t=-9.334$, $p<0.001$, Cohen's $d=-2.814$) and N2→N3 ($t=-6.341$, $p<0.001$, $d=-1.912$), supporting a dual architecture model where consciousness transitions employ both continuous integration mechanisms and discrete neural gates. These findings reconcile competing theoretical frameworks and establish a unified model for understanding consciousness state changes across biological systems.

Keywords: consciousness measurement, sleep stages, EEG analysis, EEG complexity, sleep onset, spindle gating, threshold gating, Integrated Information Theory, Global Workspace Theory, dual architecture

Introduction

The measurement and understanding of consciousness state changes represents a fundamental challenge in neuroscience and philosophy of mind. Two major theoretical frameworks have dominated recent discourse: Integrated Information Theory (IIT), which predicts gradual consciousness changes through continuous information integration (Tononi et al., 2016), and Global Workspace Theory (GWT), which proposes discrete broadcasting events and threshold mechanisms (Dehaene & Changeux, 2011). These frameworks have been treated as competing explanations, yet empirical evidence supporting each perspective has remained inconclusive.

Sleep provides an ideal natural laboratory for investigating consciousness transitions, as individuals cycle predictably through distinct states with well-characterized neural signatures. Traditional approaches to measuring consciousness during sleep have relied on subjective self-reports or binary state classifications (awake vs. asleep), which fail to capture the continuous nature of consciousness gradients. More recent quantitative approaches have attempted to measure consciousness using complexity metrics (Casali et al., 2013) or connectivity measures (Tagliazucchi et al., 2016), but these methods have not systematically evaluated whether different transitions follow distinct mechanistic patterns.

We developed the Consciousness Gradient Index (CGI), an adaptive measurement framework that employs state-specific neural metrics to quantify consciousness level changes during sleep transitions. The formula $CGI = \sqrt{(\varphi \times \rho)} \times 10$ combines information integration (φ) with adaptive response capacity (ρ), where φ is calculated using transition-appropriate neural features: alpha power (8-13 Hz) for arousal transitions, inverted spindle density (11-16 Hz) for the N1→N2 threshold, and spectral entropy for deep sleep transitions. This adaptive approach

allows the framework to capture both gradual and discrete consciousness changes using the same mathematical structure.

Here we report the results of applying this framework to 622 sleep stage transitions from 12 healthy adults, revealing a dual architecture where distinct neural mechanisms govern different transition types. We demonstrate that the apparent conflict between IIT and GWT reflects their application to different classes of consciousness transitions, and propose a unified model reconciling these theoretical perspectives.

Methods

Participants and Data

We analyzed polysomnographic recordings from 12 healthy adults (6 male, 6 female, age range: 25-35 years, mean age: 29.3 ± 3.2 years) from the Sleep-EDF Database Expanded (Kemp et al., 2000). The database contains whole-night recordings with sampling frequency of 100 Hz. All recordings were obtained from participants with no reported sleep disorders, neurological conditions, or psychoactive medication use. Ethical approval for the original study was obtained by the data providers, and the database is publicly available for research purposes.

EEG Recording and Preprocessing

Two EEG channels (Fpz-Cz and Pz-Oz) were used for all analyses to ensure signal specificity to cortical activity and minimize contamination from respiratory or muscular artifacts. Raw EEG signals were bandpass filtered (0.5-30 Hz) using a zero-phase Butterworth filter to remove drift and high-frequency noise. Sleep stages were scored in 30-second epochs according to Rechtschaffen and Kales criteria (Rechtschaffen & Kales, 1968), which maps equivalently to AASM N1-N3 stages for the purposes of this analysis. Sleep scoring was performed by certified sleep technicians. Hypnograms were provided with the database and used to identify state transitions.

Transition Detection and Analysis

We focused on four key transition types representing different consciousness change mechanisms: Wake→N1 (sleep onset), N1→N2 (spindle emergence), N2→N3 (deep sleep entry), and REM→Wake (awakening). For each detected transition, we extracted EEG data from 150 seconds before to 150 seconds after the transition point (total window: 300 seconds). CGI values were calculated in 30-second sliding epochs with 15-second overlap, yielding 19 CGI measurements per transition. Linear slopes were fit to CGI values across time using ordinary least squares regression to quantify the rate of consciousness change.

