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RESEARCH ARTICLE

Can Consciousness Nudge Randomness?

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ABSTRACT

This paper presents the Cognitive Entropy Shift Model (CESM), a structured framework for exploring how distinct cognitive states, specifically passive emotional attention and goal-directed intention may influence probabilistic systems by reducing entropy. Drawing on principles from information theory and Bayesian-inspired probability updating, CESM conceptualizes consciousness as an informational constraint capable of subtly biasing outcomes in systems typically governed by randomness. To evaluate this framework, a two-year empirical study was conducted under controlled conditions using data from a physical random number generator (RNG). CESM was used to predict when deviations from randomness would occur and the analysis revealed statistically significant deviations ($t = -4.347$, $p < 0.001$) during periods characterized by heightened emotional attention, with effect sizes in the range of 0.5–0.7%. These results aligned closely with CESM's predictions. The effect also diminished with increasing spatial distance from the presumed source of influence, highlighting proximity as a potentially critical factor. In addition to presenting new empirical results, this paper also applies CESM retrospectively to earlier studies, offering a clear and testable reinterpretation of previously reported anomalies. By distinguishing between passive and active forms of cognitive engagement, and embedding them within a quantifiable statistical model, CESM provides a structured approach for examining whether, and under what conditions, cognitive states may correspond to subtle deviations in probabilities. The findings encourage further exploration into how consciousness relates to information, including potential effects across spatial distance, within a framework that supports formal, testable hypotheses in advance of data collection, while remaining grounded in established scientific principles.

KEYWORDS

Consciousness, Entropy, Information Theory, Bayesian Updating, Cognitive States.

INTRODUCTION

The idea that human consciousness might influence the physical world has fascinated philosophers for centuries. Thinkers such as Plato (ca. 375 BCE/2007), with his theory of ideal forms, Descartes and Williams (1641/1996), with his concept of mind–body dualism, and Spinoza (1677/n.d), who proposed that mind and matter are two aspects of the same substance, all wrestled with this question. In more recent times, science has taken up this debate, transforming it into a testable empirical question. Thanks to advances in physics, neuroscience, and information theory, researchers now have new tools to explore the relationship between consciousness and the physical world.

Modern scientific investigations into the relationship between consciousness and physical systems have taken steps forward, as developments in quantum mechanics, cognitive science, and information theory have yielded new insights. In the quantum realm, classical assumptions about determinism have been challenged by interpretations from Wigner and Stapp, which suggest that observation and (potentially) consciousness may play a critical role in shaping physical states (Stapp, 2001; Wigner, 1961). Similarly, Quantum Bayesianism (QBism) proposes that probabilities in quantum mechanics are observer-dependent constructs, offering additional perspectives on the role of consciousness (Fuchs & Schack, 2013). This perspective has sparked ongoing debate over whether consciousness is merely an emergent byproduct of neural activity, or whether it represents a more fundamental aspect of nature, potentially acting as an intrinsic factor in driving the collapse of the wavefunction.

Meanwhile, cognitive neuroscience has made notable progress in identifying the neural correlates of consciousness. Early models explored mechanisms such as sensorimotor integration and neural synchrony (Cotterill, 2001; Llinás & Ribary, 2001), while later frameworks focused on global information broadcasting within the brain's fronto-parietal circuits (Baars, 1997; Koch, 2004). Two of the most prominent contemporary theories, Global Neuronal Workspace Theory and Integrated Information Theory (Tononi, 2004), have recently been subjected to large-scale empirical testing with mixed results as some of their predictions have been supported, while others have been challenged by experimental data (Cogitate Consortium et al., 2025).

Alongside these mainstream models, alternative perspectives continue to broaden the theoretical landscape. Quantum-based accounts, such as the Orchestrated Objective Reduction (Orch OR) theory, propose that consciousness arises from orchestrated quantum state reductions in neuronal microtubules (Hameroff & Penrose, 1996) and have since been further refined into a comprehensive framework integrating neurophysiology and fundamental physics (Hameroff & Penrose, 2016). In parallel, emerging clinical perspectives question whether full sentience requires cortical involvement at all (Kawkabani & Kaut, 2024).

Despite this progress, a fundamental explanatory gap remains between measurable brain activity and the qualitative nature of subjective experience. This enduring limitation, which has been famously termed the "hard problem of consciousness" (Chalmers, 1995), has fueled the search for alternative frameworks that challenge strictly reductionist explanations of the mind. Taken together, these developments underscore the importance of broadening our theoretical perspectives.

One way to deepen our understanding of consciousness is to consider it fundamentally involved in the organization of information. Information theory, originally developed by Shannon (1948), offers a framework for quantifying uncertainty and understanding how constraints can reduce entropy. Although first applied to telecommunications, these principles have since been extended to broader models explaining how order can emerge from randomness when specific constraints are applied.

Building on this insight, consciousness can be viewed as an informational constraint: cognitive processes shape what might otherwise be random input into structured and meaningful patterns. This perspective aligns with the Bayesian brain model, which suggests that the mind actively reduces uncertainty by continuously updating its internal representations based on predictive information. In this process, consciousness functions as an internal organizer, guiding perception, memory, and attention by generating probabilistic representations of reality from incoming sensory input (Clark, 2015; Friston, 2010; Seth & Bayne, 2022).

Despite these advancements, mainstream science continues to grapple with several unresolved aspects of conscious experience. These include the origin of subjectivity (Nagel, 1974), the integration of perception across the brain's modular systems (Revonsuo, 1999), the perceived continuity of conscious experience over time (Pöppel, 2004; Varela, 1999), and the basis of self-awareness (Gallagher & Zahavi, 2008; Metzinger, 2004). While significant theoretical and empirical progress has been made, most scientific models treat consciousness as a byproduct of neural computation, offering limited explanations for how or why these phenomena arise (Churchland, 1997; Dennett, 1991).

This raises a broader question: could consciousness do more than interpret information internally? If it plays an active role in reducing uncertainty within the brain, as suggested by the Bayesian brain model, it is worth asking whether this organizing function might also extend beyond the internal domain. Could cognitive states that shape perception and expectation, goal oriented or otherwise, also leave subtle yet systematic traces in external processes that are otherwise considered random? This is not only a theoretical question; it is one that can be addressed empirically.

Random number generators (RNGs), which produce high-entropy and inherently unpredictable outputs, offer a well-controlled setting for investigating whether cognitive states can measurably influence external randomness. This was explored in the late 1960s and 1970s by Helmut Schmidt, who conducted experiments testing whether the mind could influence probabilistic outcomes. He used electronic random number generators based on noise diodes or radioactive decay and found results suggesting that focused mental activity could indeed influence the behavior of random systems (Schmidt, 1969, 1970, 1973). Building on this early work, the Princeton Engineering Anomalies Research (PEAR) Laboratory provided more extensive support for the hypothesis that consciousness might influence randomness. Researchers there found that focused human intention could produce small but statistically significant deviations in RNG output beyond chance expectations (Jahn & Dunne, 1987; Jahn et al., 1997; Jahn & Dunne, 2005), suggesting that consciousness may interact with a shared informational substrate that extends beyond individual subjective experience. Extending the PEAR lab's findings, the Global Consciousness Project (GCP) investigated whether collective consciousness might produce similar effects on a global scale. The project analyzed data from a worldwide network of RNGs, looking for synchronized deviations during emotionally significant world events and the results revealed patterns that appeared to correlate with periods of heightened shared attention and emotional intensity (Nelson et al., 2002). More recently, Holmberg extended this line of research by identifying correlations between deviations in GCP data and real-world indicators such as financial market movements and internet search trends, variables that are themselves responsive to emotionally charged global events (Holmberg, 2020, 2021, 2023, 2024). These findings suggest that some of the structured anomalies observed in the GCP data may align with shifts in such seemingly unrelated variables that are themselves sensitive to the same kinds of global events believed to affect the GCP data's behavior.

Taken together, this body of research points to the possibility that human cognition may introduce subtle and systematic biases into systems that should, in principle, behave randomly. These effects are reflected in structured patterns in RNG output that standard probabilistic models do not predict. However, despite the apparent empirical support (Utts, 1991), such findings have been met with considerable skepticism, as critics have suggested that the observed effects could be explained by statistical noise, inconsistent methods, or selective reporting (Alcock, 2003; Bösch et al., 2006; Scargle, 2002), small effect sizes that heighten the risk of Type I errors (Hyman, 1996), or uncontrolled experimenter and environmental variables (Wiseman & Schlitz, 1997). Some have also pointed to Decision Augmentation Theory (DAT), which suggests that the observed effects may stem not from direct influence, but from precognitive selection of favorable outcomes (May et al., 1995).

While these alternative explanations could account for some of the reported findings, they struggle to explain the persistence of entropy-related effects observed across numerous studies, researchers, and experimental contexts. In particular, they do not adequately account for the large-scale or time-synchronized deviations reported by the Global Consciousness Project (GCP). As a result, a fundamental question remains unresolved: are these statistical anomalies simply artifacts of methodological flaws, or do they point to a deeper, underlying phenomenon?

A major challenge facing the field is the lack of a robust theoretical framework capable of predicting and coherently explaining such effects. Without a model that integrates consciousness-related variables into established probabilistic reasoning, the debate risks becoming stalled in ambiguity and speculation. In response, some researchers have re-examined these anomalies, suggesting that they may reflect overlooked regularities rather than noise or chance (Drennan, 2015; Hardy, 2005; Walach et al., 2020). Although still preliminary, these reinterpretations highlight the need for models that maintain statistical rigor while remaining open to novel mechanisms grounded in consciousness research.

In response to these challenges, there is a clear need for a testable and falsifiable model that can evolve alongside empirical discoveries. To address this gap, the present study introduces the Cognitive Entropy Shift Model (CESM), a structured probabilistic framework designed to explore how cognitive engagement may lead to measurable deviations in systems typically governed by chance. CESM is grounded in the idea that consciousness can function as an informational constraint, capable of subtly modulating entropy and influencing probabilistic outcomes in ways that are statistically observable. In this context, "informational constraint" refers to the possibility that structured cognitive activity may bias the probabilities governing physical output distributions, without implying any non-physical or extraphysical mechanism.

