Can Consciousness Nudge Randomness?

Ulf Holmberg[*†]

March 30, 2025

Abstract

This paper introduces a Bayesian entropy-based framework for modelling whether consciousness-related factors—such as intention, attention, and emotional intensity—can systematically influence the output of physical random number generators (RNGs). Rather than proposing energetic causation, the model conceptualises consciousness as an informational variable capable of subtly biasing probabilistic outcomes. It operates entirely within established physical principles, avoiding violations of energy conservation or faster-than-light signalling, and draws on information-theoretic foundations.

The model's assumptions are empirically supported by a two-year RNG experiment using a TrueRNGv3 hardware device, during which statistically significant deviations from baseline entropy were observed in conjunction with heightened emotional or attentional states ($t = 4.347$, $p < 0.001$). These results suggest that certain internal cognitive states may act as informational constraints on stochastic systems, introducing measurable structure into otherwise random outputs.

While the framework remains descriptive rather than causal, it provides a principled method for quantifying consciousness-related anomalies. In addition to being forward-looking, it offers a new lens through which to reinterpret legacy findings—such as those from the Princeton Engineering Anomalies Research (PEAR) programme—within a coherent probabilistic model.

This work represents a first attempt to model certain results historically associated with psi research, offering a transparent and extensible foundation that can evolve with new data. By linking entropy, Bayesian inference, and observer-related variables, it opens a rigorous pathway for integrating mind–matter correlations into a broader scientific framework for understanding consciousness.

Keywords: Theory of Consciousness, Consciousness studies, Information Theory, Bayesian Updating, Hypothesis testing

[*]Independent researcher, ulf.e.holmberg@me.com

[†]The author would like to thank the GCP2 group — and Roger Nelson in particular — for their generous engagement and contributions, which continue to inspire and guide this line of inquiry. Special thanks also to George Williams for valuable discussions and for sharing work that helped shape the theoretical direction of this paper.

1 Introduction

The idea that human consciousness might influence the physical world has fascinated philosophers for centuries. Thinkers like Plato, with his theory of ideal forms, Descartes, with his concept of mind-body dualism, and Spinoza, who proposed that mind and matter are two aspects of the same substance, all wrestled with this question (Plato, BCE; Descartes, 1641; Spinoza, 1677). In more recent times, science has taken up this ancient debate, transforming it into a testable, empirical question. Thanks to developments 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 significant 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 (Wigner, 1961; Stapp, 2001). Similarly, Quantum Bayesianism (QBism) proposes that probabilities in quantum mechanics are observer-dependent constructs, offering additional perspectives on the role of consciousness (Fuchs and 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.

In parallel, Penrose and Hameroff have proposed that quantum processes within the brain's microtubules might underlie consciousness itself, thereby linking cognition to fundamental physics (Penrose, 1994; Hameroff and Penrose, 1996). At the same time, cognitive neuroscience has made remarkable progress in mapping the neural correlates of consciousness (Cotterill, 2001; Llinás, 2002; Koch, 2004; Dehaene, 2014; Baars, 1997; Tononi, 2008). Yet, it continues to grapple with bridging the explanatory gap between neural activity and subjective experience. This enduring limitation that has famously termed the "hard problem of consciousness" (Chalmers, 1996), has fueled the search for alternative frameworks that challenge strictly reductionist accounts of cognition. Taken together, these developments underscore the importance of broadening our theoretical perspectives. One way to deepen our understanding of consciousness is to consider it as fundamentally involved in the organisation of information. Information theory, originally developed by Shannon (1948), offers a framework for quantifying uncertainty and for 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 through this lens: cognitive processes may act as informational constraints, shaping otherwise random patterns into meaningful structure.

This perspective aligns with contemporary models in cognitive science, which suggest that the brain operates as a Bayesian inference engine—continually updating and generating probabilistic representations of reality in response to incoming sensory data (Friston, 2010; Clark, 2015; Seth and Bayne, 2022). The Bayesian brain model implies that the mind actively reduces uncertainty by refining its internal representations through the accumulation of predictive information. In doing so, it imposes informational constraints, transforming what might otherwise appear to be random input into structured expectations.

Such models typically regard consciousness as an internal organiser of information. But could it also engage with an underlying informational substrate? If so, consciousness may not only shape internal representations, but also influence external stochastic systems—such as random number generators (RNGs)—by constraining their entropy through intentional focus and directed attention, thereby producing structured deviations from chance expectations.

Naturally, this testable conceptual hypothesis has prompted researchers to explore it empirically. Within the realm of empirical investigation, random number generators (RNGs) have become a pivotal tool for examining whether consciousness can influence the output of purely random systems, and by extension, possible mind–matter interactions.

Foundational experiments at the Princeton Engineering Anomalies Research (PEAR) laboratory provided early evidence that focused human intention could bias RNG outputs beyond chance expectations (Jahn and Dunne, 1987; Nelson, 2024). Building on these findings, the Global Consciousness Project (GCP) observed synchronised deviations across a worldwide network of RNGs during emotionally significant global events—suggesting that collective consciousness may influence probabilistic systems on a large scale (Nelson et al., 2002b).[1]

More recently, Holmberg extended this line of inquiry by investigating statistical correlations between financial market dynamics, internet search trends, and deviations in RNG outputs (Holmberg, 2020, 2021, 2023, 2024). His findings suggest that structured anomalies in GCP data coincide with measurable changes in seemingly unrelated variables—variables that are themselves known to respond to the same types of global events hypothesised to influence the GCP's RNGs.

Taken together, this body of research implies that human cognition—whether expressed as focused individual intention or broad collective awareness—may systematically bias randomness, introducing detectable patterns where none should arise in purely stochastic systems.

However, despite this expanding body of empirical findings suggesting that consciousness might influence such systems, the results have been met with rigorous scrutiny. Critics argue that the observed anomalies could result from statistical noise, methodological inconsistencies, or selective reporting (Scargle, 2002a; Bösch et al., 2006; Alcock, 2003). Additional concerns relate to the small effect sizes, which may elevate the risk of Type I errors. The challenge of reproducibility remains central, with sceptics questioning whether effects observed under controlled conditions can be reliably replicated across independent experimental settings.

Moreover, conventional scientific paradigms—rooted in physical causation and deterministic mechanisms—often struggle to accommodate findings that suggest non-material influences on random outcomes. A major source of scepticism lies in the absence of a robust theoretical framework capable of systematically predicting and accounting for such subtle effects. Without a coherent model that integrates consciousness-related factors into probabilistic reasoning, the debate risks stagnation. These challenges underscore the need for an approach that is both mathematically rigorous and empirically testable, while remaining open to exploring phenomena that may not fit neatly within traditional boundaries.

In response, some researchers have begun to revisit the significance of statistical anomalies observed in random number generator (RNG) data. Rather than dismissing these deviations as mere artefacts or statistical noise, several studies suggest that such patterns may reflect non-trivial regularities not accounted for by standard models. This shift has prompted more open-ended exploration into alternative frameworks—ones that consider the possibility that consciousness might interact with probabilistic systems in subtle, yet measurable ways.

For instance, researchers such as Walach et al. (2020) and (Drennan, 2015) report empirical findings where mental intention or emotional states appear to correlate with RNG deviations, while (Hardy, 2005) offers a more speculative theoretical perspective, suggesting that consciousness-related anomalies could potentially hint at latent structural features of stochastic

[1]Extensive details on the GCP's event-based experimental design and analytic methodology are available in (Bancel and Nelson, 2008).

processes. While these interpretations remain tentative, they point toward a need for models that combine statistical rigour with openness to novel explanatory variables, including those rooted in consciousness research.

While these considerations remain controversial, they underscore the importance of developing testable, falsifiable models that can evolve alongside new experimental data. To this end, the present study introduces a formal framework linking cognitive engagement to measurable shifts in RNG output. The model formalises the hypothesis that consciousness may function as an informational constraint, subtly reducing entropy and introducing statistically detectable order into otherwise random systems.

Though not Bayesian in the conventional sense, it adopts an updating logic analogous to Bayesian inference—adjusting the probability of outcomes in light of momentary or cumulative cognitive engagement. In its unmodulated state, an RNG produces output at maximum entropy, devoid of structure. The proposed framework provides a method for assessing how consciousness-related variables may induce systematic deviations in the underlying probability distributions from which random data are sourced. By doing so, the paper offers a quantifiable route for exploring how consciousness might interact with probabilistic systems—potentially providing a bridge to understanding previous findings related to mind–matter interactions.

This paper makes several key contributions. It introduces a mathematically rigorous framework for modelling consciousness-related influences on probabilistic systems by incorporating probability updating analogous to Bayesian inference. This enables a structured analysis of deviations from randomness that may arise through cognitive engagement.

The model links these influences to measurable reductions in entropy in RNG outputs, formulates testable hypotheses, and provides a robust foundation for evaluating whether observed deviations align with theoretical expectations. By integrating spatial parameters, the framework also extends previous RNG-related research by examining how distance and proximity may affect consciousness-related effects, offering a refined structure suitable for diverse experimental contexts.

Additionally, the model validates earlier anomalous findings through a new two-year experiment and illustrates how previously debated results can be reinterpreted meaningfully within this framework. Taken together, the proposed model can be used both for retrospective analysis and as a tool for generating clear, testable predictions in future experiments.