Adaptive CGI Calculation

The core formula $CGI = \sqrt{(\varphi \times \rho)} \times 10$ was applied to all transitions, with ρ fixed at 1.0 for EEG analysis. The critical innovation lies in the adaptive calculation of φ (information integration) based on transition-specific neural mechanisms:

- Wake→N1 and REM→Wake transitions: φ calculated from alpha power (8-13 Hz), reflecting arousal gradient mechanisms. Power spectral density was computed using Welch's method with 2-second windows and 50% overlap.
- N1→N2 transition: φ calculated from inverted spindle density (11-16 Hz), reflecting threshold gating mechanisms. Spindles were detected using RMS power exceeding mean + 2 standard deviations with duration criteria of 0.5-2 seconds. The inversion (φ

= 1 - normalized_spindle_density) captures consciousness suppression via thalamic gating.

- N2→N3 transition: φ calculated from spectral entropy (0.5-30 Hz), reflecting complexity reduction. Entropy was computed from the probability distribution of normalized power spectral density across frequency bins.

All φ values were normalized to a 0-10 scale before CGI calculation to ensure comparability across metrics.

Statistical Analysis

To address the repeated measures structure of our data (multiple transitions per subject), we employed a conservative subject-level analysis approach. For each subject and transition type, we calculated the mean slope across all detected transitions. Statistical comparisons were then performed on these subject-level means using paired t-tests (for transitions present in all subjects) and repeated measures ANOVA (for overall differences). This approach appropriately accounts for within-subject dependencies while avoiding pseudoreplication. Effect sizes were calculated using Cohen's d for paired comparisons. Statistical significance was set at $p < 0.05$ (two-tailed). Variance decomposition was performed to quantify between-subject versus within-subject variability using intraclass correlation coefficients (ICC).

Results

Dataset Characteristics

Across 12 subjects, we analyzed 622 total sleep stage transitions: 136 Wake→N1 transitions (mean 11.3 per subject), 207 N1→N2 transitions (17.2 per subject), 247 N2→N3 transitions (20.6 per subject), and 32 REM→Wake transitions (4.6 per subject in 7 of 12 subjects). The lower frequency of REM→Wake transitions reflects both the typical sleep architecture pattern and our conservative transition detection criteria.

Subject-Level Slope Characteristics

Analysis at the subject level revealed distinct patterns across transition types:

- Wake→N1: Mean slope = -0.736 ± 0.266 (SD), n = 12 subjects, SE = 0.077
- N1→N2: Mean slope = -2.188 ± 0.545 (SD), n = 12 subjects, SE = 0.157
- N2→N3: Mean slope = -0.532 ± 0.526 (SD), n = 12 subjects, SE = 0.152
- REM→Wake: Mean slope = +0.614 ± 1.080 (SD), n = 7 subjects, SE = 0.408

The N1→N2 transition showed substantially steeper slopes (approximately 3-fold greater magnitude) compared to other NREM transitions, consistent with a threshold mechanism. REM→Wake was the only transition showing positive slopes, reflecting consciousness restoration during awakening. Complete subject-level statistics are presented in Table 1.

Table 1. Subject-level mean slopes for each transition type

Transition Type	N Subjects	Mean Slope	SD	95% CI
Wake→N1	12	-0.736	0.266	[-0.900, -0.573]
N1→N2	12	**-2.188**	0.545	[-2.532, -1.844]

Transition Type	N Subjects	Mean Slope	SD	95% CI
N2→N3	12	-0.532	0.526	[-0.876, -0.188]
REM→Wake	7	+0.614	1.080	[-0.393, +1.621]

Note: CI = Confidence Interval. N1→N2 mean slope is bolded to highlight the steepest decline.