The model builds on principles of probability updating that align with Bayesian inference, where outcome likelihoods are influenced by shifts in cognitive states. Similar Bayesian frameworks have previously been used to model mind–matter interactions (May et al., 1995) and CESM extends these approaches by formalizing how internal cognitive dynamics may introduce subtle biases into external stochastic processes. It thus offers a principled framework for reinterpreting anomalous findings and provides a theoretical and statistical basis for investigating consciousness-related influences using tools from probability theory and information science.

This paper makes several key contributions. First, it presents a mathematically grounded framework for modeling potential consciousness-related influences on probabilistic systems. Second, it evaluates this framework through a two-year continuous experiment conducted under stable conditions, designed to test claims that emotionally intense periods can influence output from truly stochastic systems. Third, the model is applied retrospectively to prior research, providing a coherent interpretive lens for earlier findings and generating clearer, testable predictions for future investigations.

The remainder of the paper is organized as follows. The next section outlines the theoretical underpinnings of the model, explaining how information theory and probabilistic reasoning can be used to frame the relationship between consciousness and stochastic processes. The following section develops the mathematical structure, incorporating variables related to cognition. This is followed by a section that presents empirical tests of the model based on the new two-year dataset. A subsequent section applies the framework to prior studies and the final section concludes with a discussion.

THEORETICAL FRAMEWORK

This section outlines the theory behind how consciousness might influence systems that normally behave randomly. A natural starting point for this analysis is the concept of entropy, which quantifies the degree of uncertainty or disorder in a system.

In the context of information theory, entropy reaches its maximum when all outcomes are equally probable and no prior information improves predictive accuracy. For a discrete random variable X, entropy is defined as:

$$(X) = -\sum_{i=1}^{n} P(x_i)\ log\ P(x_i), \tag{1}$$

Where $P(x_i)$ denotes the probability of each possible outcome x_i. Under ideal conditions, such as in systems governed by purely stochastic dynamics, entropy is maximized, and outcomes are uniformly distributed. This provides a principled baseline against which any systematic deviations can be detected and evaluated.

Previous empirical work has suggested that certain anomalous patterns may emerge in such systems under specific cognitive or emotional conditions. Although the reported effects are often small, some studies have observed statistically significant deviations from randomness during periods of heightened mental engagement or shared emotional focus (Jahn & Dunne, 1987; Nelson et al., 2002; Radin & Nelson, 2003). These findings have been interpreted as potential indicators of a link between consciousness and shifts in entropy. However, the absence of a widely accepted explanatory framework has left the interpretation of such results open to debate. While some researchers attribute the findings to unrecognized environmental factors or selection biases, others turn to alternative models such as Decision Augmentation Theory (DAT) (May et al., 1995). In short, DAT proposes that individuals may unconsciously time their actions to coincide with favorable outcomes, not through a direct causal influence on the RNG, but through a precognitive process in which the mind passively perceives future RNG states.

To move beyond post hoc interpretations, a formal modeling framework is required that is capable of capturing how cognitive variables might shape probabilistic systems in ways that are both theoretically coherent and empirically testable. Within this context, it is hypothesized that consciousness-related factors may act as informational constraints, effectively injecting structure into otherwise high-entropy systems. This leads naturally to a Bayesian formulation, in which shifts in cognitive states are treated as informational updates to a system's outcome probabilities. The proposed framework adopts this probabilistic perspective by introducing a model for updating prior distributions in response to the presence of cognitive" observations", deliberate or otherwise.

Let C denote a consciousness-related factor, and let the posterior probability of observing outcome x_i in the presence of C be given by Bayes' theorem:

$$P(x_i|C) = \frac{P(C|x_i) \cdot P(x_i)}{P(C)}. \tag{2}$$

Here, $P(x_i)$ represents the prior probability of the outcome under maximum entropy, and $P(x_i|C)$ expresses the

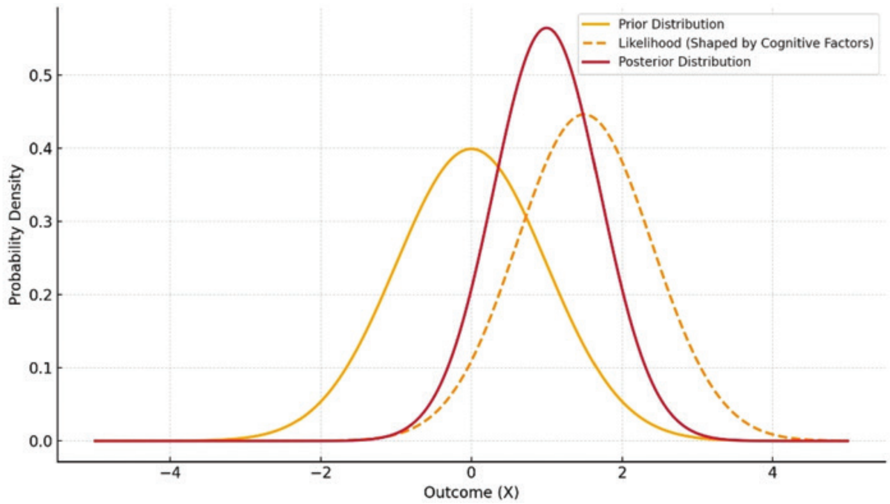

Figure 1. Illustrative Example of the Bayesian Updating Procedure.

likelihood of the cognitive influence (observation) given that outcome. Comparing the prior and posterior distributions allows for the detection of systematic deviations that may be attributable to consciousness-related influences. In this way, the model provides an information theoretical and statistical framework for testing whether internal cognitive states correlate with observable shifts in external probabilistic outcomes.

Figure 1 illustrates this process of Bayesian updating and shows how the prior distribution is updated to form the posterior distribution once the impact from cognitive influences (expressed as the likelihood) is incorporated.

Additionally, since entropy is calculated from probability distributions, it is possible to quantify the change in entropy that results from the influence of a consciousness-related factor *C* as follows:

$$\Delta H(X) = -\sum_{i=1}^{n} P(x_i|C)\ log\ P(x_i|C) + \sum_{i=1}^{n} P(x_i)\ log\ P(x_i). \quad (3)$$

Here, ΔH denotes the difference between the system's prior uncertainty (under maximum entropy) and its posterior uncertainty after accounting for observed cognitive effects. A non-zero value of ΔH could suggest that the probability distribution has been systematically altered, which could reflect that" information" has been structured by the influence of *C*. If statistical analysis confirms that $\Delta H \neq 0$ under controlled conditions, this would provide empirical support for the hypothesis that cognitive states can influence entropy within purely stochastic systems.

The preceding formalism outlines how consciousness-related factors might modulate probabilistic outcomes through entropy reduction and Bayesian updating. While the model remains grounded in measurable statistical quantities, it also resonates with a range of conceptual frameworks that attempt to describe consciousness in informational terms.

At its core, the model adopts Shannon's statistical definition of information, treating it as quantifiable and devoid of semantic content. However, several deeper interpretations of information have emerged in the philosophy of physics and consciousness studies. Among these, David Bohm introduced the notion of active information, which he described as a non-local, formative influence guiding physical systems from within. Bohm's concept of the implicate order serves as an ontological foundation from which the observable world unfolds (Bohm & Hiley, 1993).[1]

A parallel arises with interpretations of the observer effect in quantum mechanics, where measurement collapses a superposed system into a definite outcome (Jacobs, 2014). While conventional interpretations view this collapse as the result of a physical interaction, alternative perspectives propose that consciousness itself may participate in this process (von Neumann, 1932/1955; Wigner, 1961). Recent empirical work lends tentative support to this view and Radin (2025) reports statistically significant deviations in a quantum interference experiment when participants directed focused attention at the system, consistent with the von Neumann–Wigner hypothesis. Extending this logic, Williams (2024) suggests that empirical anomalies observed in consciousness-related studies might reflect unresolved informational dynamics within quantum theory, hinting at structures beyond conventional physical models.

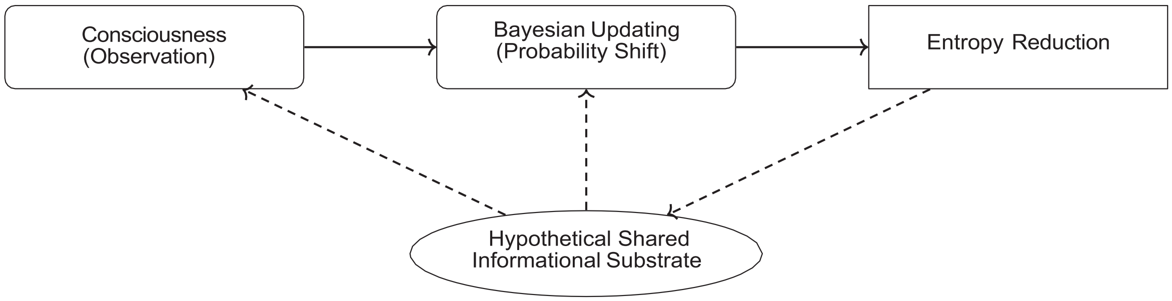

Figure 2. Conceptual Diagram of the Model and Concepts Discussed in this Section.

Further theoretical developments also challenge the sufficiency of classical determinism in accounting for the relationship between consciousness and apparent randomness. Faggin (2023), for example, argues that consciousness, creativity, and free will are incompatible with deterministic systems and instead emerge from non-algorithmic, quantum processes such as entanglement and non-locality.[2] Complementing this perspective, Bostick (2024) proposes that apparent randomness may result from partial or incomplete resonance detection. In his view, both entropy and cognition emerge from structured resonance within a coherent informational field. Consciousness, according to this model, arises as a phase-locked coherence pattern that can influence probabilistic outcomes by aligning with the underlying informational substrate.

These perspectives offer conceptual support for the presented model without requiring a commitment to any specific ontology. Rather than positing direct causation, the proposed framework adopts an information-theoretic and statistical lens to examine how and when entropy shifts may occur in conjunction with cognitive states. It remains agnostic about the ultimate origin of such effects yet allows for the possibility that they reflect interactions with a deeper informational structure not fully captured by existing physical theories. This conceptual logic is illustrated in Figure 2.

QUANTIFYING THE INFLUENCE

As outlined in the previous sections, several studies have reported statistically significant shifts in entropy ($\Delta H \neq 0$) that appear to be associated with variations in cognitive states (Jahn & Dunne, 1987; Jahn et al., 1997; Nelson, 2024). While these findings are intriguing, there is still no formal model that clearly shows how such influences might affect systems governed by chance. To move the work forward, the next section presents a flexible and general approach for measuring possible consciousness-related effects by looking at how entropy shifts over time in normalized data.