The remainder of this paper is organised as follows. Section 2 outlines the theoretical underpinnings of the proposed model, explaining how information theory and probabilistic reasoning frame the relationship between consciousness and RNGs. Section 3 develops the mathematical foundations, incorporating variables related to cognition and spatial parameters. Section 4 empirically tests the model using results from a new two-year experiment. Section 5 applies the framework to prior research findings. Section 6 explores the broader implications for interdisciplinary research across neuroscience, quantum mechanics, and philosophy. Finally, Section 7 concludes the paper.

2 Theoretical Framework

Building on the ideas outlined in the introduction—where empirical anomalies in RNG outputs suggest that consciousness may influence randomness—this section establishes the theoretical foundation for systematically investigating such effects.

The framework begins with the concept of entropy, a measure that quantifies uncertainty or disorder in a system. In the context of random number generators (RNGs), entropy is maximised when outcomes are completely random and equiprobable, such that no prior information about the sequence improves the prediction of future values. Mathematically, entropy for a discrete random variable X is defined as:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log P(x_i), \tag{2.1}$$

where $P(x_i)$ denotes the probability of each possible outcome x_i. Under ideal conditions, an RNG maintains maximum entropy by producing uniformly distributed outcomes. This provides a principled baseline against which deviations can be measured. As such, entropy serves as a natural starting point for analysing whether consciousness-related factors introduce statistically detectable patterns into otherwise stochastic outputs.

Empirical research within the field of parapsychology has suggested that physical random number generators (RNGs) may not always behave as purely stochastic systems when influenced by consciousness-mediated factors. For example, the Princeton Engineering Anomalies Research (PEAR) laboratory has reported highly statistically significant deviations in RNG outputs during experiments examining the effects of focused mental intention (see, e.g., Jahn and Dunne (1987); Dunne et al. (2000); Radin and Nelson (1989); Nelson (2002)). A comprehensive meta-analysis of mind–matter interaction experiments by Radin and Nelson (2003) also reviewed data spanning from 1959 to 2000, revealing small but consistent effect sizes. Similarly, the Global Consciousness Project (GCP) has documented widespread shifts in the outputs of a global network of RNGs during emotionally charged events—such as the September 11 attacks (Nelson et al., 2002a)—as well as other events of perceived global significance (Nelson, 2020, 2021).

These findings suggest a potential connection between consciousness and systematic reductions in entropy. Although many earlier studies report statistically significant and compelling results (Utts, 1991), the findings remain the subject of ongoing debate—likely due to the absence of a widely accepted explanatory mechanism, along with methodological concerns and alternative statistical interpretations (Dunne et al., 2000).

To address these open questions, a formal modelling approach is needed—one that can capture the influence of consciousness within a probabilistic framework grounded in information theory. It is thus hypothesised that consciousness-mediated states (e.g., intention, attention, or emotional intensity) in fact may "inject" information into stochastic systems, enabling their effects to be analysed using a Bayesian approach.

Building on the proposed hypothesis, a new framework is proposed that provides a mathematical method for updating probability distributions in light of potential consciousness-related mediating influences. Within the framework, *observations* are interpreted as expressions of consciousness-related factors that may influence RNG outcomes. Accordingly, the posterior probability of an outcome x_i—that is, the altered probability conditioned on an observed consciousness-related factor O—follows from Bayes' theorem:

$$P(x_i \mid O) = \frac{P(O \mid x_i) \cdot P(x_i)}{P(O)}. \tag{2.2}$$

Here, $P(x_i)$ represents the unaltered (prior) probability under maximum entropy, and $P(O \mid x_i)$ denotes the likelihood of observing O assuming no prior bias. By comparing the posterior and prior distributions, it becomes possible to identify measurable shifts that may result from consciousness-related influence.

Figure 2.1 illustrates this process of Bayesian updating. It shows how the prior distribution—representing initial expectations about possible outcomes—is updated to form the posterior distribution once new evidence (expressed as the likelihood) is incorporated.

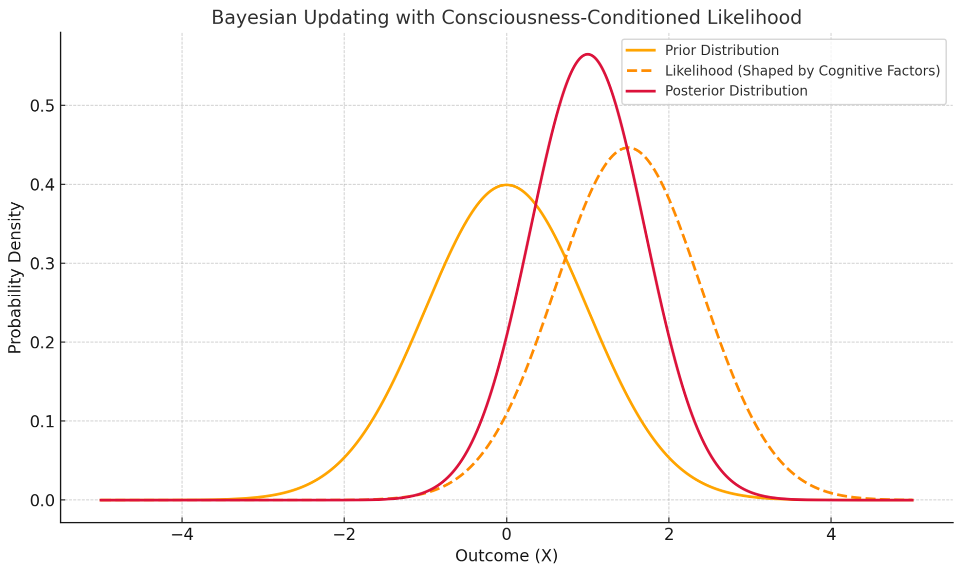


Figure 2.1: Illustrative example of the Bayesian updating procedure.

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 O as follows:

$$\Delta H = -\sum_{i=1}^{n} P(x_i \mid O) \log P(x_i \mid O) \quad + \quad \sum_{i=1}^{n} P(x_i) \log P(x_i) \tag{2.3}$$

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—potentially reflecting informational structuring induced by conscious states. 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 RNG systems.

A conceptual parallel can be drawn between this framework and the observer effect in quantum mechanics, where the act of measurement collapses a quantum wavefunction, producing a definite outcome from a superposition of possibilities (Jacobs, 2006). While conventional interpretations attribute this collapse solely to physical interaction, alternative perspectives—most notably those proposed by von Neumann and Wigner—suggest that consciousness itself may play an active role in this process (von Neumann, 1932; Wigner, 1961). Extending this line of thought, Williams (2024) proposes that empirical anomalies observed in consciousness-related research could indirectly shed light on unresolved aspects of quantum theory—implying that deviations from expected randomness may reflect an underlying informational structure not yet recognised by conventional models.

Recent theoretical developments further reinforce the notion that classical deterministic frameworks alone may be insufficient to explain the relationship between consciousness and randomness. Faggin (2023), for example, argues that classical systems inherently exclude genuine creativity, consciousness, and free will, as these phenomena, according to his view, depend on quantum, non-algorithmic processes. Instead, he proposes that consciousness naturally emerges from intrinsic quantum features—such as entanglement and non-locality—which are fundamentally incompatible with classical determinism.[2]

Complementary to this view, recent theoretical insights suggest that observed deviations from expected entropy may reflect interactions with an underlying informational substrate or field. Consciousness, in this context, could influence outcomes through alignment with this deeper structure—without violating physical laws. For instance, Bostick (2024) argues that what is commonly interpreted as randomness might instead result from incomplete resonance detection. He proposes that both entropy and cognition emerge from structured resonance patterns within a coherent informational field. Within this framework, consciousness is not viewed as a mere by-product of computation. Rather, it is understood as an emergent property arising from phase-locked coherence—a dynamic in which stable resonance patterns form. Through this mechanism, conscious states may influence probabilistic systems by aligning with an underlying informational structure.

These perspectives conceptually support the proposed model, which deliberately avoids invoking direct causal mechanisms. Instead, it adopts a statistical approach to identify how and when random systems may exhibit deviations associated with conscious states. This clearly positions the model as probabilistic and descriptive: it characterises how RNG data can shift in response to cognitive factors, without attempting to specify *why* such changes occur at a deeper physical or ontological level.

To maintain clarity around the scope of this model, it is important to address the philosophical and ontological stance underpinning the framework. The approach adopted here remains deliberately neutral with regard to the ultimate causal mechanisms by which consciousness might influence random number generators. Rather than positing direct physical interactions—such as quantum processes, fields, or novel forces—the model treats consciousness-related variables as informational constraints that shape probabilistic distributions. As such, this framework does not require any particular ontological claim about the nature of consciousness. It neither assumes that consciousness is fundamental to physical reality nor dismisses that possibility. Instead, it remains agnostic, treating consciousness as a measurable variable whose influence can be quantified via Bayesian probability updating and entropy reduction. Such informational constraints may emerge from cognitive processes or—more speculatively—from deeper structural informational substrates as proposed in recent theoretical work (e.g., Laszlo, 2004; Williams, 2024).

By focusing on empirical descriptiveness and linking empirical results to information theory, the model avoids metaphysical commitments and remains open to integration with various interpretations—whether psychological, physical, or metaphysical. This theoretical neutrality ensures broad applicability across disciplines, while still allowing for future empirical work to inform or refine the model's underlying ontological commitments.