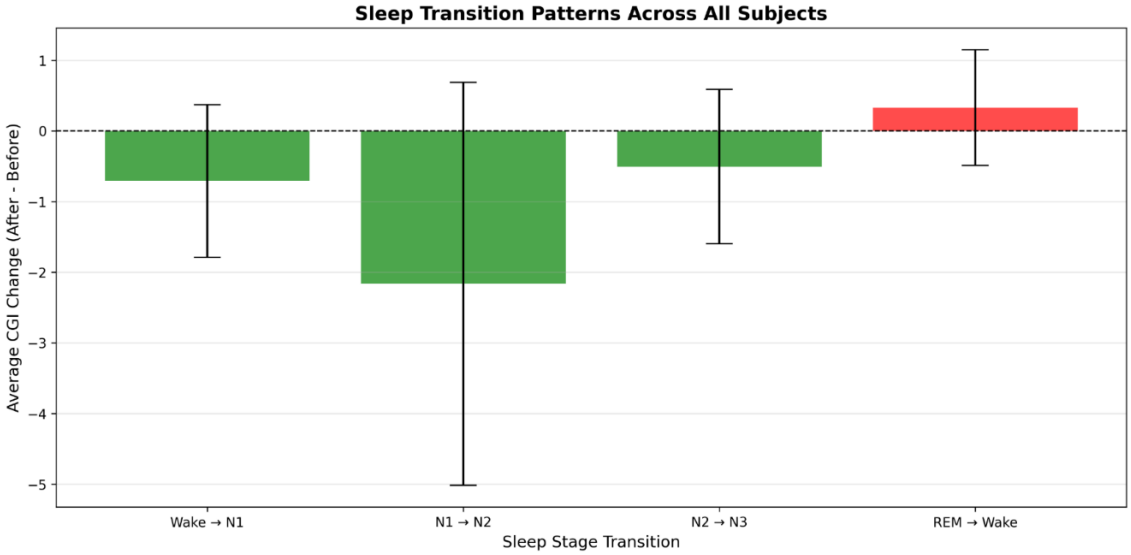
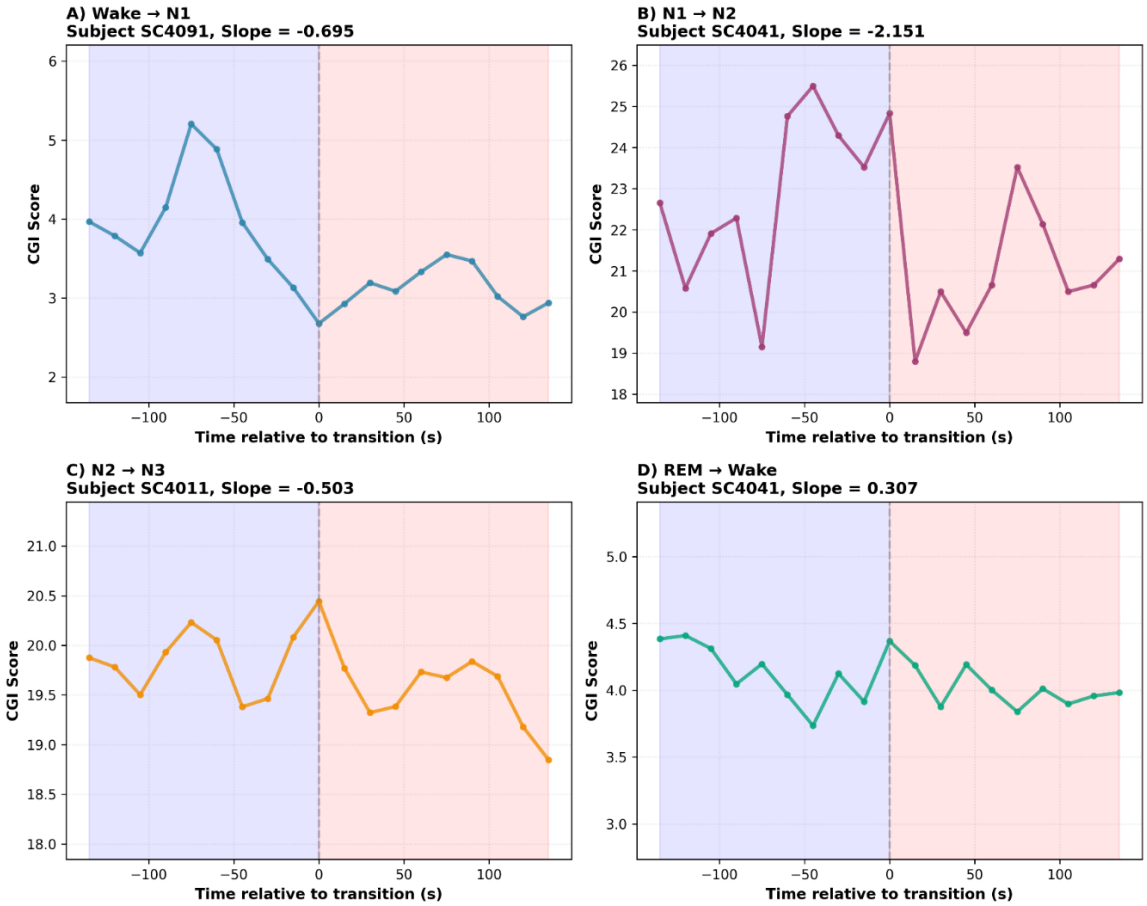