To better understand how consciousness might influence systems governed by chance, it helps to distinguish between two qualitatively different modes of cognitive engagement: active and passive influence. Active influence involves deliberate, goal-directed mental effort, consistent with established models of volitional control and intention-based behavior (Gollwitzer, 1999; Fishbein & Ajzen, 2010; Sheeran, 2002). Passive influence, by contrast, refers to spontaneous, emotionally driven engagement that occurs without conscious intent. It is best described as a state of emotional attentional presence i.e., a heightened, non-volitional form of awareness shaped more by emotional intensity than by deliberate thought (Posner & Petersen, 1990).

In the proposed framework, these two forms of cognitive influence are formalized as the variables intention (I) and attention (A), respectively. Whereas I reflects deliberate attempts to influence outcomes, A captures more diffuse and spontaneous attentional states that emerge in emotionally engaged contexts. This distinction is supported by a range of empirical findings. Experimental research conducted at the Princeton Engineering Anomalies Research (PEAR) laboratory demonstrated that focused mental intention could produce small but statistically significant deviations in the behavior of random systems (Jahn & Dunne, 1987, 2005). In contrast, studies from the Global Consciousness Project (GCP) revealed that subtle reductions in entropy often occur during large-scale emotionally charged events such as global tragedies or mass celebrations, without deliberate intention to influence the system (Nelson, 2002, 2020, 2021, 2024).

Additional evidence suggests that emotional reactivity may be a particularly important factor, especially in the context of widespread shared experiences. Studies of group consciousness effects have found measurable entropy shifts during collective emotional engagement (Nelson et al., 1996;

Nelson, 2024). Other exploratory analyses have expanded on these findings by showing correlations between deviations in GCP data and other real-world indicators sensitive to emotionally charged events such as financial market fluctuations (Holmberg, 2020, 2021, 2024) and internet search activity (Holmberg, 2023). Together, these lines of evidence reinforce the hypothesis that both intention and attention, though distinct in their cognitive profiles, may influence high-entropy systems through mechanisms that remain poorly understood, but which are nonetheless amenable to formal modeling and empirical investigation.

While the precise mechanism underlying such effects is not yet known, it is possible to outline a statistical framework capable of describing how consciousness might introduce structure into processes that would otherwise behave randomly. Such a framework enables the formulation of testable hypotheses in advance of data collection and provides a principled basis for analyzing how specific cognitive states may modulate entropy within stochastic systems.

At the core of this model are the two variables discussed above: intention (*I*), representing goal-directed mental effort, and attention (*A*), representing emotionally modulated, non-volitional engagement. Both are heuristically scaled from 0 (no influence) to 10 (maximum influence), allowing for a continuous representation of cognitive intensity. To capture possible synergy between the two, the model also incorporates a multiplicative interaction term ($I{\cdot}A$), based on the premise that high levels of both intention and attention may jointly amplify the overall effect.

Another important consideration is spatial distance i.e., the physical separation between the participant and the system in question. The empirical literature on this topic is mixed. Some studies suggest that intention-related effects are largely independent of distance (e.g., Jahn et al., 1991), while others find evidence that can be interpreted as support in favor of that distance could be important, particularly in emotionally charged contexts where attention dominates (see e.g., Jahn et al., 1997; Leskowitz, 2011).

To accommodate both perspectives, the proposed model integrates distance-dependent and distance-independent components into a single unified expression. The general form that captures this logic is given by:

$$E_{RNG,m} = \frac{\left[\sum_{i=1}^{n} \sum_{C\in\{I,A,I\cdot A\}} \left(\beta_C \cdot \frac{C_{i,m}}{e^{\alpha\cdot d_{i,m}}}\right)\right] \cdot \frac{\Phi^{-1}(q)}{\left(1+\frac{1}{n}\right)}}{1+n} + \varepsilon_m. \qquad (4)$$

In this equation:

- $E_{RNG,m}$ denotes the predicted shift in output from RNG_m, due to consciousness-related effects.
- $C_{i,m}$ stands for the value of each consciousness related variable (intention, attention, and their interaction) experienced by participant *i*. Each variable is weighted by a corresponding coefficient β_C.
- $d_{i,m}$ denotes the spatial distance between participant *i* and RNG_m, and the exponential term ($e^{\alpha\cdot d_{i,m}}$) describes how influence decays with distance, moderated by the parameter α.
- Φ denotes the cumulative distribution function (CDF) of the standard normal distribution, mapping the standardized entropy deviation into a probabilistic significance estimate.

To improve sensitivity to rare but meaningful deviations, the model incorporates a high quantile threshold q = 0.999999999, which corresponds to approximately six standard deviations under a standard normal distribution (Φ–1(q) ≈ 6). This scaling defines an upper-bound window for identifying statistically anomalous cases under the null model, thus making rare events more visible. A normalization term involving the number of participants (n) prevents the effect from growing uncontrollably as the sample size increases and a final residual term, $\varepsilon_m \sim N(0,1)$, captures baseline random variation in RNG output. The RNG output thus simplifies to a standard normal distribution in the absence of consciousness-related influences, as expected under maximum entropy conditions.

The expected value of the output $E_{RNG,m}$ can thus be interpreted as a standardized deviation from randomness, expressed in units equivalent to a Z-score. Higher absolute values of $E_{RNG,m}$ indicate increasingly improbable outcomes under the null model, thereby allowing direct comparison between model predictions and empirical results from RNG-based studies.

A central assumption of Equation (4) is that each participant contributes a small, additive influence on the RNG output. As a result, the total effect scales linearly with the number of participants (n), while the denominator serves to normalize the output to ensure it remains bounded even as n increases. This additive component is best interpreted as the system's raw bias i.e., the total deviation from expected entropy introduced by the cognitive variables.

By incorporating both additive influence and statistical normalization, the framework formalized by Equation (4) provides a robust and extensible basis for quantifying how cognitive and emotional factors may affect the output from RNGs. The model however also remains open to further refinement and allows for future exploration and integration of additional consciousness-related parameters (e.g., emotional coherence, expectation, group synchrony, and so forth).

Importantly, the model is not tied to any specific statistical test for detecting entropy shifts. Instead, it expresses deviations in standardized units relative to an expected mean, making it possible to reinterpret earlier results through the lens of the proposed framework. Whether previous findings were based on Gaussian Z-tests, t-tests, or other well-established methods is not critical. What matters is that the results were obtained using sound statistical procedures and reported in a way that allows deviations from a hypothesized mean to be meaningfully assessed. This flexibility makes the model especially useful for the retrospective analysis of historical data.

In practical applications where individual-level data are unavailable, a simplified version of the model can be used. If all participants are assumed to contribute equally i.e., with the same levels of attention and intention, and at the same distance from the device producing the stochastic data, then the summation collapses into a single scalar multiple of n, the number of individuals. In addition, if one is only interested in the magnitude of the effect rather than its direction, the expression can be further simplified by taking the absolute value. The simplified equation for a representative RNG is given by:

$$|E_{RNG}| \approx \frac{\left(\beta_A \cdot \frac{A}{e^{\alpha \cdot d}} + \beta_I \cdot I + \beta_{I \cdot A} \cdot \frac{I \cdot A}{e^{\alpha d}}\right) \cdot n \cdot \frac{\Phi^{-1}(q)}{\left(1+\frac{1}{n}\right)}}{1+n} + |\varepsilon|. \quad (5)$$

The simplified version of the model is especially useful in cases where detailed participant-level data on attention or intention are not available, as is often the case in many historical studies. As such, the framework can be applied retroactively to previously published results, offering a consistent way to reinterpret past findings through a shared lens.

This approach, which treats consciousness-related variables as informational influences that may locally reduce entropy, will be referred to as the Cognitive Entropy Shift Model (CESM). CESM provides a structured and testable framework for exploring how attention and intention could interact with stochastic physical systems. It also serves as the theoretical foundation for the empirical analyses that follow.

Figure 3 provides a schematic overview of the model's logic. Input variables, namely intention, attention, their interaction, and spatial distance, are all fed into scaling and decay functions and combined using parameter weights (β_c) and the spatial decay ($e^{\alpha d}$). These modified inputs are then aggregated across n participants, passed through a high quantile filter Φ–1(q), and normalized to yield the final standardized output $E_{RNG,m}$, representing the predicted deviation from baseline entropy.

However, to meaningfully apply either the full model (Equation (4)) or its simplified form (Equation (5)), plausible values must be assigned to its key parameters. These include the strength of the consciousness-related effect on calculated output (β_c) and a distance decay parameter (α) that governs how quickly the influence weakens with spatial separation. The true values of these parameters are not yet known and will need to be determined through future empirical work designed with that goal in mind. For now, however, initial working estimates, based on the structure of the model and guided by insights from earlier experimental findings are presented in Appendix A.

TESTING THE MODEL IN A NEW EXPERIMENT

With the theoretical framework in place, the next step is to apply the model to empirical data. The following section

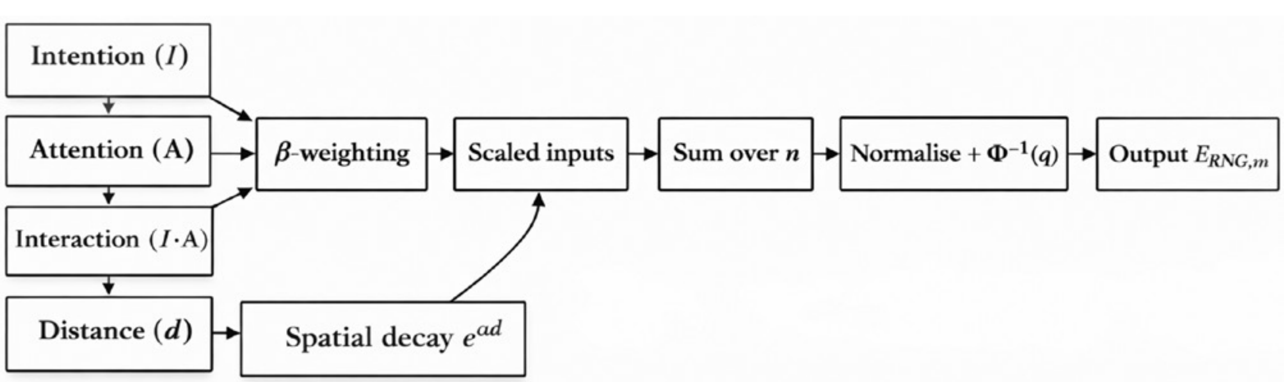

Figure 3. Visual Representation of the Consciousness–RNG Influence Model.

describes a two-year experiment conducted in a stable domestic environment, using a physical random number generator (RNG) that continuously recorded data. The setting was a private apartment in Stockholm, and the individuals whose psychological states were hypothesized to influence the RNG output included two young children and one adult, all residing in the household.