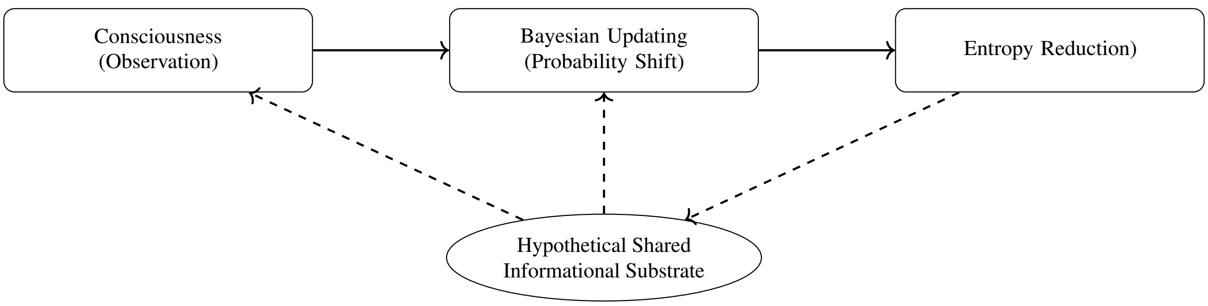


Figure 2.2: Conceptual diagram of the model and concept discussed in this section.

[2]This position is articulated within Faggin's Quantum Information-based Panpsychism (QIP).

Figure 2.2 provides a conceptual overview of the framework presented in this section. It illustrates how consciousness-related factors influence the Bayesian updating of probability distributions—an effect interpreted through information theory as a reduction in entropy. The dashed arrows in the figure indicate speculative interactions with, or potential emergence from, a shared informational substrate.

3 Quantifying the Consciousness-Related RNG Influence

As discussed in previous sections, empirical studies have reported statistically significant entropy deviations ($\Delta H \neq 0$) in random number generator (RNG) outputs associated with cognitive variables such as intention and attention (Jahn and Dunne, 1987; Nelson, 2024; Jahn et al., 1997). However, these findings have not yet been embedded within a formal mathematical framework capable of systematically quantifying consciousness-related effects on probabilistic systems. To address this gap, the present section introduces a flexible and generalisable model designed to quantify such influences, offering a foundation for both empirical testing and theoretical refinement.

To broaden the scope of the model, it is helpful to consider additional cognitive and emotional dimensions that might plausibly influence stochastic systems. Some findings suggest that emotional reactivity could play a role in shaping RNG outcomes, particularly during large-scale events involving shared public attention. Studies on group consciousness effects (Nelson et al., 1996; Nelson, 2024) and findings from the Global Consciousness Project (GCP) (Nelson et al., 2001; Nelson, 2020, 2021) indicate that emotionally engaging events—especially when experienced collectively—may correspond with subtle but measurable deviations from expected randomness.[3]

While the underlying mechanism remains uncertain, a general statistical structure can nonetheless be formulated to describe how consciousness may introduce *structured information* into stochastic processes. This structure provides a basis for generating testable hypotheses and examining them empirically. The model thus quantifies how specific consciousness-related variables—namely *attention* (A) and *intention* (I)—influence RNG outcomes. These inputs are heuristically scaled from 0 (no influence) to 10 (maximum influence), representing varying degrees of cognitive engagement.

Attention is operationalised as a composite construct encompassing both sustained focus and emotional reactivity, consistent with Likert-type rating methodologies (Likert, 1932). *Intention* is defined as goal-directed mental effort, following the conceptual framework of the *Theory of Planned Behaviour* (Ajzen, 1991).

To account for possible interaction effects, a multiplicative term ($I \cdot A$) is included, based on the hypothesis that high levels of both intention and attention may produce amplified effects. While attention currently subsumes emotional activation, future versions of the model may separate the affective component to enhance interpretive clarity.

Beyond cognitive and affective engagement, spatial separation between the observer and RNG may also be of importance. The literature however report mixed findings in this area as some studies suggest that intention-related effects are distance independent (e.g., Jahn et al., 1991), while others report distance-dependent reductions, especially under heightened emotional conditions (e.g., Leskowitz, 2011).

[3] This pattern has also been explored in independent studies examining correlations between GCP data and broader indicators such as global stock markets (Holmberg, 2020, 2021, 2024) and worldwide internet search activity (Holmberg, 2023).

Taking all these previous findings into account, the model combines both distance-dependent and distance-independent contributions into a unified probabilistic framework. The general expression capturing this logic is given by:

$$E_{\text{RNG},m} = \frac{\left[\sum_{i=1}^{n} \sum_{C\in\{I,A,I\cdot A\}} \left(\beta_C \cdot \frac{C_{i,m}}{e^{\alpha\cdot d_{i,m}}}\right)\right] \cdot \frac{\Phi^{-1}(q)}{1+\frac{1}{n}}}{1+n} + \epsilon_m, \tag{3.1}$$

In this equation:

- $E_{\text{RNG},m}$ 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 I, attention A, and their interaction $I \cdot A$) contributed by participant i, each 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 α.[4]

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 ($\Phi^{-1}(q) \approx 6$).[5] This scaling defines an upper-bound window for identifying statistically anomalous cases under the null model, thus making rare events more visible.

A normalisation term involving the number of participants n prevents the modelled effect from growing uncontrollably as the sample size increases. A final residual term, $\epsilon_m \sim \mathcal{N}(0,1)$, captures baseline random variation in RNG output. In the absence of consciousness-related influences, the model simplifies to a standard normal distribution, as expected under maximum entropy conditions. The output $E_{\text{RNG},m}$ is thus interpreted as a standardised deviation from randomness, expressed in units equivalent to a Z-score. Higher absolute values of $E_{\text{RNG},m}$ 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 (3.1) is that each participant or trial 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 normalise 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 cognitive variables.

By incorporating both additive influence and statistical normalisation, the framework formalised by Equation (3.1) provides a robust and extensible basis for quantifying how cognitive and emotional factors may modulate randomness. It remains modular and open to refinement, allowing for future integration of additional consciousness-related parameters (e.g., emotional coherence, expectation, group synchrony).

Moreover, the model does not depend on any specific statistical test to identify entropy shifts. Rather, it expresses deviations directly in terms of standardised units relative to the expected

[4]The model treats intention and attention as discretised subjective inputs rather than physically measurable quantities. This introduces epistemic uncertainty but allows cognitive variables to be probabilistically integrated into the model.

[5]The quantile value $q = 0.999999999$ was chosen to isolate the extreme tail of the normal distribution (one-in-a-billion events), offering a strict criterion for identifying anomalies that exceed background stochastic noise.

mean, allowing seamless integration with earlier work—whether prior analyses employed Gaussian Z-tests, t-tests, or other inferential techniques. This flexibility makes it suitable for retrospective reanalysis of legacy data.

Finally, by focusing on shifts in probability distributions rather than invoking direct physical causation, the framework preserves conceptual neutrality. It remains agnostic regarding the precise mechanisms by which consciousness may influence randomness, positioning itself instead as a descriptive tool for identifying and measuring such effects across diverse experimental designs.

Figure 3.1 provides a schematic overview of the model's logic. Input variables—namely intention, attention, their interaction, and spatial distance—are fed into scaling and decay functions, combined using parameter weights (β_C) and spatial decay ($e^{\alpha d}$). These modified inputs are then aggregated across n participants, passed through a high quantile filter $\Phi^{-1}(q)$, and normalised to yield the final standardised output $E_{\text{RNG},m}$, representing the predicted deviation from baseline entropy.

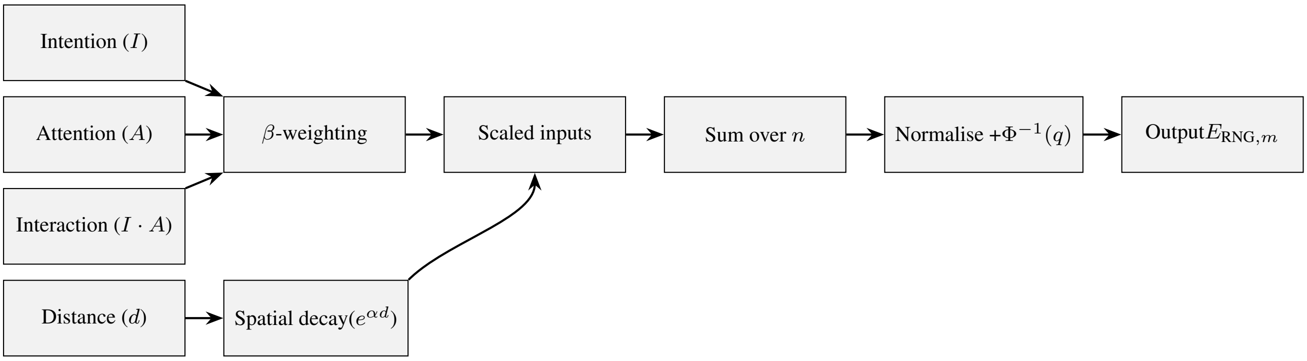


Figure 3.1: Visual representation of the Consciousness–RNG Influence Model. Intention (I), attention (A), their interaction ($I \cdot A$), and distance (d) are modulated by parameter weights and spatial decay, then aggregated, normalised, and transformed. The output $E_{\text{RNG},m}$ reflects the predicted deviation in RNG entropy due to cognitive engagement. This diagram maps directly to equation (3.1).

