

Sāṅkhya-Informed Cognitive AI:

A Scientific Framework for Designing the MindBalance EEG Wearable

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Abstract. Contemporary mental health technologies predominantly operate within reactive, diagnosis-driven paradigms, intervening only after psychological distress becomes clinically manifest. In contrast, Indian Knowledge Systems (IKS), particularly the Sāṅkhya philosophical tradition, conceptualize mental suffering as the cumulative outcome of long-term imbalance in fundamental cognitive qualities. Central to this framework is the Triguṇa model, which describes mental functioning as a dynamic composition of Sattva (clarity), Rajas (activity), and Tamas (inertia). Despite its conceptual rigor, Triguṇa theory has remained largely qualitative, limiting its integration with modern neuroscience and wearable mental health systems.

This paper presents the scientific foundations of the MindBalance EEG wearable, a cognitive AI system that operationalizes Triguṇa theory using non-invasive electroencephalography (EEG). Sattva, Rajas, and Tamas are modeled as continuous state variables inferred from normalized EEG spectral power across delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–45 Hz) bands. A mathematically explicit mapping defines raw guṇa scores as weighted combinations of band powers, normalized to yield a Triguṇa state vector constrained to the probability simplex at each time window.

Using exploratory datasets comprising over 78 million EEG epochs from more than 4,000 individuals across meditative, cognitive, and fatigue-related states, we observe consistent alignment between Triguṇa dominance and neural spectral patterns. The results demonstrate internal coherence between Sāṅkhya theory and measurable neural dynamics, reframing mental health monitoring as a continuous, interpretable, and preventive process grounded in Indian philosophical psychology.

Keywords: Indian Knowledge Systems; Sāṅkhya–Triguṇa framework; electroencephalography (EEG); cognitive state modeling; wearable neurotechnology

1 Introduction

Introduction

Mental health and cognitive well-being have emerged as critical challenges of the twenty-first century. Rising prevalence of stress-related disorders, burnout, anxiety, and affective dysregulation has placed increasing strain on healthcare systems worldwide. Despite advances in clinical psychology, neuroscience, and digital health technologies, most contemporary mental health interventions remain fundamentally reactive. Assessment and intervention typically occur only after psychological distress has escalated into clinically recognizable symptoms, leaving limited scope for early detection or prevention.

This reactive orientation reflects deeper assumptions embedded within dominant psychological and psychiatric paradigms. Western mental health models largely conceptualize cognition and emotion in terms of discrete disorders, symptom clusters, or trait-based classifications. While these frameworks have yielded important diagnostic and therapeutic tools, they provide limited mechanisms for continuously monitoring cognitive balance or identifying subtle precursors of future mental suffering. As a result, cognitive imbalance often remains invisible for extended periods before manifesting as overt pathology.

In contrast, Indian Knowledge Systems (IKS) offer a markedly different conception of mental functioning. Classical Indian philosophical traditions—particularly Sāṅkhya and Yoga—view mental suffering not as a sudden dysfunction but as the cumulative outcome of prolonged imbalance within underlying cognitive processes. The Yoga Sūtra explicitly asserts that suffering which has not yet manifested can be avoided, implying that early indicators of imbalance are both detectable and correctable. This preventive orientation positions mental health as a dynamic process of maintaining equilibrium rather than merely treating disorder.

Central to Sāṅkhya psychology is the Triguṇa framework, which describes cognition as a dynamic composition of three fundamental qualities: Sattva (clarity and equilibrium), Rajas (activity and agitation), and Tamas (inertia and obscuration). These guṇas are not moral or metaphysical abstractions but functional properties that jointly govern perception, attention, emotion, and behavior. Importantly, Sāṅkhya treats mental states as continuously varying proportions of these guṇas rather than as discrete categories. Mental well-being, in this view, arises from sustained balance among Sattva, Rajas, and Tamas, while suffering emerges from persistent dominance or instability of particular guṇas.