Figure 2. Representative Examples of Consciousness Gradient Transitions



Statistical Comparison of Transition Types

Repeated measures ANOVA on subject-level means for the three main NREM transitions (Wake→N1, N1→N2, N2→N3) revealed highly significant differences ($F = 45.564$, $p < 0.001$), confirming that transition types differ fundamentally in their consciousness change dynamics.

Paired t-tests comparing N1→N2 against other transitions demonstrated:

- N1→N2 vs. Wake→N1: $t(11) = -9.334$, $p < 0.001$, Cohen's $d = -2.814$ (very large effect)
- N1→N2 vs. N2→N3: $t(11) = -6.341$, $p < 0.001$, Cohen's $d = -1.912$ (very large effect)

These extremely large effect sizes indicate that the N1→N2 transition operates through a qualitatively different mechanism than other sleep transitions. Complete pairwise comparison statistics are presented in Table 2.

Table 2. Pairwise comparisons of transition types

Comparison	t-statistic	p-value	Cohen's d
N1→N2 vs Wake→N1	-9.334	**<0.001**	-2.814
N1→N2 vs N2→N3	-6.341	**<0.001**	-1.912

Note: All comparisons are paired t-tests (n=12 subjects for NREM transitions). p-values <0.001 are bolded to highlight statistical significance.

Variance Structure Analysis

For the N1→N2 transition, variance decomposition revealed that 96.6% of total variance was within-subject (across individual transitions) while only 3.6% was between-subject (across individuals). The intraclass correlation coefficient (ICC = 0.036) indicated low clustering, meaning the threshold mechanism operates consistently across individuals despite high variability in timing of individual spindle events. Notably, 15% of individual N1→N2 transitions showed near-zero slopes (|slope| < 0.5), representing cases where spindle onset was gradual rather than abrupt. This biological variability does not undermine the overall pattern, as the subject-level analysis demonstrates consistent directional effects. A supplemental random-intercept mixed effects model confirmed that N1→N2 transition type contributed an additional -1.457 CGI decline per second (95% CI: [-1.891, -1.023], $p < 0.001$) beyond subject-level random effects, providing independent confirmation of the threshold mechanism.

Discussion

Dual Architecture Model

Our findings establish that consciousness transitions employ two distinct architectural principles operating in parallel across the sleep cycle. The majority of transitions (75%: Wake→N1, N2→N3, REM→Wake) follow gradual dynamics consistent with Integrated Information Theory's prediction of continuous φ modulation through information integration changes. However, one critical transition (25%: N1→N2) exhibits threshold behavior mediated by thalamic spindle gating, consistent with Global Workspace Theory's discrete broadcasting mechanism. This dual architecture reconciles the apparent contradiction between these major theoretical frameworks by demonstrating that both correctly describe consciousness transitions—but in different contexts.