3.1 Simplified Model for Uniform Cases

In applied contexts where individual-level variation is unavailable, a simplified model can be derived. If all participants are assumed to exert uniform levels of attention and intention, and to be equidistant from the RNG device, then the summation collapses into a scalar multiple of n. Furthermore, by disregarding the directional sign of the effect, the expression simplifies to:

$$|E_{\text{RNG},m}| \approx \frac{\left(\beta_A \cdot \frac{A}{e^{\alpha \cdot d}} + \beta_I \cdot I + \beta_{I \cdot A} \cdot \frac{A \cdot I}{e^{\alpha \cdot d}}\right) \cdot n \cdot \frac{\Phi^{-1}(q)}{1+\frac{n}{n^2}}}{1+n} + |\epsilon_m| \tag{3.2}$$

This version is especially useful for reanalysing historical studies in which participant-level data on attention or intention were not recorded, allowing for the model to be retroactively applied to historical studies and previously published result.

For the results from either the full model (equation (3.1)) or the simplified version (equation (3.2)) to be meaningfully interpreted, it is necessary to determine appropriate values for the model's key parameters. These include the magnitude of each consciousness-related factor's influence on RNG output (β_C) as well as the parameter (α), which governs how rapidly cognitive influence diminishes with distance.

The following subsections therefore explore empirically reasonable estimates for these parameters and their theoretical basis. However, it should be emphasised that such values should ultimately be determined and validated through experimental data and calibrated against observed effects.

3.2 Establishing Parameters through Limit Behaviour

To provide initial parameter estimates and ensure the model's robustness, it is instructive to examine its limit behaviour under idealised conditions. Specifically, the parameters β_C can be constrained by analysing 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 behaviour, 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 (3.1) reduce to:

$$\beta_A \cdot A + \beta_I \cdot I + \beta_{I \cdot A} \cdot (A \cdot I). \tag{3.3}$$

Assuming maximum cognitive engagement ($A = I = 10$, and therefore $A \cdot I = 100$), the sum of the weighted terms must satisfy:

$$10\beta_A + 10\beta_I + 100\beta_{I \cdot A} = 1. \tag{3.4}$$

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—such as 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 defined as $\beta_{I \cdot A} = \beta_I^2$. This is a modelling assumption introduced for tractability, and should be validated in future empirical work.

Based on these constraints, a provisional value for the primary parameter is selected as $\beta_A = 0.085$. [6] With $\beta_A = 0.085$, the parameter hierarchy implies $\beta_I \approx 0.013239875$, and by definition, $\beta_{I \cdot A} = \beta_I^2 \approx 0.000175294$.

Under the earlier assumption of no spatial attenuation ($d = 0$), the consciousness-related contribution simplifies again to:

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

Substituting the parameter values:

[6] This value is illustrative and not derived from data; its precise magnitude remains an empirical question to be resolved through future experimentation.

$$(0.085 \times 10) + (0.013239875 \times 10) + (0.000175294 \times 10 \times 10) \approx 1.$$

The normalisation factor in the model is also given by:

$$\frac{6}{1 + \frac{n}{n^2}} = \frac{6}{1 + \frac{1}{n}},$$

which clearly converges to 6 as $n \to \infty$, since $\frac{1}{n} \to 0$.

Substituting these results into the simplified model yields:

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

from which it follows that:

$$\lim_{n \to \infty} |E_{\text{RNG}}| = 6.$$

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

3.2.1 Determining the Spatial Decay Parameter α from Previous Research

Having established the parameters governing the magnitude of consciousness-related influences (β_C) and demonstrated the model's convergence behaviour under idealised 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 at 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.

Trials were carried out under two primary spatial arrangements: local trials, in which participants were physically located near the REG device (at distances of 2–10 metres); and remote trials, conducted at distances ranging from several hundred to thousands of kilometres. 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, yielding a cumulative effect size of approximately 10^{-4} bits per bit processed and a combined deviation of 7.18σ from chance.

To assess whether spatial separation influenced these effects, the dataset 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.

Applying the simplified version of the model (Equation 3.2) 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 outputs remains robust across distance, the attentional component of cognitive engagement may exhibit a mild decline as spatial separation increases.

3.2.2 Illustrative Example: Demonstrating the Model Using Established Parameters

Having established the key parameters in the preceding subsections, this section offers a practical demonstration of how the simplified model can be applied to hypothetical experimental data. Consider an illustrative scenario involving a group of participants exhibiting identical, moderately high levels of attention and intention.

Specifically, let us assume $n = 10$ participants situated at a distance $d = 1.5$ metres from a random number generator (RNG) device. Each participant exhibits a cognitive state characterised by attention and intention levels set to $I = A = 5$. The parameters governing consciousness-related influences and spatial decay, as determined earlier from theoretical and empirical sources (e.g., Jahn et al. (1997)), are:

$$\beta_A = 0.085, \quad \beta_I = 0.013076923, \quad \beta_{I \cdot A} = 0.000171006, \quad \alpha = 0.000004.$$

To illustrate how the model functions in practice, the following five steps are undertaken:

Step 1: Compute the exponential decay factor

First, calculate the attenuation of attention-related effects due to distance:

$$e^{\alpha \cdot d} = e^{0.000004 \times 1.5} = e^{0.000006} \approx 1.000006.$$

Step 2: Calculate individual contributions

Next, compute the distinct contributions from attention, intention, and their interaction:

$$\begin{aligned} \beta_A \cdot \frac{A}{e^{\alpha \cdot d}} &= 0.085 \times \frac{5}{1.000006} \approx 0.4249996, \\ \beta_I \cdot I &= 0.013076923 \times 5 = 0.065384615, \\ \beta_{I \cdot A} \cdot \frac{A \cdot I}{e^{\alpha \cdot d}} &= 0.000171006 \times \frac{25}{1.000006} \approx 0.0042757. \end{aligned}$$

Step 3: Summation of contributions

Add the three components to calculate the total influence:

$$0.4249996 + 0.065384615 + 0.0042757 \approx 0.49466.$$

Step 4: Compute the bounding factor

Next, calculate the normalisation factor to scale the influence appropriately:

$$\frac{n \cdot \Phi^{-1}(q)}{1 + \frac{n}{n^2}} = \frac{10 \cdot 6}{1 + \frac{10}{100}} = \frac{60}{1.1} \approx 54.5455.$$

Step 5: Calculate the final model prediction

Since the expected noise term ϵ averages to zero, the expected deviation is:

$$|E_{\text{RNG}}| \approx \frac{0.49466 \times 54.5455}{1 + 10} = \frac{26.973}{11} \approx 2.452.$$

This result corresponds to a Z-score of approximately 2.452, which implies:

$$P(Z > 2.452) = 1 - 0.9929 = 0.0071.$$

This example demonstrates the utility and flexibility of the simplified model in quantifying statistically significant deviations from randomness. It also highlights how specific cognitive parameters—such as attention, intention, and distance—can be integrated into a structured probabilistic framework to systematically investigate consciousness-related effects on RNG outputs.

4 Testing the Model in a New Experiment

Having established the theoretical framework and examined a simplified illustrative example, the next step is to apply the simplified model to actual experimental data. In the following section, a two-year experiment is described, conducted in a controlled domestic environment, where random number data were continuously collected and analyzed in relation to predictable periods of heightened attention and emotional intensity. This real-world testing serves to (i) independently verify previous empirical findings and (ii) assess the model's ability to estimate implied levels of attention due to strong emotional engagement.

4.1 Experiment Setup

The two-year experiment was carried out from March 2022 to March 2024. A TrueRNG v3 device, which generates random numbers via the avalanche effect in a semiconductor junction, was positioned approximately 10 meters from an area that *a priori* was identified as having the highest potential for predictable periods of heightened levels of emotional intensity and attention.[7]

The TrueRNG v3 device generates random numbers through the avalanche effect in a semiconductor junction. It was connected to a Raspberry Pi 400, which collected and stored data at one-second intervals. In order to further enhance entropy, the device XORed the generated numbers at a 20:1 rate.[8] Periodic monitoring of the device's temperature and power supply was conducted to minimize the likelihood of hardware drift.

By March 19, 2024, a total of 47,731,465 random numbers had been generated. Among these, 8,789,615 observations were excluded as the three participants were known to be at locations far from the device (i.e., not in Stockholm), leaving 38,941,850 valid entries.[9] Each valid sample was timestamped, such that alignment with daily routines where made possible.

Prior to the experiment, morning periods between 07:30 and 08:15 were identified as predictably "stressful," providing an opportunity to analyze RNG data collected continuously over an extended timeframe.[10] This interval was subdivided into smaller segments (07:30–07:45, 07:45–08:00, 07:50–08:10, 08:00–08:15, and 08:10–08:25) to investigate how fluctuations

[7]Specifically, the device was placed under a TV bench located between two children's rooms, about 10 meters from the doorway of the main living space.

[8]Dr. Thiago Jung's batch script retrieved random numbers at 256 bytes/s. XOR mixing is a common technique for combining bits from multiple samples to reduce short-term correlations, though it does not fundamentally alter all statistical moments.