From a scientific perspective, the Triguṇa model exhibits several features that make it especially amenable to formalization. First, it is inherently dynamical, emphasizing temporal variation and interaction rather than static traits. Second, it is compositional, describing mental states as mixtures constrained by relative dominance rather than absolute values. Third, classical texts consistently associate guṇa dominance with observable cognitive and behavioral signatures, suggesting that internal mental qualities produce measurable external correlates. These characteristics closely align with modern systems-theoretic and dynamical approaches to cognition.

Despite this conceptual compatibility, Triguṇa theory has remained largely qualitative and has seen limited integration with contemporary neuroscience or mental health technologies. Existing efforts to bridge Indian psychology with modern science have often remained interpretive or philosophical, lacking operational definitions that can be empirically tested or deployed in real-world systems. At the same time, modern affective computing and wearable mental health technologies typically rely on abstract constructs such as valence and arousal or on opaque machine-learning models that offer limited interpretability and weak theoretical grounding.

This paper seeks to bridge this gap by presenting the MindBalance EEG wearable as a scientifically grounded instantiation of Sāṅkhya psychology. Rather than treating Indian philosophical concepts as metaphors or post-hoc explanations, MindBalance embeds Triguṇa theory directly into system design, signal processing, and mathematical modeling. Using non-invasive electroencephalography (EEG), the system continuously measures neural oscillatory activity and infers Sattva, Rajas, and Tamas as quantitative, time-varying cognitive state variables.

The primary contribution of this work is threefold. First, we demonstrate how Sāṅkhya philosophy can function as a generative scientific framework, guiding the design of measurable, interpretable cognitive models. Second, we present a mathematically explicit Triguṇa computation model grounded in established EEG spectral features, enabling continuous estimation of cognitive balance. Third, using large-scale exploratory EEG datasets, we show consistent alignment between Triguṇa dominance and neural spectral patterns across meditative, cognitive, and fatigue-related states.

By reframing mental health monitoring as a continuous, preventive process rooted in Indian Knowledge Systems and modern neuroscience, this work contributes to ongoing interdisciplinary efforts at the intersection of philosophy, brain science, and cognitive AI. The MindBalance wearable illustrates a principled pathway for integrating IKS into contemporary neurotechnology while maintaining scientific rigor, interpretability, and ethical clarity.

This paper makes one seminal contribution – converting EEG signals into Triguṇa quantitatively.weight

2 ture Review

Litera

2.1 EEG and Cognitive State Representation

Electroencephalography (EEG) has long been employed as a primary tool for investigating neural correlates of cognition due to its high temporal resolution and sensitivity to oscillatory brain dynamics. Foundational research has established that neural oscillations across canonical frequency bands—delta, theta, alpha, beta, and gamma—are systematically associated with cognitive, attentional, and affective processes (Buzsáki, 2006; Klimesch, 1999).

Alpha and theta oscillations have been repeatedly linked to internalized attention, working memory, and meditative absorption, while beta and gamma activity are associated with active cognition, executive control, and cognitive effort (Klimesch, 1999; Fries, 2005). Delta activity, by contrast, is typically observed during sleep or low-arousal states but also appears during fatigue and disengagement (Harmony, 2013). These findings collectively support the view that EEG spectral composition provides a meaningful representation of moment-to-moment cognitive states.

Recent work has increasingly emphasized state-based rather than localization-based interpretations of EEG, focusing on distributed patterns of oscillatory activity rather than isolated neural generators (Michel & Murray, 2012). This shift aligns closely with dynamical and systems-oriented models of cognition, wherein mental states are understood as emergent configurations of neural activity evolving over time.

2.2 Affective Computing and Mental State Inference

Affective computing aims to infer emotional and cognitive states from physiological signals, behavior, and contextual data (Picard, 1997). Many EEG-based affective systems employ dimensional models of emotion, most commonly the valence–arousal framework, which maps mental states onto axes of pleasantness and activation (Russell, 1980).

While valence–arousal models have demonstrated utility in emotion recognition tasks, they have been criticized for their limited interpretability and insufficient granularity in capturing complex cognitive qualities such as clarity, inertia, or agitation (Barrett, 2006). Moreover, many modern systems rely heavily on machine learning classifiers trained for prediction accuracy rather than explanatory coherence, resulting in black-box models that provide limited insight into underlying cognitive mechanisms.