The analysis focuses on periods that were anticipated to involve heightened emotional states and attentional engagement, based on prior knowledge of daily routines. The central hypothesis is that emotionally intense cognitive states among the participants may produce subtle, structured deviations in the statistical properties of the RNG output, in line with the predictions of the Cognitive Entropy Shift Model (CESM).

This section thus serves two main purposes: (i) to provide an independent test of earlier claims that consciousness may influence physical RNGs, and (ii) to assess the model's capacity to estimate levels of attentional involvement based on observed deviations in entropy. Additional methodological details are provided in Appendix D.

Experiment Setup and Test Statistic

The two-year experiment ran from March 2022 to March 2024 using a TrueRNG v3 device, which generates random numbers via the avalanche effect at a semiconductor junction. The device was placed approximately 10 meters from an area that was a priori identified as likely to involve predictable periods of elevated emotional intensity and attentional presence, conditions which according to CESM, may reduce entropy in the device output.[3] The TrueRNG v3 device was connected to a Raspberry Pi 400, which recorded one random value per second throughout the study. To maintain high-quality output, the device's internal firmware applied XOR mixing to the raw signal before each value was logged.[4]

This built-in whitening process combines approximately 20 raw bits to generate each final output bit, reducing short-term correlations while preserving the overall entropy of the signal.[5] To further safeguard data quality, the device's temperature and power supply were periodically monitored throughout the study to reduce the likelihood of hardware-related anomalies or placement-induced effects.[6]

By the end of the experiment on March 19, 2024, the device had generated a total of 47,731,465 values. Of these, 8,789,615 were excluded, as the three participants were known to be far away from the local area during those times. This left 38,941,850 valid observations that was timestamped to allow alignment with known routines and periods of emotional engagement.

Before the experiment began, the morning window between 07:30 and 08:15 was identified in advance as a predictably "stressful" period. This time frame was chosen based on the hypothesis that heightened emotional intensity and focus (common during school preparations) could amplify attention and potentially lead to measurable deviations in the RNG output.[7]

To better capture the dynamics predicted by CESM, the 45-minute morning window (07:30–08:15) was first divided into three non-overlapping 15-minute segments: 07:30–07:45, 07:45–08:00, and 08:00–08:15. This allowed for a more detailed look at how fluctuations in emotional intensity and attentional presence may have influenced entropy during different parts of the morning routine.

However, given the assumption that emotional engagement would peak as participants exited the premises, a targeted window from 07:50 to 08:10 was also selected for closer examination. This interval, representing the most behaviorally intense portion of the morning routine, was contrasted with a control period from 08:10 to 08:25, during which usually no participant remained near the device such that no localized stress was expected. As can be understood from the above, the working hypothesis was that 07:50–08:10 would exhibit the strongest deviation from baseline entropy, followed by 08:00–08:15, as both intervals encompassed the critical departure period marked by elevated emotional intensity and attentional engagement. In contrast, the 08:10–08:25 window served as both a behavioral and spatial control. However, because these segments partially overlapped with the previously defined time windows, the resulting statistical comparisons were not entirely independent. To account for the increased risk of false positives due to multiple testing, a conservative Bonferroni correction was applied.

To put the morning results in context, the full 45-minute period from 07:30 to 08:15 was also compared to several other 45-minute intervals spread throughout the day. These served as matched control periods, helping to assess whether any observed effects were unique to the morning routine or simply part of broader fluctuations in entropy.

After defining these intervals, the output from the device was normalized using the different subsets empirical mean and variance, using rolling data over one month. Given that the raw data automatically had undergone XOR processing, a method capable of masking subtle deviations, it was essential to employ a statistical approach sensitive to more underlying structural changes.[8] As such, the Welch's t test was selected due to its robustness against unequal variances and its ability to detect shifts in both mean and variance.

Formally, Welch's t-statistic is given by:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}, \tag{6}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the full dataset and the selected subset, σ_1^2 and σ_2^2 their variances and n_1 and n_2 the respective sample sizes.

RESULTS

Table 1 presents descriptive statistics, and the results of the Welch t-test based on the normalized RNG data. As predicted by the CESM, the RNG output exhibited deviations during intervals of heightened attention. The mean values for each tested interval exceeded those of the full dataset, resulting in negative differences between the subsets and the overall sample. Statistically significant deviations from randomness were observed in the intervals 07:55–08:10 ($p \approx 1.38 \times 10^{-5} < 0.001$) and 08:00–08:15 ($p \approx 3.91 \times 10^{-4} < 0.001$) Therefore, the broader 45-minute window (07:30–08:15), which encompasses these segments, also yielded a highly significant deviation ($p \approx 9.86 \times 10^{-5} < 0.001$) In contrast, the control period (08:10–08:25) showed no significant deviation from chance ($p \approx 0.585$) suggesting that the observed morning anomalies are unlikely to be due to random variation alone.

The small yet statistically significant mean shifts observed during peak intervals (e.g., a deviation of −0.00676 during 07:55–08:10) are notable as the RNG's internal firmware performed XOR whitening by combining approximately 20 raw bits into each final output bit to reduce short-term correlations. That the observed effects persist after whitening suggests that the underlying raw signal was consistently biased, with the post-whitening deviations implying a sustained bit stream skew of approximately 3–6% above chance, pointing towards a subtle but systematic departure from ideal randomness.[9]

It is conceivable that environmental factors such as temperature shifts, device instability, or time-of-day-related variables like increased movement or nearby electronic activity, could in principle have affected the RNG output. However, such effects would be expected to manifest more strongly during periods like 07:30–07:45, when movement and interaction levels were typically highest. The fact that the most pronounced deviations occurred instead during 07:55–08:10 and 08:00–08:15, while neighboring intervals like 07:30–07:45 and 08:10–08:25 remained unaffected, makes it less likely that the effects were due to mundane environmental noise. That said, future studies should incorporate more detailed environmental logging to better account for potential unnoticed influences. Still, the distinct temporal specificity and strong statistical significance of the results suggest that ordinary explanations are unlikely to fully account for the observed deviations.

In summation, the results from the experiment strongly suggest that $\Delta H \neq 0$ in Equation (3) during periods marked by heightened emotional intensity and increased attentional engagement. The observed shift in mean RNG output was modest as it ranged from approximately 0.5% to 0.7%, yet highly statistically significant ($p < 0.001$) Although these effects fall below the thresholds needed for real-time detection, they align closely with findings from earlier RNG studies and underscore the importance of large sample sizes when probing for such subtle deviations.

Despite these challenges, the present dataset provides strong grounds for confidence in the robustness of the observed effects. A 0.5% change in the normalized mean corresponds to only 0.005 standard-deviation units, yet power analysis shows that a two-sided Welch t-test at the 1% significance level with 95% power would require "only" about 7.1×10^5 observations to detect such a shift, which is well below the 3.9×10^7 data points analyzed in this study. Even subtler changes of 0.15% could be reliably detected with approximately 8.0×10^6 observations, a quantity easily achievable within a few months of continuous recording.[10] These figures not only affirm the statistical power of the current results but also provide clear and practical benchmarks for future preregistered studies designed to replicate and extend CESM-based predictions under controlled conditions.

Given CESM's structure and its formal link between entropy shifts and attentional states, a natural next step is to ask how much attentional engagement would be needed to account for the observed deviations. Since the participants were largely unaware of the RNG's presence, no direct cognitive measurements were collected during the studied periods.[11] However, CESM allows for a retrospective estimation. Specifically, the simplified version of the model, Equation (5), was designed to accommodate precisely this kind of constraint and is therefore applied

Table 1. Experiment Data: n = 38,941,850 ≈ 15.2 Months.

Subsample	*n*	$\Delta\bar{X}$	$\Delta\sigma$	t-stat	*p*	*Bonf·p*	*A*
07:30–08:15†	1,136,553	−0.00367	−0.00013	**−3.894**	< **0.001**	< **0.001**	7.70
07:30–07:45	411,242	−0.00174	−0.00247	−1.118	0.264	1.000	–
07:45–08:00	389,082	−0.00337	0.00017	**−2.110**	**0.035**	0.209 (4.16*)	
08:00–08:15	434,059	−0.00531	0.01884	**−3.546**	< **0.001**	< **0.001**	7.01
07:55–08:10	410,357	−0.00676	0.00031	**−4.347**	< **0.001**	< **0.001**	8.60
08:10–08:25	394,016	−0.00085	−0.00118	−0.536	0.592	1.000	–

Note. $\Delta\bar{X} = X_1 - X_2$; $\Delta\sigma = \sigma_1 - \sigma_2$ where "1" represent the full sample compared with the subsample "2". Bold values indicate significance at the 5% level using a two-sided Welch's t-test. Bonf. p = Bonferroni-corrected p-value. (*) Result not significant after Bonferroni correction.[17]

†The 07:30–08:15+ sample is slightly more restricted than the sum of the three adjacent 15-minute intervals, excluding 97 830 data points to reduce overlap and maintain clearer statistical separation between comparisons. By using a distinct sample for the full 45-minute period, the analysis preserves statistical robustness and ensures that p-values remain interpretable under Bonferroni correction without inflating the Type I error rate due to hidden overlap (cf. Wilcox (2010).

here to estimate the level of emotional engagement needed to elevate attention (*A*) to a degree consistent with the empirical results.