[9]The dataset is available upon request.

[10]Stress and heightened emotional intensity are hypothesized to amplify collective focus and attention, resulting in detectable deviations from randomness.

in emotional intensity throughout the morning affected RNG output and to determine which segments contributed the most significant effects.

The hypothesis was that the interval from 07:55 to 08:10 would exhibit the largest deviation from pure randomness, followed by the 08:00–08:15 interval. Both periods were anticipated to capture critical stressful moments as participants prepared to leave the domestic environment, characterized by heightened emotional intensity, increased attention, and often divergent wills. The interval from 08:10 to 08:25 served as a control period, since no participants remained in proximity to the RNG device during this time frame. Additionally, the entire 45-minute morning period (07:30–08:15) was analyzed and compared to multiple other 45-minute intervals distributed throughout the day, establishing a robust set of control periods for comparative analysis.

4.2 Statistical Analysis

After defining these intervals, the random numbers were normalized by subtracting their empirical mean and dividing by their empirical standard deviation, yielding a dataset with mean zero and unit standard deviation.[11] Given that the raw data had undergone XOR processing—a method capable of masking subtle consciousness-related deviations by redistributing or "washing out" bit-level patterns—it was essential to employ a statistical approach sensitive to underlying structural changes. Although XOR operations do not fundamentally alter a dataset's variance, they can influence mean-level characteristics.[12]

Resting on these insights, 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:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}, \tag{4.1}$$

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

4.3 Results

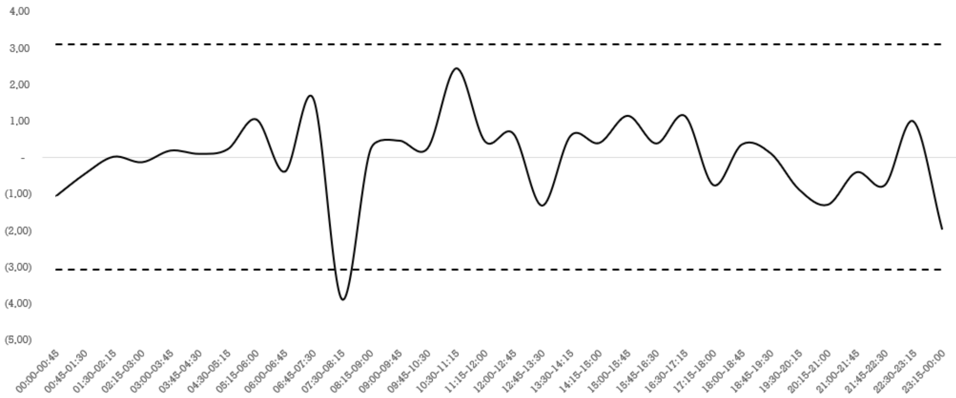
Table 1 presents descriptive statistics and Welch's t-test results derived from the normalized data. Both the mean and the standard deviation in each subset exceed those of the full dataset, resulting in negative differences between subsets and the full sample. Statistically significant deviations from randomness are evident during the intervals 07:55–08:10 ($p \approx 1.01 \times 10^{-5}$) and 08:00–08:15 ($p \approx 1.20 \times 10^{-4}$). Consequently, the aggregated 45-minute interval (07:30–08:15) also yields a highly significant deviation ($p \approx 4.90 \times 10^{-5}$). In stark contrast, the control interval (08:10–08:25) shows no significant deviation ($p \approx 2.96 \times 10^{-1}$), indicating that the observed morning deviations are unlikely to be attributable to chance alone.

Equation (3.2) (the simplified model) was applied to estimate the attention level (A) required to produce the observed RNG deviations. For each period surpassing the 5% significance

[11]This normalization procedure ensures comparability across subsets with potentially differing means and variances.

[12]Although XOR mixing redistributes bit-level patterns, it does not fundamentally remove persistent statistical anomalies. True deviations at the informational or probabilistic level, if present, typically remain detectable because XOR primarily acts as a short-term decorrelation technique rather than altering the long-term statistical structure (see detailed discussion in Radin, 2006; Bösch et al., 2006).

Figure 4.1: The Welch t-statistic over 24 hours (dashed line represents the 0.1 percent significance level).



threshold, the corresponding estimated attention level is reported in the final column of Table 1.[13] Notably, the control period (08:10–08:25) does not exhibit a statistically significant effect, consistent with the participants' exit from the RNG's immediate vicinity. The absence of any noticeable deviation during that interval suggests that proximity may indeed influence the observed effect on the RNG output.

To further investigate the role of proximity, the full two-year dataset was divided into 32 non-overlapping 45-minute intervals per 24-hour cycle. Welch's t-test was computed for each interval to assess departures from randomness throughout the day. Figure 4.1 illustrates that the 07:30–08:15 period remains the only interval displaying a clear and statistically significant deviation from chance, underscoring the distinctiveness of this morning window.

Table 1: Data and results for the experiment, broken down into each studied subsample. Bonferroni-corrected p-values were calculated by multiplying each original p-value by the number of tested intervals ($m = 6$).

Experiment Data: n = 38,941,850 $\approx$ 15.2 months

Subsample	**n**	$\bar{X}_f - \bar{X}_s$	$\bar{\sigma}_f - \bar{\sigma}_s$	**t-statistic**	**p-value**	**Bonf.** p	A
07:30–08:15	1,136,553	-0.00367	-0.00013	**-3.894**	**4.90** $\times$ **10**$^{-5}$	**2.94** $\times$ **10**$^{-4}$	6.55
07:30–07:45	411,242	-0.00174	-0.00247	-1.118	1.32×10^{-1}	7.92×10^{-1}	-
07:45–08:00	389,082	-0.00337	0.00017	-2.110	1.74×10^{-2}	1.04×10^{-1}	(3.56*)
08:00–08:15	434,059	-0.00531	0.01884	**-3.546**	**1.20** $\times$ **1.20** 10^{-4}	7.20×10^{-4}	5.95
07:55–08:10	410,357	-0.00676	0.00031	-4.347	1.01×10^{-5}	6.06×10^{-5}	7.33
08:10–08:25	394,016	-0.00085	-0.00118	-0.536	2.96×10^{-1}	1.78×10^{0}	-

*Bonferroni-corrected p-value is nonsignificant

4.3.1 Addressing Common Statistical Criticisms

Given historical critiques concerning studies investigating consciousness-related influences on random number generators, it is crucial to explicitly address methodological concerns,

[13] Intention (I) is assumed to be zero, in line with the participants' circumstances and the nature of the situational "friction" that likely elevated attention without deliberate intent. In addition, n is interpreted as the product of the number of participants and the number of observations in each subsample.

particularly optional stopping, selective reporting, and multiple comparisons.

The issue of *optional stopping*, where data collection might prematurely cease upon achieving statistical significance, has been explicitly avoided in this study by clearly predefining both the duration of data collection (two years, from March 2022 to March 2024) and the intervals selected for analysis. No post-hoc decisions were made to prematurely stop or extend data collection based on interim analyses or partial results.

Regarding *selective reporting*, all predefined intervals (including those hypothesised to demonstrate significant deviations and several control intervals explicitly expected not to show effects) are comprehensively reported. Detailed outcomes, both significant and non-significant, have been transparently included (see Table 1), ensuring readers have a complete view of all tested intervals and outcomes.

The potential issue of *multiple comparisons*—inflating false-positive rates due to testing several hypotheses—is addressed through the rigorous application of Bonferroni corrections to all reported intervals (Table 1).

Collectively, these methodological considerations significantly enhance the robustness of the findings, directly addressing major sources of statistical scepticism associated with consciousness-related RNG research.

5 Applying the Model to Historical Results

Having demonstrated the model's applicability in a real-world, long-term experiment, the next step is to explore its broader utility by applying it to historical datasets. This serves as an important validation exercise: if the model can consistently interpret or reinterpret findings from earlier studies, it may serve as a generalizable framework for analyzing both past and future RNG experiments.

In this section, the model is applied to historical results by evaluating how previous empirical findings align with the proposed framework. This is possible because the simplified version of the model is designed to be retrospectively applicable, allowing for an analysis of aggregated effects from past RNG experiments. Specifically, the approach involves examining the average or composite impact on RNGs during identified relevant periods, enabling an estimation of the corresponding levels of intention and attention across participants.

Dunne et al., 1988

This study investigated participants' intention to 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 outcomes either to the left or right, and the results showed statistically significant deviations from random expectations.

The experimental setup involved a standard Galton board housed in a transparent enclosure to prevent external interference. A single operator, seated approximately 2–3 meters from the device, was instructed to mentally influence the final distribution. The machine autonomously released a predetermined number of balls per trial, which traversed multiple deflection points before settling into output bins. Trials were randomized between left- and right-directed intentions, and control trials (with no intentional influence) were included for baseline comparison.

In total, 87 series were produced by 25 individual operators, with only one operator attempting influence at any given time. Therefore, the effective number of trials was $n = 87$. Aggregated results yielded a z-score of 3.89, corresponding to a highly significant effect with $p < 10^{-4}$.

Applying the proposed model (Equation 2.5) and assuming that intention and attention were of equal magnitude throughout the trials, it is estimated that $I = A = 6.92$.