Recent critiques within affective neuroscience have called for theoretically grounded, interpretable models that preserve meaningful psychological structure while remaining empirically testable (Pessoa, 2017). This has renewed interest in frameworks that emphasize cognitive organization, stability, and regulation rather than discrete emotional labels.

2.3 Neurofeedback and Wearable EEG Systems

EEG-based neurofeedback systems have been widely studied in the contexts of meditation training, stress reduction, and attentional enhancement (Hammond, 2011). Commercial and research-grade wearables increasingly enable real-time monitoring of neural activity in naturalistic settings, expanding the scope of cognitive and mental health research beyond laboratory environments.

However, many wearable EEG systems reduce complex neural dynamics to single scalar metrics such as “attention,” “calmness,” or “focus,” often without clear theoretical justification. These simplifications risk obscuring the multidimensional nature of cognition and limiting the interpretability of feedback provided to users.

Recent work emphasizes the importance of grounding neurofeedback metrics in well-defined cognitive or phenomenological frameworks (Brandmeyer & Delorme, 2021). This perspective supports the development of systems that prioritize explanatory structure and user interpretability over purely data-driven abstraction.

2.4 Indian Knowledge Systems and Psychological Modeling

Indian philosophical traditions have long articulated systematic models of mind that differ fundamentally from dominant Western paradigms. Sāṅkhya, in particular, offers a structured psychological theory in which cognition arises from the interaction of three fundamental qualities—Sattva, Rajas, and Tamas—rather than from isolated mental faculties or traits (Larson & Bhattacharya, 1987).

Scholars of cross-cultural psychology have argued that Triguṇa theory represents a functional taxonomy of mental states, describing patterns of clarity, activation, and inertia that are observable in behavior and experience (Paranjpe, 1998; Cornelissen, 2006). Unlike trait-based models, Triguṇa theory is inherently dynamical, emphasizing continuous variation and balance rather than fixed dispositions.

Despite its descriptive richness, Triguṇa theory has seen limited empirical operationalization. Existing integrations with modern psychology have largely remained conceptual, lacking formal definitions or measurable variables that could support systematic experimentation or technological deployment.

2.5 Neurophenomenology and Bridging First- and Third-Person Data

Neurophenomenology emerged as a methodological response to the challenge of integrating subjective experience with objective neural data (Varela, 1996). Rather than reducing experience to neural activity or dismissing it as epiphenomenal, neurophenomenological approaches treat phenomenological categories as legitimate scientific variables.

Subsequent work has demonstrated that carefully defined experiential states—such as different forms of meditation or attentional engagement—can be reliably associated with distinct neural dynamics (Lutz et al., 2007; Lutz et al., 2015). This body of research supports the feasibility of grounding experiential classifications in measurable brain activity, provided that the categories themselves are well structured.

Triguṇa theory, with its emphasis on experiential quality, balance, and stability, offers a natural phenomenological taxonomy that aligns with this approach. However, explicit computational models linking Triguṇa states to neural measures remain largely absent from the literature.

2.6 Identified Research Gap

Taken together, existing literature reveals a clear gap at the intersection of neuroscience, affective computing, and Indian Knowledge Systems. EEG research provides robust tools for measuring cognitive dynamics but lacks theoretically rich, interpretable psychological frameworks. Affective computing offers scalable

inference mechanisms but often relies on reductive or opaque models. Indian psychological theories provide sophisticated cognitive taxonomies but remain largely not operationalized.

3 n Philosophy of the MindBalance Wearable

Desig

The design of MindBalance begins with a philosophical commitment: mental balance is a continuous, measurable process, not an episodic clinical event. This commitment leads to several design principles derived directly from Sāṅkhya.

First, the system prioritizes continuous monitoring over episodic assessment. Second, it emphasizes interpretability over opaque prediction. Third, it treats individual baselines as essential, reflecting Sāṅkhya's emphasis on dynamic equilibrium rather than normative thresholds.

EEG was selected as the primary sensing modality because neural oscillations provide a direct window into cognitive dynamics while remaining non-invasive and wearable. Frontal electrode placement was chosen to balance signal relevance, comfort, and feasibility for long-term use, aligning with the system's preventive orientation.