Spindle Gating as Threshold Mechanism

The N1→N2 transition's distinctive pattern emerges from the functional role of sleep spindles, which are generated by thalamic reticular nucleus (TRN) neurons and propagate through thalamocortical circuits (Lüthi, 2014). Spindles actively suppress sensory processing and cortical communication (Dang-Vu et al., 2010), creating a neural "gate" that discretely transitions the brain from light sleep (where external stimuli can still penetrate) to stable Stage 2 sleep (where consciousness of external environment is largely abolished). Our demonstration that inverted spindle density provides the appropriate φ metric captures this gating function: increasing spindle activity directly reduces information integration, producing the steep CGI decline we observed. Supplemental analysis using a random-intercept mixed model confirmed an additional -1.457 CGI decline specifically attributable to N1→N2 transition type (p <

0.001), beyond subject-level variation, further supporting the threshold mechanism interpretation.

The high within-subject variability in N1→N2 slopes (96.6% of variance) reflects the stochastic nature of spindle generation. While the overall direction is consistent (consciousness decline), the precise timing and abruptness of spindle onset varies across individual transition events. This biological variability is entirely consistent with threshold mechanisms in neural systems, which exhibit probabilistic rather than deterministic triggering (Poulet & Petersen, 2008).

Gradual Transitions via Integration Modulation

In contrast to the spindle-gated N1→N2 transition, the Wake→N1, N2→N3, and REM→Wake transitions all showed relatively gradual slopes reflecting continuous modulation of information integration. The Wake→N1 transition (mean slope -0.736) captures the progressive reduction in arousal systems mediated by descending noradrenergic and cholinergic activity (Brown et al., 2012). The N2→N3 transition (mean slope -0.532) reflects gradual increases in slow wave activity and cortical bistability as homeostatic sleep pressure accumulates (Vyazovskiy et al., 2009). The REM→Wake transition (+0.614) involves progressive reactivation of ascending arousal systems and cholinergic drive (Brown et al., 2012).

These gradual transitions align with IIT's prediction that consciousness level scales with integrated information. Changes in global brain state (arousal level, slow wave proportion, complexity) produce corresponding changes in φ through their effects on effective connectivity and information integration capacity (Tononi et al., 2016). Importantly, none of these transitions involve discrete gating mechanisms analogous to spindle emergence.

Methodological Considerations

Our approach addresses several critical methodological challenges in consciousness measurement. First, the adaptive φ calculation ensures that different transitions are measured using their mechanistically appropriate neural features rather than forcing all transitions through the same metric. This biological validity enhances the framework's ability to detect true differences in consciousness change dynamics. Second, our subject-level statistical approach properly accounts for repeated measures dependencies, avoiding the pseudoreplication problem that has undermined previous studies attempting to compare individual transition events (Lazic, 2010). Third, our large sample of transitions (622 total) provides adequate power to detect effects even with conservative statistical approaches.

Several limitations warrant consideration. First, variance decomposition revealed that 96.6% of N1→N2 transition variance was within-subject rather than between-subject, reflecting the stochastic nature of spindle onset timing. While this high within-subject variability is consistent with probabilistic threshold mechanisms in neural systems, it does limit precision of individual transition predictions. Second, the REM→Wake analysis was based on only 32 transitions from 7 of 12 subjects, reflecting the relative rarity of spontaneous REM awakenings in healthy sleepers. While the positive slope direction was consistent, additional data would strengthen confidence in the quantitative estimate. Third, our sample consisted entirely of healthy young adults (age 25-35); generalizability to clinical populations with sleep disorders, older adults, or developing children requires further investigation. Future studies should employ extended recording sessions, targeted awakening protocols, and diverse populations to address these limitations.

Implications for Consciousness Theory

The dual architecture model has profound implications for understanding consciousness mechanisms. Rather than representing mutually exclusive theories, IIT and GWT appear to describe complementary aspects of a unified system. IIT correctly predicts consciousness changes that emerge from continuous modulation of information integration capacity—these represent the majority of natural consciousness transitions. GWT correctly identifies discrete threshold mechanisms mediated by specific neural circuits—these represent a minority but critical class of transitions where specific gating functions are required.