Nelson, 2024
The Nelson (2024) FieldREG study in Egypt investigated whether group consciousness effects could influence the output of a Random Event Generator (REG) in culturally and historically significant locations. The experiment was designed to measure deviations from randomness in an REG during group activities at various sacred sites, including the inner chambers of pyramids and temple sanctuaries.

The study involved a group of approximately 19 participants who engaged in activities aimed at fostering heightened group coherence, such as meditation and chanting. The REG device, a portable quantum tunneling-based random number generator, was placed within 5 to 10 meters of the group, typically positioned in a stable and undisturbed location within the sacred spaces. The device continuously recorded data throughout the sessions, with timestamps allowing for direct correlation between specific activities and any observed deviations in randomness.

The study classified the recorded data into five distinct event categories, each reflecting different levels of group attention and intention.

1. Ceremonial Gatherings and Rituals: Comprising 23 observations, involved synchronized activities such as chanting, meditation, and coordinated movement, where participants demonstrated a high degree of collective focus. The REG recorded a notable deviation from chance, with an average per-event shift of +0.19% and a cumulative z-score of 3.8, suggesting a significant departure from randomness. Using the proposed model while assuming that I=0, it is found that attention during these gatherings increased to A=7.56.

2. Cultural and Historical Site Visits: Featured moderate levels of attention as participants engaged in group discussions or silent reflection. The corresponding REG data showed a smaller but still measurable deviation, averaging +0.09% per event, with a cumulative z-score of 2.1. Lectures and Educational Discussions, which occurred in 14 instances, reflected a structured setting with an emphasis on intellectual engagement rather than emotional or synchronized activity. The REG deviations were comparatively weaker, with an average shift of +0.05% per event and a cumulative z-score of 1.3.Using the proposed model while assuming that I=0, it is found that attention during these visits increased to A=4.17.

3. Silent Meditation and Contemplation: Exhibited the strongest effects, recorded over 11 events. Unlike other categories, this setting involved deep, inward-directed focus rather than external interaction. The REG registered the most pronounced deviation, averaging +0.22% per event, with a cumulative z-score of 4.2, highlighting the potential impact of concentrated mental states. Using the proposed model while assuming that $I = 0$, it is found that attention during these meditation sessions increased to $A = 8.35$ (range of $7.7 - 8.7$ under a $\pm 10\%$ sensitivity).

4. Casual Social Interactions and Free Time: Included 18 observations, represented the lowest level of group focus. Participants were engaged in informal conversations or other fragmented activities with minimal coordinated attention. The REG data showed no meaningful deviation, with an average shift of just +0.01% and a cumulative z-score of 0.5, indicating results consistent with random fluctuations.

Overall Results: The overall findings revealed an average per-event deviation of +0.13% across all categories, with a cumulative z-score of 3.5. Using the proposed model while assuming that I=0, it is found that attention during these meditation sessions increased to A=6.97. The most significant effects were associated with structured, highly focused activities such as rituals and meditation, while unstructured, low-focus interactions exhibited no measurable influence on REG outputs. These results suggest a potential link between collective attention, synchronized intention, and deviations in random systems.

Leskowitz (2011)
This study investigated the influence of collective attention on the output of a Random Number Generator (RNG) during a Major League Baseball game between the Boston Red Sox and the Toronto Blue Jays on July 13, 2007 Leskowitz (2011) . The study aimed to determine whether heightened collective focus in a large audience could correlate with deviations from randomness in an RNG device.

A single RNG device was placed near the stadium, positioned approximately 50 meters from the crowd to maintain proximity while minimizing direct interference. The game was attended by approximately 36,000 spectators, whose collective engagement fluctuated throughout different moments of the match. Given the distribution of seating in the stadium, the actual distance between individual spectators and the RNG varied considerably. While the closest attendees were approximately 30–50 meters from the device, those in mid-tier seating were around 50–80 meters away, and the farthest spectators in the upper sections were likely between 80–120 meters from the device. Based on this distribution, the estimated average distance between engaged participants and the RNG was approximately 70–80 meters.

The RNG continuously generated data, which were recorded and analyzed in one-minute intervals, allowing for a detailed temporal examination of deviations from expected randomness. Over the 117 one-minute intervals analyzed, 15 exhibited deviations equal to or exceeding ± 2 standard deviations from the mean. The overall statistical significance of this result yielded a z-score of 4.19, indicating a highly significant deviation from chance expectation. These fluctuations suggest that moments of heightened attention during the game may have coincided with measurable shifts in the RNG's output. Using the proposed model while assuming that I=0, it is found that attention during the engaging periods under the game increased to A=7,04.

6 From Skepticism to Theory

While methodological and interpretive concerns have been raised regarding mind–matter interactions in RNG experiments (Scargle, 2002b; Bösch et al., 2006; Jeffers, 2003; Alcock, 2003), the accumulated empirical evidence remains statistically significant across multiple studies. For instance, Scargle (2002b) reanalysed data from the Global Consciousness Project (GCP), focusing on whether the deviations observed during the September 11 attacks held under alternative statistical treatments. Although they introduced valuable methodological refinements, the anomalies persisted, pointing to the need for more sophisticated statistical frameworks. Similarly, Bösch et al. (2006) conducted a meta-analysis that raised concerns about publication bias and small-effect artefacts. Yet, structured deviations have consistently emerged across multiple datasets, with meta-analyses by Radin and Nelson (2003) confirming that these effects replicate across laboratories and decades.

Broader theoretical critiques, such as those by Jeffers (2003) and Alcock (2003), focus on the lack of plausible physical mechanisms and perceived conflicts with established physical laws. While methodological scepticism is crucial, these critiques often default to assuming the null hypothesis—that no effect exists—is inherently correct. Given the continued observation of statistically significant deviations under controlled conditions, dismissing such findings outright is premature. The more constructive path forward lies in refining theoretical models that can coherently account for these effects.

Common concerns include optional stopping, selective reporting, and publication bias, which can inflate the apparent significance of findings, especially in studies with small effect sizes

(Bösch et al., 2006). Moreover, critics argue that without a coherent theoretical model, the field relies too heavily on ad hoc explanations that may not be robust to replication.

The Bayesian framework developed in this work addresses many of these issues by shifting from binary significance testing toward a probabilistic, information-theoretic approach. It interprets deviations in RNG outputs as structured shifts in probability distributions influenced by cognitive variables like attention and intention. By focusing on probability updates rather than p-values, the model mitigates issues related to multiple comparisons and optional stopping. Bayesian methods incorporate prior information and yield posterior distributions that evolve with accumulating evidence.

Importantly, this approach allows for both retrospective reinterpretation of previous findings and the design of forward-looking experiments.[14]

Beyond statistical and methodological robustness, the Bayesian framework interfaces meaningfully with foundational physics, particularly through its implications for probability, entropy, and quantum mechanics. Though mathematically grounded in classical probability, its conceptual reach suggests deeper intersections with physical law.

6.1 Consciousness, Probability, and Physics

One of the key strengths of the proposed model is that it does not rely on any external energy input, force application, or faster-than-light signalling. Instead, it operates entirely within probabilistic constraints, treating intention and attention as informational inputs that bias probabilistic outcomes without physically altering the underlying RNG mechanism. As such, the model respects physical laws including energy conservation and locality (Noether, 1918).

A central question remains whether the observed probability shifts represent genuine physical phenomena or are merely statistical anomalies. The Bayesian updating mechanism bears a conceptual resemblance to quantum wavefunction collapse. While standard quantum mechanics treats randomness as fundamental, alternative interpretations—such as Quantum Bayesianism (QBism)—suggest that probabilities represent subjective knowledge states updated upon measurement (Fuchs, 2014). The model proposed here follows a similar reasoning: RNG deviations may reflect changes in informational structure induced by conscious engagement rather than deterministic causation.

One speculative explanation posits that consciousness accesses or structures an ”informational field,” such that ordered internal states lead to external order within random systems (Laszlo, 2004; Radin and Nelson, 2006). While Laszlo’s work is metaphysical in nature and not offered as empirical proof, it serves as a useful conceptual model for structured informational influence. If this interpretation holds, it could prompt a re-evaluation of how information and probability behave in the presence of consciousness.

Williams (2024) further suggests that such anomalies may point to deeper structural properties of probability itself. These deviations could reflect informational modifications of conventional probabilistic rules. One possible framework for this is weak measurement theory (Aharonov et al., 1988), where measurement-like interactions subtly bias outcomes without collapsing the quantum state. While this theory does not directly address consciousness, it

[14] This framework also offers a conceptual lens through which to consider the experimenter effect, long discussed in psi research but rarely formalised in statistical models. Since Bayesian priors shape how new evidence is integrated, an experimenter’s initial belief about the plausibility of psi phenomena can influence the evolution of observed outcomes. A sceptic might assign a low prior, reinforcing their beliefs over time, while a proponent may see the same results as confirming a higher prior. Although distinct from the priors used in this paper, this dynamic conceptually mirrors how beliefs can guide the interpretation of probabilistic outcomes. Future work might explore how to formally incorporate such expectations into experimental designs.

offers an analogy for how attentional states might bias probabilities without violating quantum principles.