This analysis is limited to time windows that surpassed the 5% significance threshold, and the corresponding attention values are reported in the final column of Table 1. Given that *A* is bounded between 0 and 10, it can be understood from the results that attentional presence was substantially elevated during certain periods, reaching a value of 8.60 during the 07:55–08:10 interval.[12]

The control period from 08:10 to 08:25 was chosen because participants had typically left the premises by then. As anticipated, this interval showed no statistically significant deviation, lending further support to the idea that emotional intensity and heightened attention can influence the RNG output. Another aspect that changed after 08:10 was physical proximity and to examine this relationship more closely, the observed results were re-evaluated using Equation (5), but this time after assuming increased spatial separation. Holding the previously estimated attention level constant, the analysis revealed that the observed effect disappears entirely when the distance is scaled up from approximately 10 meters (about 33 feet) to 1 000 meters (roughly 0.6 miles), representing a hundredfold increase, suggesting that proximity may be a critical factor in modulating the effect. This pattern strongly calls for more research to be made on calibrating the spatial decay parameter (α) more thoroughly.

To investigate whether similar deviations appear elsewhere in the dataset, the full two-year time series was divided into 32 non-overlapping 45-minute intervals distributed across the 24-hour cycle. The Welch's t-test was then applied to each window to detect any departures from randomness and as shown in Figure 4, only the 07:30–08:15 interval displayed a robust and statistically significant effect as it was the only 45-minute period that breached the conservative Bonferroni adjusted significance threshold.

Addressing Common Statistical Criticisms

Given the ongoing skepticism surrounding studies on consciousness-related influences in random systems, it is important to address key methodological concerns directly and transparently. These concerns are not new; they have been repeatedly emphasized in critical appraisals of psi-related research, particularly with regard to analytic flexibility, optional stopping, and the absence of preregistration (e.g., Wagenmakers et al., 2011). The present study was designed with these issues in mind. The most frequently raised methodological points, including optional stopping, selective reporting, and multiple comparisons, are each considered in turn below.

Optional stopping was not a factor in this study as the data collection period (March 2022 to March 2024) was determined in advance and as no decisions to terminate or extend the experiment were made based on interim results. Although notable effects began to appear within the first year, the data collection proceeded exactly as planned.[13] Concerns about selective reporting were also addressed by including all predefined time windows in the analysis, regardless of whether they yielded significant results. The outcomes are thus presented transparently in Table 1 and visualized in Figure 4, ensuring that no intervals were omitted or selectively emphasized. Finally, the risk of inflated false positives due to multiple comparisons

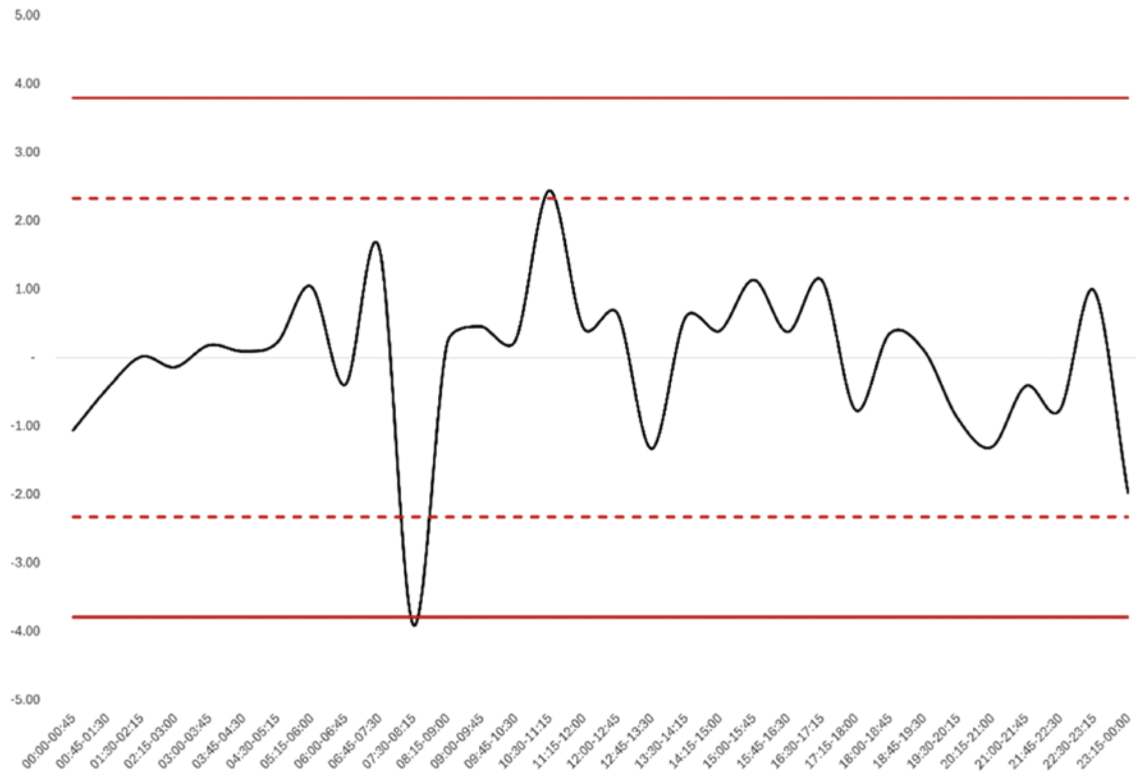

Figure 4. The Welch t-statistic over a 24-hour Period.
Note: The dashed red line is the 1% significance threshold while the solid red line marks the conservative Bonferroni 1% significance threshold, corrected for 32 comparisons under a 1% family-wise error rate.

has been handled using the conservative Bonferroni correction. This adjustment was applied to control for the overlapping time segments, where the chance of spurious significance would otherwise increase.

Taken together, these safeguards were built into the study design from the outset to meet standard statistical expectations. They help ensure that the findings are interpreted on a fair and robust foundation, particularly in a field where critical scrutiny is both expected and warranted. Although direct numerical comparisons are difficult due to differing effect-size metrics, the subtle yet statistically significant deviations observed here (approximately 0.5–0.7%) resonate with the general pattern of small but consistent anomalous effects reported in related meta-analyses such as Bem et al. (2015).

APPLYING THE MODEL TO HISTORICAL RESULTS

Having demonstrated the practical usefulness of the model in Equation (5) through a long-term real-world experiment, the next step is to test its broader relevance by applying it to previously published studies. This serves as a critical validation: if the model can reliably interpret or reinterpret past results, it may offer a general framework for analyzing both historical and future RNG-related findings. This section therefore examines how earlier empirical results align with the structure of the proposed framework. Since the simplified version of the model was designed specifically for retrospective use, it allows for estimation of average levels of cognitive engagement. More precisely, the degree of goal-directed intentional mental effort (I) and emotionally modulated attentional presence (A) are calculated using the studies reported normalized deviations in RNG output.

When applying the model to earlier studies, it is assumed that experiments involving participants who deliberately attempted to influence RNGs include both goal-directed intention ($I > 0$) also engage in some heightened degree of attention (A) For simplicity and tractability, the model assumes $I = A$ in such cases, meaning that participants are directing their attention toward a task in a deliberate and purposeful way. This assumption reflects the idea that intentional mental effort typically requires a corresponding level of focused attention, a claim that should be studied and challenged in future research. In contrast, studies where participants were unaware of the device or made no conscious effort to affect it, intention is set to zero ($I = 0$) such that only attention needs to be estimated.[14]

Dunne et al. (1988)

This study investigated if participants could influence the distribution of balls in a physical cascade machine, specifically a Galton board (Dunne et al., 1988). Each participant directed their intention toward shifting the results to the left or right, and the results showed statistically significant deviations from the random expectations.

In the experiment, one person sat about 2–3 meters away from the device and tried to mentally influence how the balls would land. The machine automatically dropped a set number of balls each time, which bounced through a series of pins before landing in the bins at the bottom. Some trials involved focusing intention to the left or right, while others were control trials with no intention, used to compare against a baseline.

In total, 87 series were run by 25 different participants, with just one person trying to influence the outcome at a time. When all the results were combined, the overall z-score came out to 3.89, revealing a strong effect with a significance level of $p < 10^{-4}$. Using the model from Equation (5), and assuming that intention and attention were equally strong during the trials, the estimated values were $I = A = 6.70$.

Nelson (2024)

The Nelson (2024) presents a FieldREG study conducted in Egypt to explore whether group consciousness might influence the output of a RNG during visits to culturally and historically significant sites.

The experiment focused on sacred locations such as the inner chambers of pyramids and ancient temple sanctuaries, where participants engaged in activities aimed at enhancing group coherence. The study involved approximately 19 participants and used a portable RNG, positioned within proximity of the group. The device recorded continuously throughout the sessions, with precise timestamps enabling alignment between specific activities and fluctuations in RNG output.[15]

For the analysis, the data were sorted into five well-defined categories and for this retrospective analysis, the Z-scores in Table 3 of the Nelson (2024) study are used as they show how strongly the REG output during each event category deviated from what you'd expect by pure chance (after adjusting for randomness using resampling). In terms of CESM, these adjusted Z-scores tell us how much entropy seems to have been reduced during each type of group activity, helping us estimate the average attention level (A) required to produce such effects.

- *Category A – Sacred Sites with Group Ritual Activity*: This category included 26 visits to temples and pyramid chambers, where participants engaged in coordinated rituals such as chanting and meditation. These were the most focused and emotionally intense activities, and the data showed a clear deviation from chance ($Z = 3.45$). Using CESM, attention is estimated to have been $A = 6.85$.
- *Category B – Sacred Sites Without Formal Group Activity:* This included 20 site visits where no coordinated rituals were performed, even though the group was present in resonant locations. Despite the absence of structured group activities, the data revealed a significant deviation ($Z = 3.02$). Using CESM, emotionally modulated attention is estimated to have been $A = 6.01$.
- *Category C – Group Activity at Non-Sacred Sites*: These 15 visits involved group engagement in settings not considered spiritually significant (e.g., hotels or restaurants). The results were consistent with chance ($Z = 0.45$).
- *Category D – Visits to Other Notable but Non-Sacred Locations:* This category captured 18 instances of visits to engaging but secular locations like museums or historical landmarks. A modest deviation from randomness was observed ($Z = 2.16$), yielding an estimated attention level of $A = 4.31$.
- *Category E – Personal or Solo Experimenter Events:* This final category involved 10 solo experiences by the experimenter. The result ($Z = 0.99$) was statistically insignificant.

Leskowitz (2011)

In this study, it was investigated whether collective attention from a large audience could influence the output of a random number generator (RNG). The study was conducted during a Major League Baseball game between the Boston Red Sox and the Toronto Blue Jays on July 13, 2007 (Leskowitz, 2011).