4 m Architecture and Signal Processing

Syste

The MindBalance wearable consists of four integrated layers: EEG acquisition, signal preprocessing, feature extraction, and Triguṇa computation. Two frontal electrodes acquire raw EEG signals, which are filtered to remove noise and artifacts. Signals are segmented into short temporal windows, and power spectral density is computed using standard Fourier methods.

Band-specific power values are extracted for delta, theta, alpha, beta, and gamma frequencies. Rather than feeding these features into an unconstrained classifier, MindBalance uses them as inputs to a mathematically defined Triguṇa model rooted in Sāṅkhya theory.

5 mational Modeling of Triguṇa States

Mathe

Each guṇa is modeled as a weighted function of EEG band powers. Sattva emphasizes alpha and theta activity, reflecting clarity and internal coherence. Rajas emphasizes beta and gamma activity, reflecting cognitive effort and agitation. Tamas emphasizes delta dominance, reflecting inertia and disengagement.

Raw guṇa scores are normalized to produce a three-dimensional state vector that sums to unity at each time point. This formulation preserves interpretability while enabling personalization through adaptive calibration. Over time, the system constructs an individualized cognitive profile consistent with Sāṅkhya's dynamic balance model.

EEG-grounded implementation of Trigūṇa theory within a wearable cognitive AI system. By embedding Sāṅkhya psychology directly into signal processing and modeling, the MindBalance wearable advances both the scientific study of cognition and the practical design of preventive mental health technologies.

6 Signal Processing and Feature Extraction (Formal Specification)

Let the raw EEG signal acquired from electrode $e \in \{Fp1, Fp2\}$ be denoted as:

$$x_e(t), t \in R$$

6.1 Preprocessing

The raw signal is band-pass filtered:

$$x_e^f(t) = B_{0.5-45}(x_e(t))$$

where $B_{0.5-45}$ denotes a 4th-order Butterworth filter with passband 0.5–45 Hz.

A notch filter at 50 Hz is applied to remove mains interference:

$$x_e^n(t) = N_{50}(x_e^f(t))$$

6.2 Windowing and Spectral Decomposition

The filtered signal is segmented into overlapping windows of duration:

$$T_w = 2.4 \text{ s}$$

with 50% overlap.

For each window w , the discrete Fourier transform is computed:

$$X_e^{(w)}(f) = F\{x_e^n(t)\}$$

The power spectral density (PSD) is estimated as:

$$P_e^{(w)}(f) = |X_e^{(w)}(f)|^2$$

6.3 Band Power Computation

Band-specific powers are computed by integrating the PSD:

$$P_\delta = \int_{0.5}^4 P(f) df \quad P_\theta = \int_4^8 P(f) df \quad P_\alpha = \int_8^{13} P(f) df \quad P_\beta = \int_{13}^{30} P(f) df$$

$$P_\gamma = \int_{30}^{45} P(f) df$$

The total power is:

$$P_{\text{tot}} = P_\delta + P_\theta + P_\alpha + P_\beta + P_\gamma$$

Normalized band powers are then defined as:

$$\hat{P}_i = \frac{P_i}{P_{\text{tot}}}, i \in \{\delta, \theta, \alpha, \beta, \gamma\}$$

7 al Triguṇa Computation Model

Form

7.1 Philosophical → Computational Mapping

Based on Sāṅkhya descriptions:

- Sattva → clarity, integration, internal coherence
- Rajas → activity, excitation, cognitive effort
- Tamas → inertia, withdrawal, obscurity

These are mapped to EEG bands by functional correspondence, not arbitrary fitting.

7.2 Raw Guṇa Score Definitions

Let $\hat{P}_\delta, \hat{P}_\theta, \hat{P}_\alpha, \hat{P}_\beta, \hat{P}_\gamma$ denote normalized band powers.

Raw guṇa scores are defined as:

Sattva score:

$$S_{\text{raw}} = 0.5 \hat{P}_\theta + 1.0 \hat{P}_\alpha + 0.2 \hat{P}_\beta$$

Rajas score:

$$R_{\text{raw}} = 1.0 \hat{P}_\beta + 0.5 \hat{P}_\gamma$$

Tamas score:

$$T_{\text{raw}} = 1.0 \hat{P}_\delta + 0.5 \hat{P}_\theta$$

These weights were initialized based on neurophysiological literature and refined empirically to preserve interpretability rather than maximize classification accuracy.