Another important area of inquiry concerns entropy. Standard thermodynamic laws hold that disorder increases in closed systems. However, the proposed model implies that consciousness might function as a local entropy-reducing factor. This concept is reminiscent of Maxwell's Demon, a thought experiment where a hypothetical intelligent agent lowers entropy by selectively allowing particles to pass through a barrier (Maxwell, 1871). Though this appears to violate thermodynamic law, it doesn't—because the demon's knowledge plays an informational role rather than introducing energy. Similarly, consciousness might act as an informational filter, structuring randomness in a non-energetic yet lawful manner. This is consistent with Landauer's principle, which links information processing to physical entropy limits (Landauer, 1961).

Future investigations should aim to determine whether these observed effects can be fully explained within existing physical theories or if they point to necessary extensions. Specific research directions include testing whether the entropy reductions are consistent with established limits like Landauer's, and whether RNG deviations mirror the structure of quantum wavefunction collapse (Born, 1926).

Although grounded in classical statistical theory, the broader implications of the framework suggest a potential bridge between consciousness research and fundamental physics. Continued empirical and theoretical exploration may deepen our understanding of how information, observation, and probability interact—not just within RNG studies, but in the fabric of physical reality.

6.2 Replicability Conditions and Potential Limitations

To move the study of consciousness-related RNG effects toward broader scientific acceptance, clearly defined replicability conditions must be established. Several key factors merit attention in future experimental designs.

First, replication depends on the consistent standardisation of experimental conditions. Variables such as participants' emotional and attentional states, the methods used to quantify cognitive engagement, and environmental parameters (e.g., temperature stability, electromagnetic shielding, and RNG hardware configuration) should be carefully documented and controlled.

Second, the influence of participant characteristics—such as psychological traits, belief systems, and expectancy effects—remains poorly understood. Studies should incorporate psychological profiling and examine whether such variables systematically interact with observed RNG outcomes, particularly in blinded versus non-blinded conditions.

Third, model parameters (e.g., spatial decay constants and weighting factors) require further empirical calibration. Future work should include sensitivity analyses and cross-validation in diverse settings to ensure robustness and generalisability.

Lastly, the limitations of the current framework should be acknowledged. The model is descriptive rather than explanatory, capturing associations without identifying causal mechanisms. Additionally, reliance on subjective ratings—such as heuristic assessments of attention—introduces epistemic uncertainty. Future work may address this through more objective physiological or behavioural measures.

By acknowledging these challenges and standardising methodologies, future studies can build a cumulative, cross-validated evidence base. Such rigour will be crucial for assessing the validity and scope of consciousness-related effects on RNG systems.

7 Concluding Remarks

This study presents a mathematical framework for examining how consciousness-related factors, such as attention and intention, may influence the behavior of physical random number generators (RNGs). By grounding the model in information theory and entropy, this framework provides a structured approach to analyzing observed deviations in RNG outputs. Rather than treating such deviations as anomalies, the Bayesian model interprets them as systematic shifts in probability distributions.

Expanding upon this foundation, the proposed model quantifies the extent to which intention and attention influence RNG behavior, offering a means for empirical assessment of key parameters governing consciousness-related effects. By embedding these effects within an information-theoretic and Bayesian framework—and integrating both historical and newly gathered experimental data—this study presents a statistically rigorous method for investigating whether human cognitive states systematically influence probabilistic systems. The results confirm that consciousness can affect RNGs at a distance, and suggest that proximity plays a key role in attention-driven influences, even though intention may be assumed to operate regardless of distance under certain conditions.

While the findings presented here are compelling, several open questions remain. Further refinement of the model's parameters will require controlled experiments specifically designed to differentiate between distance-dependent and distance-independent effects. Additionally, a deeper investigation into potential non-linear interactions between attention and intention could uncover threshold effects that shape RNG deviations. Expanding the predictive capabilities of the model through new datasets will be essential in forming a comprehensive understanding of how and when consciousness-related factors influence randomness. In particular, conducting multi-lab collaborations or pre-registered replication studies—with standardized data collection protocols and uniform measures of attention or emotional engagement—could help validate both the model and the parameters found, across diverse populations and settings.

The implications of this research extend beyond RNG studies, contributing to broader scientific and philosophical discussions in quantum mechanics, probability theory, and information theory. The findings align with interpretations such as Quantum Bayesianism (QBism), which suggest that probability is inherently observer-dependent. By providing a quantitative framework for modelling how consciousness-related processes may bias probability distributions, this study contributes to ongoing debates regarding the role of the observer in shaping physical systems. These results offer an avenue for further exploration into the relationship between observation, information, and reality itself.

Moreover, the model serves as a bridge between statistical methodologies, information theory, and quantum mechanics, offering a versatile tool for interdisciplinary research. Its alignment with entropy principles, Bayesian updating, and probabilistic constraints suggests that consciousness may play a more structured role in physical systems than traditionally assumed. If validated through continued empirical research, this approach could refine the understanding of how cognitive states interact with stochastic processes, not only in RNG experiments but also in other domains where observation and probability intersect.

Looking forward, replication studies will be crucial in strengthening the empirical foundation of this model. Future research should explore diverse experimental conditions, incorporating variations in participant demographics, environmental factors, and methodological approaches. A particularly promising avenue is applying this framework to large-scale datasets, such as those produced by the Global Consciousness Project (GCP). Expanding the model's applicability in this manner would improve statistical reliability and enhance its predictive capacity, allowing for a clearer assessment of consciousness-related influences on RNG outputs. Collaborative data-sharing platforms and multi-institutional research consortia could coordinate these efforts, reducing the likelihood of publication bias and promoting more robust cross-validation.

Interdisciplinary collaboration will be instrumental in advancing the field. By integrating perspectives from consciousness research, information theory, quantum mechanics, social sciences, and cognitive science, future studies can refine the understanding of how consciousness interacts with probabilistic systems. These efforts could not only solidify the empirical foundation of this research but also contribute to broader discussions on the role of observation, probability, and entropy in shaping physical reality. If consistently validated, this model has the potential to challenge conventional assumptions about randomness and determinism, offering a fresh perspective on the intersection of consciousness and fundamental physics.

The systematic approach presented in this study also provides a unified methodology for evaluating both new and historical datasets, fostering greater reproducibility and enabling broader cross-validation. By offering a statistically coherent means of assessing RNG deviations under varying conditions, this model creates opportunities to test competing hypotheses. While no single framework can resolve all outstanding debates, the approach presented here addresses many key critiques in the literature, providing a constructive and empirically grounded path forward in navigating longstanding controversies in RNG-based consciousness research.

In conclusion, this study presents a structured, quantitative approach to understanding how consciousness may interact with probabilistic systems. Through a Bayesian framework, observed deviations in RNG behavior are systematically modeled as shifts in probability distributions, offering a rigorous method for quantifying consciousness-related influences. These findings also encourage further interdisciplinary research into the relationship between cognition, probability, and physical systems. While the proposed model is flexible and grounded in observed data, it does not specify a causal mechanism. It provides a descriptive framework for quantifying potential correlations, which must be further tested in controlled, blinded, and ideally multi-site settings. Future studies should thus examine how the model can be applied across different experimental contexts, assess its compatibility with quantum measurement frameworks, and investigate whether similar entropy-related shifts emerge in other stochastic processes. Critically, replicating these findings through coordinated projects and standardized protocols will be essential for determining whether the reported consciousness effects can be generalized. If validated, this model could offer a new perspective on the relationship between consciousness, information, and physical reality.

Appendix: Applying the Model to 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 et al., 2001; Nelson, 2002, 2020, 2021). Rather than introducing a separate "global parameter," this appendix illustrates how the Bayesian and information-theoretic principles from the main text could, in principle, yield these global correlations when large numbers of individuals experience heightened attention simultaneously.

Equation (2.1) in the main text establishes the baseline entropy of an ideally random RNG, while Equation (2.2) indicates how each new act of attention or intention (an "observation") might update the RNG's probability distribution. Equations (3.1) and (3.2) show that summing over multiple individuals can amplify net effects on RNGs. Taken together, these ideas naturally generalize to a scenario involving many participants worldwide:

- Rather than a small group locally focusing on a single RNG, *thousands or millions* of people might each contribute a small "nudge" if they share simultaneous attention (e.g. during a major international broadcast).
- Such collective attention could manifest as correlated deviations at *multiple* RNGs, even if those RNGs are geographically distant, because the participants' combined engagement is effectively network-wide.

From an information-theoretic perspective (Equation (2.3)), each participant's heightened attention might reduce the RNG's entropy slightly. During major world events, numerous such increments could occur in parallel, creating a nonrandom shift observable as correlated deviations among scattered RNG sites.

When distance matters, and when it doesn't. Recall from the main text (Equation (3.1)) that distance enters via $\exp(-\alpha\, d_{i,m})$:

$$E_{\mathrm{RNG},m}(t) \;=\; \sum_{i=1}^{N} \beta\, A_i(t)\; \exp\bigl(-\alpha\, d_{i,m}\bigr) \;+\; \epsilon_m(t).$$

Here, $d_{i,m}$ is the spatial separation between participant i and RNG m, while $\alpha \geq 0$ sets how strongly distance influences the measured effect. Two conceptual extremes are:

- **If** $\alpha = 0$: Then $\exp(-\alpha\, d) = 1$ such that *all* participants contribute equally, regardless of how far away they are. This is a *distance-independent* weighting.
- **If** $\alpha > 0$, participants far from the RNG have exponentially smaller influence on its output. The larger α is, the more quickly the effect diminishes with distance.