Approximately 36,000 spectators attended the game, with their collective attention and emotional engagement varying significantly throughout the match. A single RNG continuously produced data from a fixed location within the stadium.

Although Leskowitz did not report precise distances, reasonable assumptions can be made based on typical stadium layouts. Actively engaged spectators were likely positioned at distances ranging from 30 to 120 meters, with a weighted average estimated at approximately 70–80 meters.

RNG outputs were recorded and analyzed in one-minute intervals, allowing for detailed temporal assessment of deviations from expected randomness. Out of 117 analyzed intervals, 15 showed deviations equal to or greater than ±2 standard deviations from the mean. This yielded an overall z-score of 4.19, representing a highly significant deviation from chance expectation.

Fluctuations in the RNG output were also found to coincide with moments that were assessed as involving heightened audience attention. Applying the simplified model from Equation (5), and assuming no deliberate intention ($I = 0$), the level of attentional engagement during these high-intensity intervals is estimated to be $A = 8.76$.

CONCLUDING REMARKS

This paper introduced the Cognitive Entropy Shift Model (CESM), a formal and testable framework for exploring whether consciousness, specifically cognitive states such as deliberate intention or emotionally modulated attention, can subtly influence the behavior of systems governed by chance.

Grounded in Bayesian inference and information theory, and building on earlier Bayesian approaches to mind–matter modeling, CESM differs by treating consciousness not merely as a modulator of outcome probabilities, but as an informational constraint capable of reshaping entropy within stochastic systems. To test this proposal, data from a high-entropy random number generator (RNG) was collected over two years, and CESM was applied to predict when measurable deviations from randomness would occur. The analysis revealed statistically significant deviations ($t = -4.347$, $p < 0.001$) during periods characterized by heightened emotional attention, consistent with the model's predictions of entropy reduction under cognitive engagement. While the results are not conclusive, they reveal robust and highly significant correlations that not only align with prior findings in the field but also suggest that entropy-based cognitive constraints may play a meaningful role in shaping probabilistic physical systems.

Although RNGs served as the controlled source of probabilistic data in this study, CESM is not conceptually limited to them. Its purpose is not to explain the mechanism underlying deviations from randomness, but to detect and model structural departures from statistical expectation, regardless of the data source. The framework applies broadly to stochastic systems found in natural, biological, digital, or engineered settings. This generality enables both prospective testing in new environments and retrospective analysis of anomalous datasets within a unified statistical framework.

The strength of the current findings lies not only in the statistical robustness of the signal, detected across tens of millions of data points, but also in CESM's capacity to differentiate between distinct cognitive influences. The results indicate that attention, particularly when emotionally engaged and spatially focused, produces measurable entropy shifts that diminish with increasing distance. This may involve not only physical separation but also psychological detachment from the target system, a possibility that future research could explore. In contrast, broader, potentially nonlocal effects associated with goal-directed intention are not directly demonstrated here but are consistent with patterns reported in earlier research. This observed asymmetry aligns with emerging perspectives of consciousness as both embodied and extended, with the potential to interact meaningfully with nonlocal environments (von Lucadou et al., 2007).

Philosophically, CESM builds on and synthesizes insights from multiple fields. It aligns conceptually with Quantum Bayesianism (QBism) (Fuchs, 2014), which treats probabilities as belief updates conditioned on observation, and with Stapp's view that mental states might modulate quantum events via informational channels (Stapp, 2017). The model also resonates with Bohm's concept of active information (Bohm & Hiley, 1993) and Laszlo's hypothesis of a universal coherence field (Laszlo, 2004), where meaning and form guide physical systems.

From a thermodynamic perspective, CESM draws a conceptual analogy to Maxwell's Demon (Maxwell, 1871), a thought experiment in which an intelligent agent appears to violate the second law of thermodynamics by selectively allowing faster or slower particles to pass through a gate. This selective sorting seems to reduce entropy without performing any physical work. The paradox was later resolved by recognizing that Maxwell's demon must acquire, store, and eventually erase information in order to carry out its task. These processes require energy and therefore uphold the second law. This resolution led to Landauer's principle (Landauer, 1961), which formalizes the connection between information and thermodynamics by showing that erasing even a single bit of information necessarily increases the entropy of the environment. In this light, CESM does not suggest that cognitive states violate physical laws. Rather, it proposes that they may act as informational constraints that influence probabilistic systems. Much like the demon, consciousness could reshape entropy distributions through information-based processes instead of direct energetic intervention.

Looking ahead, CESM provides a flexible platform for systematic research across a wide range of domains. To strengthen its reliability and replicability, future studies should emphasize preregistration, the use of validated psychological measures, and standardized data collection protocols. Beyond refining CESM's core parameters, such as the rate of spatial or psychological decay and the strength of influence exerted by different cognitive states, researchers can also explore its application to other complex and probabilistic systems, including biological and economic systems. Investigating nonlinear interactions, contextual factors, and the role of group or collective mental states could help shape a more general and robust second-generation version of the model. A related extension, developed in Appendix B, examines how the framework may be adapted to analyze effects on large-scale coherence measures, such as those explored by the Global Consciousness Project, thereby allowing CESM to be formulated at the level of collective rather than strictly individual cognitive dynamics. Moreover, future work may examine whether other forms of conscious entities, human or non-human, can similarly nudge randomness in measurable ways.

In closing, CESM re-frames the question of consciousness and physical systems not in terms of energetic causation, but as a matter of informational influence. It suggests that consciousness may exert a subtle but systematic organizing role in probabilistic environments, and that it can subtly nudge randomness. This perspective invites a reconsideration of the mind's role in nature as it suggests that it is a lawful contributor to how reality unfolds. While the mechanisms remain to be fully uncovered, CESM offers a philosophically neutral, empirically grounded framework for advancing both theoretical insight and scientific inquiry into the interplay between consciousness, information, and randomness.

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DATA AVAILABILITY

The dataset is available from the author upon request.

END NOTES

1 While the proposed framework remains ontologically neutral and focused on measurable entropy shifts, it is conceptually compatible with the idea that reductions in entropy may reflect interactions with a deeper, potentially conscious informational substrate.

2 This view is developed within Faggin's framework of Quantum Information-based Panpsychism (QIP).

3 The device was positioned under a TV bench located between two children's rooms, about 10 meters from the main entrance. To minimize electromagnetic noise, the TV remained unused during morning hours throughout the study.

4 Further details about the experimental setup, participants, spatial layout, data filtering, and environmental controls can be found in Appendix D.

5 A detailed discussion on XOR mixing and what it does with the data can be found in Appendix C.

6 Data was retrieved at 256 bytes per second using a batch script provided by Dr. Thiago Jung.

7 It was hypothesized that stress and emotional engagement might increase attentional presence, which CESM predicts could subtly reduce entropy in the system.

8 Although XOR mixing redistributes short-term bit-level patterns, it does not fundamentally remove persistent statistical anomalies. A more detailed explanation, including its relevance for detecting cognition-linked effects in entropy, is provided in Appendix C.

9 This estimate is based on binomial modelling of the XOR whitening process, where each output bit reflects the parity of ~20 biased input bits.

10 Required sample sizes were estimated using the standard normal approximation for power analysis.

11 Only one participant was aware of the device, but even this participant disregarded its presence due to the nature of the study period and the extended duration over which the data were collected.

12 Intention (I) is assumed to be zero, in line with the nature of the situational "friction" that likely elevated attention without deliberate goal direction. Additionally, n is interpreted as the product of the number of participants and the number of observations within each subsample.

13 The one-year preliminary results were presented on a recorded GCP2-team meeting in March 2023.

14 These modeling assumptions are introduced to allow parameter estimation from incomplete historical data and should be tested and refined in future controlled experiments.

15 While the study does not state the exact distance between participants and the device, the described setup implies proximity. For modelling purposes, this is approximated to $d = 10$ while assuming that $I = 0$.

16 Thes values are illustrative and not derived from data. There precise magnitude remains an empirical question to be resolved through future experimentation.

17 The table summarizes statistically significant mean shifts in the normalized RNG output, where the expected value under the null hypothesis is zero. The observed deviations, ranging from approximately 0.34% to 0.68%, reflect persistent shifts in the post-whitening output from the expected mean. When accounting for the 20-bit XOR whitening process used by the device, and assuming a moderate to high autocorrelation in the raw bitstream (e.g., $\rho \approx 0.80$), these shifts correspond to an underlying raw bitstream bias of approximately 3%–6% above chance. This suggests a subtle but measurable departure from ideal randomness that persists even after standard entropy-flattening procedures.

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APPENDIX A

PARAMETER SELECTION AND LIMIT BEHAVIOR

This appendix outlines the rationale and assumptions behind the parameter values used in the Cognitive Entropy Shift Model (CESM). The aim is to ensure internal consistency and provide plausible starting points for empirical testing. Two key aspects are addressed: the model's asymptotic behavior under idealized conditions, and the influence of spatial distance, based on prior experimental findings.

Limit Behavior and Scaling of Cognitive Parameters

To provide initial parameter estimates and ensure the model's robustness, it is instructive to examine its limit behavior under idealized conditions. Specifically, the parameters β_C can be constrained by analyzing a scenario in which participants exhibit maximum levels of attention (A = 10) and intention (I = 10), with no spatial distance (d = 0), and where the number of participants and observations approaches infinity ($n \to \infty$). By doing so, it is possible to establish theoretical upper bounds that can later assist in empirical calibration within more realistic experimental contexts.

To ensure well-defined asymptotic behavior, the model parameters must be selected such that the function converges precisely to $\Phi{-}1(q)$, where q = 0.999999999, as $n \to \infty$. Under the assumption that distance is zero (i.e., d = 0), the exponential decay term simplifies to $e^{\alpha \cdot d} = e^0 = 1$. Consequently, the consciousness-related terms in Equation (4) reduce to:

$$\beta_I \cdot I + \beta_A \cdot A + \beta_{I \cdot A} \cdot (A \cdot I).$$

Assuming maximum cognitive engagement, the sum of the weighted terms must satisfy: $\beta_I \cdot 10 + \beta_A \cdot 10 + \beta_{I \cdot A} \cdot 100 = 1$. This constraint ensures that consciousness-related influences scale appropriately, allowing the model to converge to the theoretical upper bound $\Phi{-}1(q)$ as $n \to \infty$.