Weights were chosen to reflect known neurophysiological correlates of attention (alpha–theta), cognitive effort (beta–gamma), and hypoarousal (delta), ensuring theoretical interpretability rather than purely data-driven fitting

7.3 Normalization (State Vector Constraint)

The Triguṇa state is normalized to enforce a compositional constraint:

$$S + R + T = 1 \quad S = \frac{S_{\text{raw}}}{S_{\text{raw}} + R_{\text{raw}} + T_{\text{raw}}} \quad R = \frac{R_{\text{raw}}}{S_{\text{raw}} + R_{\text{raw}} + T_{\text{raw}}} \quad T = \frac{T_{\text{raw}}}{S_{\text{raw}} + R_{\text{raw}} + T_{\text{raw}}}$$

Thus, at each time window w , the cognitive state is represented as:

$$G^{(w)} = (S^{(w)}, R^{(w)}, T^{(w)}) \in \Delta^2$$

where Δ^2 is the 2-simplex.

7.4 Temporal Stability and Cognitive Balance

Temporal smoothness is assessed via:

$$\sigma_G = \text{Var}_t(S, R, T)$$

Low variance corresponds to cognitive stability (Sattvic dominance), while high variance corresponds to Rājasic fluctuation.

A Cognitive Balance Index (CBI) is defined as:

$$\text{CBI} = S - (R + T)$$

with:

- $\text{CBI} > 0 \rightarrow$ balanced / integrative state
- $\text{CBI} < 0 \rightarrow$ imbalanced / dysregulated state

8 itative Empirical Observations

Quant

7.1 Dataset Description

- Subjects: >4,000 individuals
 - EEG records: ~78 million epochs, epochs were short windows, exploratory, for pattern coherence
 - Sampling rate: 250 Hz
 - Window size: 2.4 s
 - Epochs per hour: ~1,500
 - Includes:
 - o Meditative practitioners
 - o Cognitive task states
 - o Rest and fatigue states
-

8.1 Observed Numerical Ranges

Cognitive State	Mean S	Mean R	Mean T
Deep meditation	0.62–0.75	0.15–0.25	0.05–0.15
Focused task	0.30–0.45	0.45–0.60	0.10–0.20
Fatigue	0.15–0.30	0.10–0.25	0.50–0.70

Exploratory analyses across large EEG datasets collected from diverse participants—including experienced contemplative practitioners—reveal consistent patterns. Meditative states show elevated Sattva indices with dominant alpha–theta activity. Cognitively demanding tasks show increased Rajas via beta–gamma amplification. Periods of fatigue or disengagement correspond to Tamas dominance marked by delta activity.

These observations do not constitute clinical validation. Rather, they demonstrate internal coherence between philosophical expectations and measurable neural patterns, supporting the feasibility of Triguna-based cognitive monitoring.

9

Discus
sion

MindBalance demonstrates that Sāṅkhya philosophy can function as a generative framework for scientific system design rather than as a post-hoc interpretive lens. By constraining model structure through theory, the system achieves interpretability often lacking in contemporary AI-driven mental health tools.

The approach reframes mental health from diagnosis to balance maintenance, aligning ancient preventive insight with modern ethical concerns about over-medicalization and opaque surveillance.

9. Limitations and Future Work

Limitations include reliance on EEG as a proxy for complex mental phenomena, the exploratory nature of current datasets, and the need for longitudinal validation. Future work will focus on multimodal sensing, controlled studies, and ethical governance frameworks for large-scale deployment.

10. Conclusion

This paper has presented a full scientific account of how the MindBalance wearable operationalizes Sāṅkhya’s Triguna theory using EEG and cognitive AI. The work demonstrates that Indian Knowledge Systems can inform rigorous, interpretable

neurotechnologies and offers a pathway toward preventive, continuous mental health monitoring grounded in philosophical and scientific coherence.

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