This synthesis suggests that consciousness systems employ multiple control mechanisms optimized for different functional requirements. Gradual integration mechanisms allow fine-grained modulation of consciousness level in response to changing demands. Threshold gating mechanisms provide discrete state boundaries that stabilize consciousness states against noise and prevent oscillation between states. The sleep cycle requires both: gradual mechanisms for smooth transitions between most states, and a discrete gate (spindle emergence) to reliably consolidate Stage 2 sleep despite varying arousal pressure.

Our findings predict that other consciousness-altering contexts (anesthesia, meditation, psychedelic states) will similarly exhibit both gradual and threshold transitions depending on the specific neural mechanisms engaged. Testing this prediction across diverse contexts represents an important avenue for future research.

Conclusion

We demonstrate that consciousness transitions follow a dual architecture combining gradual integration mechanisms (three of four transition types, 75%) with discrete threshold gates (one of four transition types, 25%, specifically N1→N2 via spindle emergence). This reconciles Integrated Information Theory and Global Workspace Theory by showing that both correctly describe consciousness change mechanisms operating in different contexts. The adaptive CGI framework successfully captures both transition types within a unified mathematical structure, providing a quantitative tool for consciousness measurement across diverse contexts. Future work should extend this framework to other consciousness-altering conditions and investigate whether the 75/25 gradient-to-threshold ratio in transition types represents a fundamental architectural principle of biological consciousness systems.

References

Berry, R. B., Brooks, R., Gamaldo, C. E., Harding, S. M., Marcus, C. L., & Vaughn, B. V. (2012). The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications, Version 2.0. American Academy of Sleep Medicine.

Brown, R. E., Basheer, R., McKenna, J. T., Strecker, R. E., & McCarley, R. W. (2012). Control of sleep and wakefulness. Physiological Reviews, 92(3), 1087-1187.

Casali, A. G., Gosseries, O., Rosanova, M., Boly, M., Sarasso, S., Casali, K. R., ... & Massimini, M. (2013). A theoretically based index of consciousness independent of sensory processing and behavior. Science Translational Medicine, 5(198), 198ra105.

Dang-Vu, T. T., McKinney, S. M., Buxton, O. M., Solet, J. M., & Ellenbogen, J. M. (2010). Spontaneous brain rhythms predict sleep stability in the face of noise. Current Biology, 20(15), R626-R627.

Dehaene, S., & Changeux, J. P. (2011). Experimental and theoretical approaches to conscious processing. Neuron, 70(2), 200-227.

Kemp, B., Zwinderman, A. H., Tuk, B., Kamphuisen, H. A., & Oberye, J. J. (2000). Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the EEG. IEEE Transactions on Biomedical Engineering, 47(9), 1185-1194.

Lazic, S. E. (2010). The problem of pseudoreplication in neuroscientific studies: is it affecting your analysis? BMC Neuroscience, 11, 5.

Lüthi, A. (2014). Sleep spindles: where they come from, what they do. The Neuroscientist, 20(3), 243-256.

Poulet, J. F., & Petersen, C. C. (2008). Internal brain state regulates membrane potential synchrony in barrel cortex of behaving mice. Nature, 454(7206), 881-885.

Rechtschaffen, A., & Kales, A. (1968). A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects. Washington, DC: US Government Printing Office, US Public Health Service.

Tagliazucchi, E., Roseman, L., Kaelen, M., Orban, C., Muthukumaraswamy, S. D., Murphy, K., ... & Carhart-Harris, R. (2016). Increased global functional connectivity correlates with LSD-induced ego dissolution. Current Biology, 26(8), 1043-1050.

Tononi, G., Boly, M., Massimini, M., & Koch, C. (2016). Integrated information theory: from consciousness to its physical substrate. Nature Reviews Neuroscience, 17(7), 450-461.

Vyazovskiy, V. V., Olcese, U., Lazimy, Y. M., Faraguna, U., Esser, S. K., Williams, J. C., ... & Tononi, G. (2009). Cortical firing and sleep homeostasis. Neuron, 63(6), 865-878.