Drawing on empirical considerations, it is observed that intention typically occurs in conjunction with attention, whereas attention can manifest independently in emotionally engaging scenarios without deliberate intention. Accordingly, it is reasonable to assume a hierarchical relationship among the parameters, such that $\beta_A > \beta_I$ Furthermore, since the interaction term $A \cdot I$ is numerically greater than either A or I alone, the corresponding parameter $\beta_{I \cdot A}$ is constrained to be smaller than both β_A and β_I to preserve proportionality. For mathematical simplicity and theoretical consistency, the interaction parameter is thus defined as $\beta_{I,\cdot A} = \beta_I^2$. This is a modeling assumption introduced for tractability and should be reined or validated in future empirical work.

Based on these constraints, a provisional value for the primary parameter is selected as β_A = 0.085 and the assumed parameter hierarchy implies that $\beta_I \approx 0.013239875$ and by definition: $\beta_{I \cdot A} = \beta_I^2 \approx 0.000175294$.[16] Under the earlier assumption of no spatial dependence (d = 0), the consciousness-related contribution after substituting the parameter values is given by: 0.085 × 10 + 0.013239875 × 10 + 0.000175294 × 10 × 10 ≈ 1.

The normalization factor in the model is also given by $6/(1 + 1/n)$, which clearly converges to 6 as $n \to \infty$, since $1/n \to 0$. Substituting these results into the simplified model yields:

$$|E_{RNG}| \approx 6 \cdot \frac{n}{1+n} + |\varepsilon|,$$

from which it follows that: $\lim_{n \to \infty} |E_{RNG}| = 6.$

Thus, the selected parameters ensure that the model converges to the desired theoretical limit under conditions of maximum cognitive influence. In the absence of any such influences, the model naturally reduces to the baseline stochastic behavior, as expected from RNG systems.

Estimating the Distance Decay Parameter α

Having established the parameters governing the magnitude of consciousness-related influences (β_C) and demonstrated the convergence behavior of the model under idealized conditions, the next step is to estimate the spatial decay parameter α. Although α is ultimately an empirical parameter, useful guidance can be drawn from earlier experimental research that systematically examined the distance dependence of consciousness-related effects.

A particularly relevant study is the 12-year investigation conducted by the Princeton Engineering Anomalies Research (PEAR) laboratory (Jahn et al., 1997), which assessed whether human intention could measurably influence the output of a random event generator (REG). The study compiled over 2.5 million trials, involving more than 100 participants performing structured tasks under controlled laboratory conditions.

The trials were carried out under two primary spatial arrangements: local trials, in which the participants were physically located close to the REG device (at distances of 2 to 10 meters); and remote trials, conducted at distances ranging from several hundred to thousands of kilometers. The experimental design included three conditions: a high intention state (HI), where participants attempted to increase the frequency of 1s; a low intention state (LO), aimed at increasing the frequency of 0s; and a contrast condition, measuring the net difference between the two. Across all conditions, statistically significant deviations from randomness were observed.

To assess whether spatial separation influenced these effects, the data set was stratified into local and remote trials. In the 522 series of local HI trials, participants achieved a Z score of 3.809, corresponding to an effect size of 20.8×10^{-5} per bit across 3.35×10^{8} samples. In comparison, the 212 series of remote HI trials produced a Z-score of 2.214, with an effect size of 16.4×10^{-5} per bit over 1.83×10^{8} samples. These results suggest a modest reduction in effect size with increasing distance, although statistically significant deviations from randomness were present in both spatial conditions.

While the difference is modest, it could still indicate a distance-sensitive mechanism particularly given that small effects can accumulate meaningfully across large data sets. As such, it is used here and explored within the context of the proposed CESM framework.

Applying the simplified version of the model (Equation 5) to quantify this distance dependence, it is found that setting $\alpha = 0.000004$ yields a consistent combined intention and attention value of $I = A \approx 6.32$, under both local and remote conditions. This analysis suggests that, while the core intentional influence on RNG output remains robust across distance, the attentional component of cognitive engagement may exhibit a mild decline as spatial separation increase.

However, it is important to explicitly acknowledge that the empirical estimation for the distance decay parameter presented here remains uncertain. Future studies should empirically verify this value and explore alternative functional forms to further clarify this aspect of CESM.

APPENDIX B

CESM AND THE GLOBAL CONSCIOUSNESS PROJECT

Empirical findings from the Global Consciousness Project (GCP) suggest that, during major world events, random number generators (RNGs) distributed across the globe sometimes display correlated deviations in unison (Nelson, 2002, 2020, 2021). This appendix illustrates how the Bayesian and information-theoretic principles underlying CESM from the main text can account for these global correlations, provided that large numbers of individuals experience heightened attention simultaneously.

Equation (1) in the main text establishes the baseline entropy of an ideally random RNG, while Equation (2) shows how each new act of cognitive engagement (e.g., heightened emotion and attention or intention, interpreted as an "observation") could update the RNG's probability distribution. In this framework, the "observation" in Equation (2) should be interpreted in a Bayesian sense, that is as an informational update rather than a literal observation of the RNG. Equation (4) makes this idea operational by introducing measurable cognitive parameters such as attention (A) and intention (I).

In the context of the Global Consciousness Project (GCP), I is typically set to zero as participants in general are unaware of the RNG network and therefore exert no deliberate mental effort to influence it. However, emotionally modulated attentional presence (A) may still be significant, especially during global events that evoke widespread emotional engagement.

As reflected in equations (4) and (5), the aggregate impact on RNG outputs can increase with the number of individuals affected, consistent with the GCP's core hypothesis that large-scale emotional coherence may correspond with measurable entropy shifts. These concepts extend naturally to global scenarios involving mass participation or shared emotional focus:

- Instead of a small local group (unconsciously) affecting a single RNG, thousands or even millions of people may each contribute small, simultaneous informational "nudges," provided they share a heightened attentional state.
- When a widespread event trigger distributed attention, correlated deviations can arise at multiple RNGs, even those geographically distant, because each device responds independently to the same globally shared cognitive effect.

When applying the CESM framework to Global Consciousness Project (GCP) data, it can be assumed that participants direct their attention and emotional engagement toward the event itself, rather than the RNG devices. This mirrors the setup used in the experiment described in the main text. Because participants are generally unaware of the RNGs, they cannot deliberately try to influence them through intention. Instead, any observed effects are interpreted as the result of shared emotional attention, with the RNGs responding indirectly to a widely distributed cognitive or emotional state. From this perspective, correlations in RNG outputs are not due to communication between devices, but rather to a common informational influence affecting all of them.

From an information-theoretic perspective, each instance of emotional attentional presence, when an individual becomes cognitively and affectively engaged with an engaging event, can contribute a slight reduction in the entropy of an RNG. During major global events, the simultaneous emergence of such "attentional updates" across large populations may collectively bias the output of geographically dispersed devices. The resulting nonrandom shift manifests as a weak but measurable correlation among RNGs, consistent with the CESM hypothesis that shared emotional engagement can act as a distributed informational constraint on stochastic systems.

In CESM, distance is incorporated through the exponential decay term ($e^{\alpha \cdot d}$), where $\alpha \geq 0$ governs how the effect decreases with spatial separation. Two main scenarios help illustrate how this related to the GCP experiments:

- If $\alpha = 0$: All participants contribute equally to the RNG's entropy shift, regardless of where they are located. This yields a distance-independent model.
- If $\alpha > 0$: Participants exert diminishing influence as their distance from a given RNG increases.

For truly global events (e.g., the September 11 attacks or the onset of the COVID-19 pandemic), the engaged population tends to be broadly distributed worldwide, with no single geographic center dominating. Approximating $\alpha \approx 0$ may therefore be practical, since network-wide coherence in RNG output can appear uniform across large distances. In such cases, each RNG is locally responding to a surge of collective attention rather than direct inter-device signaling. Importantly, observing globally correlated deviations does not exclude a small but non-zero α; it only indicates that any distance effect is overshadowed by the widespread emotional or cognitive engagement.

In contrast, for more localized or region-specific events, using $\alpha > 0$ allows greater nuance. Participants near the emotional epicenter of the event may experience stronger emotional resonance, thereby influencing nearby RNGs more strongly. Distant RNGs can still register an effect but to a lesser extent. This behavior is testable: if RNGs closer to the event show stronger deviations, it supports $\alpha > 0$; if deviations are uniform regardless of distance, $\alpha = 0$ becomes the more likely scenario.

Preliminary evidence for spatial structure in GCP data was reported by Nelson et al. (2002), who noted that deviations in RNG output occasionally appeared stronger for devices located nearer to the emotional epicenter of a global event. A later analysis by Nelson and Bancel (2011) conducted a regression across inter-device distances and found a small but statistically significant decline in network synchrony as spatial separation increased, with results suggesting that geographic distance may affect the strength of correlated deviations. While these findings support the idea of distance-sensitive effects, no formal exponential decay model has been proposed or tested within the GCP framework. The CESM parameter α introduced here therefore offers a novel formalization of this hypothesis, allowing distance-based attenuation to be modeled explicitly and tested empirically in future analyses.

In practice, small but non-zero values of α can still produce a measurable distance decay. For example, setting $\alpha \approx 0.000004$, as in the main text, implies that the RNG effect falls to half its original value only after roughly 173 km (about 108 miles). This seemingly modest effect can still matter for global projects like the GCP. If an emotionally intense event increases collective attention (with $I = 0$ but high A) among millions or billions of people, the model predicts a statistically robust shift if those individuals are on average near the RNGs. However, when average distances grow beyond a few hundred kilometers, the predicted effect may drop below detection thresholds. As a result, major events in more remote regions might not show up clearly in GCP data if the RNG network lacks geographical coverage.

Future analyses could refine the GCP methodology by introducing distance-sensitive weighting. For instance, RNGs could be grouped into geographic clusters, and effect sizes compared across regions. If closer clusters consistently exhibit larger deviations, this will support $\alpha > 0$. If no such pattern emerges, the simpler model with $\alpha = 0$ may be sufficient, and a revision of the CESM would then be warranted. In fact, the analysis done by the GCP could in principle be used to determine a more exact value of α, which is an interesting avenue for future research to explore.

APPENDIX C

XOR WHITENING AND BIAS PERSISTENCE

In the experiment described in the main text, a TrueRNG v3 device was used. This device generates true random numbers based on the avalanche effect in a semiconductor junction and applies a firmware-based whitening process to the raw entropy stream before writing output to disk. The purpose of this whitening step is to suppress local bias and enhance short-term entropy. A natural concern is whether such preprocessing might obscure the type of structured deviations predicted by CESM. This appendix clarifies how the whitening procedure operates, how it interacts with bias and temporal correlation, and why long-window deviations remain theoretically and empirically detectable.

The whitening technique employed by the TrueRNG v3 is based on the XOR (exclusive OR) operation, a binary function defined as:

$$X_1 \otimes X_2 = \begin{cases} 1, & if\ X_1 \neq X_2 \\ 0, & if\ X_1 = X_2 \end{cases}.$$

When applied to two independent biased bits X_1, X_2 ~ *Bernoulli*(p), the resulting output $Y = X_1 \otimes X_2$ has an expected value $P(Y = 1) = 2p(1-p)$ which is maximized when $p = 0.5$. As such, the XOR operation suppresses direct bias and drives the output toward uniformity.

According to the manufacturer, the TrueRNG v3 device uses a firmware-based XOR whitening method to process its raw bitstream. The whitening algorithm operates on fixed-length blocks of 20 consecutive raw bits, which are sampled sequentially from the underlying entropy source. For each such block, a single output bit is produced by computing the XOR (exclusive OR) across all 20 bits:

$$Y = X_1 \otimes X_2 \otimes \cdots \otimes X_{20}.$$

This operation is then repeated for the next block of 20 bits, meaning the output sequence is constructed from non-overlapping windows of raw data as Y_1 is based on X_1 through X_{20}, Y_2 is on X_{21} through X_{40}, and so on.

The XOR function returns 1 if the number of 1s in the block is odd, and 0 otherwise. Consequently, the whitening process aims to eliminate systematic biases by making the output less sensitive to any consistent skew in the input bits. If the raw bits are assumed to be independent and identically distributed (i.i.d.) with a fixed bias p, the probability that the XOR output is 1 corresponds to the probability of an odd number of ones in a 20-bit binomial distribution. Formally, this is given by:

$$P(Y = 1) = \sum_{\substack{k=1 \\ k\ odd}}^{20} \binom{20}{k} p^k (1-p)^{20-k}.$$

For instance, if $p = 0.55$, the resulting probability becomes $P(Y = 1) \approx 0.5000000000000044$, which is effectively indistinguishable from fair coin tosses. Therefore, under i.i.d. conditions, the XOR whitening process effectively suppresses visible bias in the output stream.

However, this conclusion no longer holds when temporal dependencies are present in the raw entropy stream, as might occur if the device is influenced by cognitive factors. If the bit sequence $\{X_t\}$ is governed by, for example, a first-order Markov process, where the value of each bit depends probabilistically on the previous one, the assumption of independence breaks down. In such cases, the effective number of independent bits within a 20-bit XOR window is reduced.

To illustrate how such structured bias can persist through XOR whitening, consider a raw bitstream with a sustained bias of p=0.55 and a lag-one autocorrelation of ρ=0.80. Following Bartlett's formula for autocorrelated sequences (Bartlett, 1935), the effective number of independent observations in each 20-bit XOR window is reduced to:

$$e_{eff} = 20 \cdot \left(\frac{1 - \rho}{1 + \rho} \right) = 20 \cdot \left(\frac{1 - 0.8}{1 + 0.8} \right) \approx 2.22.$$

The analytical approximation for the expected mean of the XOR-whitened output under this autocorrelated bias is given by:

$$\mathbb{E}[Y] \approx 0.5 - e_{eff} \cdot (p - 0.5)^2 = 0.5 - 2.22 \cdot 0.0025 = 0.4944.$$

Thus, the expected shift from 0.5 is approximately −0.0056 after whitening. As such, under these conditions, the whitening procedure no longer fully eliminates structured dependencies.

To test whether this shift is statistically detectable, the standard error of the mean over n=100,000 samples, assuming a Bernoulli variance under the null, is given by:

$$SEM = \frac{0.5}{\sqrt{100,000}} \approx 0.00158,$$

with a corresponding z-score of:

$$z = \frac{-0.0056}{0.00158} \approx -3.51.$$

This yields a two-tailed p-value of approximately 0.00044, well below the 1% significance threshold. Thus, a persistent and autocorrelated bias in the raw stream when aggregated over 100,000 samples, leads to a statistically significant deviation.

This limitation of the XOR whitening procedure is central to the findings reported in the experiment in the main text, where long-window deviations are found to be highly significant as they do not only persist after whitening but also align with the predictions of the Cognitive Entropy Shift Model (CESM).

APPENDIX D

EXPERIMENTAL DESIGN AND PROTOCOL

This appendix details the full experimental setup, participant information, data filtering procedure, and modeling framework used in the experiment described in main text.

Study Setting

The study was conducted continuously over a two-year period, from June 2021 to June 2023, in a private apartment located in central Stockholm, Sweden. The building was situated next to a city park and directly close to a local high school, which began daily activities at 08:15. The apartment housed four individuals, but only three were considered participants in the study: either the author or his spouse (depending on the day), and their two young children, aged 8 and 5 at the start of the observation period. These three individuals were typically present in the apartment during the relevant time windows, particularly during emotionally engaging morning routines. The children were unaware that an experiment was taking place, ensuring that no expectancy effects or demand characteristics influenced their behavior. No instructions were given, and no active involvement was required beyond ordinary daily activities.

Device and Data

A TrueRNG v3 device was installed inside a TV bench in the apartment's living room (see Figure 5), which measured approximately 25 square meters and featured overhead skylights. The device remained in a fixed position throughout the study. It was powered continuously and connected to a Raspberry Pi 400 microcomputer, which timestamped and recorded the device's output in real time. The generated bitstream was XOR-whitened internally using fixed-length blocks of 20 raw bits sampled sequentially from the entropy source, which helps to reduce local bias while preserving longer-range statistical features (see Appendix C for more detail). One data point per second was generated using a batch script, while the underlying raw entropy stream was logged at 256 bytes per second.

Identification of High-Attention Periods

High-attention periods were identified prior to the data collection and analysis based on well-established household routines, daily school departure schedules, and firsthand knowledge of the participants' behavior. Specifically, the period between 07:30 and 08:15 on weekday mornings was predictably marked by emotionally engaging activity, such as preparing two young children for school under time constraints. These moments reliably involved frequent interpersonal interaction, conflicting wills and mild time pressure, all of which contributed to a state of collective emotional intensity and shared attentional focus. Although no formal logging of cognitive states was conducted, this period clearly stood out as a natural and recurrent window for studying potential effects of heightened emotional and cognitive engagement. Accordingly, the time windows were pre-designated based on lived experience and later matched with timestamped RNG data for statistical analysis.

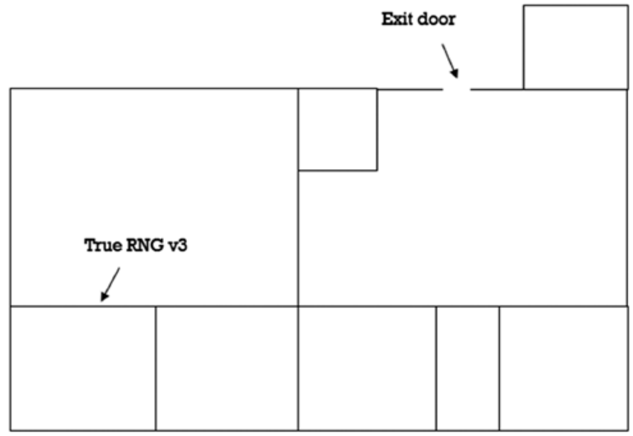

Figure 5. Schematic Drawing Over the Apartment.

Data Filtering and Subsampling

In total, the RNG device generated 47,731,465 valid one-second samples over the study period, corresponding to approximately 552.4 days, or 18.4 months assuming a 30-day month. This reflects the total span of continuous recording time prior to data filtering, as data also from weekends where included. Technical malfunctions such as power interruptions, bitstream errors, or corrupted write operations were identified through log inspection and excluded. A second filtering step removed all intervals during which participants were confirmed absent or their location was uncertain, based on travel records, household calendars, and retrospective observational notes. After this filtering, 38,941,850 valid one-second samples were obtained, corresponding to approximately 450.6 days or 15.0 months. For empirical analysis, 1,136,553 valid seconds were identified within the recurring 07:30–08:15

morning window, amounting to approximately 13.2 days of accumulated data across the two-year period. This 45-minute period was also divided into three non-overlapping 15-minute intervals: 07:30–07:45 (411,242 seconds), 07:45–08:00 (389,082 seconds), and 08:00–08:15 (434,059 seconds). Additionally, a more narrowly defined subsample covering the most emotionally intense interval, 07:55–08:10 (410,357 seconds), was compared to a post-departure control period from 08:10 to 08:25 (394,016 seconds), which overlapped with the start of the school day but occurred after participants had left the apartment. These subsets formed the empirical foundation for testing the hypothesis that structured cognitive-emotional states may induce measurable shifts in entropy in a physical random number generator.

Spatial Proximity

To further interpret the relationship between emotional proximity and entropy patterns, spatial distance was estimated using straight-line physical separation (in meters) between participants and the RNG device, derived from floor plans and direct measurements of the apartment layout. During the early part of the target morning window (07:30–07:45), participants typically remained in their bedrooms or adjacent areas, resulting in short distances of approximately 1 to 5 meters. Later segments (07:45–08:15) involved movement toward and eventually out through the apartment door, increasing the physical distance to around 10 meters during peak engagement. These within-day spatial variations provided additional context for evaluating how movements around the device, proximity and attentional intensity may have contributed to the observed deviations in the RNG output.

Environmental Controls and Artifacts

Finally, it should be noted that a television located near the device was never used during the relevant time windows, minimizing the potential for audiovisual or electromagnetic interference. No major modifications were made to the physical environment during the study period and room temperature and electrical stability were monitored passively. While the skylights occasionally caused elevated indoor temperatures on sunny summer days, these periods mostly coincided with the participants being away from Stockholm for vacation. Such intervals were analyzed separately and showed no measurable deviation from chance, effectively ruling out temperature fluctuations or environmental drift as explanatory factors.