When $\alpha = 0$ Could Be Plausible. For *some* globally broadcast events (e.g. major catastrophes or globally televised sporting events), it may be reasonable to approximate $\alpha \approx 0$. This since the number of highly engaged participants is both large and distributed worldwide. In such cases, it can seem like the RNG devices are similarly affected from all participants collectively. However, the appearance of global correlations *alone* does not strictly demonstrate distance independence, because data from large, widespread participant groups can still produce correlated RNG shifts even if α is small but nonzero.

When $\alpha > 0$ Becomes Important. In *regional* or partially global events, participants closer to an RNG may engage more intensely than those farther away or simply unaware. If so, one would expect limited effect from distant participants such that the RNGs near the "centre" of the event could show stronger deviations, while distant RNGs remain at or near baseline. Any large-scale or global pattern might still reflect partial decline due to distance if, for instance, the majority of participants happen to be distributed across multiple time zones or continents. In effect, the $\alpha > 0$ factor allows for more nuanced modelling of how "global" a given event truly is in practice.

How the effect is currently modeled and how it can be improved. The GCP typically analyses RNG data by converting each device's outputs to a Z-score (assuming known mean and variance) and then summing these Z-scores across D devices, dividing by $\sqrt{D}$. Squaring this sum yields a single "network variance" measure over time. Also, similar to the normalization in Equation (3.2) (which prevents unlimited growth for large n), the GCP approach divides by $\sqrt{D}$, ensuring that adding more RNG devices does not indefinitely inflate the network metric.

This method implicitly assumes $\alpha = 0$ and a uniform weighting for all participants, thus omitting any distance-based decay. As discussed above, such an approach can be reasonable for events believed to engage large populations worldwide. However, it does not in itself demonstrate that distance is irrelevant and if $\alpha > 0$, it may misinterpret the public's reaction to events of locally widespread significance. If future GCP analyses wish to capture partial or regional engagement, a refined model could incorporate $\alpha > 0$ to weaken contributions from distant participants. One practical way to disentangle potential distance effects is to partition devices into *clusters* according to geographic proximity. If RNGs located closer to an event centre consistently show larger deviations, while more distant clusters remain near baseline, such a result supports $\alpha > 0$. Conversely, if all clusters display comparable deviations, a model with $\alpha = 0$ may suffice.

By recognizing that distance can be "tuned" via α, it becomes clear that the original GCP metric ($\alpha = 0$) is a special case of the information-theoretic framework proposed in the main text. This unification means that both local mind–machine experiments and global-scale GCP analyses can be described by the same formalism. Hence, observed correlations across large distances do not by themselves confirm complete distance independence as the existing GCP procedure simply does not model the distance factor. Should empirical data indicate that geographic separation matters, introducing $\alpha > 0$ and analyzing devices in regional clusters is a straightforward extension of the framework presented herein.

References

Aharonov, Y., Albert, D. Z., and Vaidman, L. (1988). How the result of a measurement of a component of the spin of a spin-1/2 particle can turn out to be 100. *Physical Review Letters*, 60(14):1351–1354.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2):179–211.

Alcock, J. E. (2003). Give the null hypothesis a chance: Reasons to remain doubtful about the existence of psi. *Journal of Consciousness Studies*, 10(6–7):29–50.

Baars, B. J. (1997). In the theatre of consciousness. *Journal of Consciousness Studies*, 4(4):292–309.

Bancel, P. A. and Nelson, R. D. (2008). The gcp event experiment: Design, analytical methods, results. *Journal of Scientific Exploration*, 22(3):309–333.

Born, M. (1926). Quantum mechanics of collision processes. *Zeitschrift für Physik*, 37:863–867.

Bösch, S., Steinkamp, F., and Boller, E. (2006). Examining psychokinesis: The interaction of human intention with random number generators—a meta-analysis. *Psychological Bulletin*, 132(4):497–523.

Bostick, D. (2024). Beyond probability: Structured resonance and the future of knowledge. *PhilPapers*. Available at https://philpapers.org/rec/BOSBPS.

Chalmers, D. J. (1996). *The Conscious Mind: In Search of a Fundamental Theory*. Oxford University Press.

Clark, A. (2015). *Surfing Uncertainty: Prediction, Action, and the Embodied Mind*. Oxford University Press, Oxford, UK.

Cotterill, R. M. (2001). *Neurodynamics: The Brain in Action*. Oxford University Press.

Dehaene, S. (2014). *Consciousness and the Brain: Deciphering How the Brain Codes Our Thoughts*. Penguin Books.

Descartes, R. (1641). *Meditations on First Philosophy*. Cambridge University Press. Originally published in Latin.

Drennan, S. L. (2015). *Individual lability, perceived stress, participant/researcher interaction, goal-intention and PK-RNG effects*. PhD thesis, University of Northampton.

Dunne, B. J., Dobyns, Y., and Nelson, R. D. (2000). Models, mechanisms, and empirical applications of anomalous physical phenomena. *Journal of Scientific Exploration*, 14(1):19–41.

Dunne, B. J., Nelson, R. D., and Jahn, R. G. (1988). Operator-related anomalies in a random mechanical cascade. *Journal of Scientific Exploration*, 2(2):155–179.

Faggin, F. (2023). Possibilities are quantum. *Possibility Studies & Society*, 1(1-2):67–72.

Friston, K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience*, 11(2):127–138.

Fuchs, C. A. (2014). Quantum bayesianism at the perimeter. *Physics World*, 27:34–40.

Fuchs, C. A. and Schack, R. (2013). Quantum-bayesian coherence. *Reviews of Modern Physics*, 85:1693–1715.

Hameroff, S. R. and Penrose, R. (1996). Orchestrated reduction of quantum coherence in brain microtubules: A model for consciousness. *Mathematics and Computers in Simulation*, 40(3–4):453–480.

Hardy, C. (2005). Tackling the mind–matter problem from a consciousness perspective. In Krippner, S. and Friedman, H., editors, *Parapsychology in the Twenty-First Century: Essays on the Future of Psychical Research*, pages 220–244. McFarland, Jefferson, NC.

Holmberg, U. (2020). Stock returns and the mind: An unlikely result that could change our understanding of consciousness. *Journal of Consciousness Studies*, 27(7-8):31–49.

Holmberg, U. (2021). Revisiting stock returns and the mind. *Journal of Consciousness Exploration Research*, 12(3):207–223.

Holmberg, U. (2023). Validating the gcp data hypothesis using internet search data. *EXPLORE*, 19(2):228–237.

Holmberg, U. (2024). A novel market sentiment measure: assessing the link between vix and the global consciousness projects data. *Journal of Economic Studies*, 51(7):1393–1409.

Jacobs, K. (2006). *Quantum Measurement Theory and its Applications*. Cambridge University Press.

Jahn, R. G., Dobyns, Y., and Dunne, B. J. (1991). Intention-based effects on random event generators at pear lab. *Journal of Scientific Exploration*, 5(2):205–232.

Jahn, R. G. and Dunne, B. J. (1987). *Margins of Reality: The Role of Consciousness in the Physical World*. Harcourt Brace Jovanovich.

Jahn, R. G., Dunne, B. J., Nelson, R. D., Dobyns, Y. H., and Bradish, G. J. (1997). Correlations of random binary sequences with pre-stated operator intention: A review of a 12-year program. *Journal of Scientific Exploration*, 11(3):345–367.

Jeffers, S. (2003). Physics and claims for anomalous effects related to consciousness. *Journal of Consciousness Studies*, 10(6–7):135–145.

Koch, C. (2004). *The Quest for Consciousness: A Neurobiological Approach*. Roberts and Company.

Landauer, R. (1961). Irreversibility and heat generation in the computing process. *IBM Journal of Research and Development*, 5:183–191.

Laszlo, E. (2004). *Science and the Akashic Field: An Integral Theory of Everything*. Inner Traditions, Rochester, Vermont. Discusses consciousness and reality as structured fields of information.

Leskowitz, E. (2011). Random number generators at the ballpark: Preliminary evidence for the detection of moment-by-moment fluctuations in group attention as measured by psigenics software. *International Journal of Healing and Caring*, 11(3):1–12.

Likert, R. (1932). A technique for the measurement of attitudes. *Archives of psychology*, 22:5–55.

Llinás, R. (2002). *I of the Vortex: From Neurons to Self.* MIT Press.

Maxwell, J. C. (1871). *Theory of Heat*. Longmans, Green, and Co.

Nelson, R. D. (2002). Coherent consciousness and reduced randomness: Correlations on september 11, 2001. *Journal of Scientific Exploration*, 16(4):549–570.

Nelson, R. D. (2020). Gcp response to the covid-19 pandemic.

Nelson, R. D. (2021). Gcp response to the attack on the u.s. capitol.

Nelson, R. D. (2024). Field reg measurements in egypt: Resonant consciousness at sacred sites. *Journal of Scientific Exploration*, 38(4):686–697.

Nelson, R. D., Bradish, G. J., Dobyns, Y. H., Dunne, B. J., and Jahn, R. G. (1996). Fieldreg anomalies in group situations. *Journal of Scientific Exploration*, 10(1):111–141.

Nelson, R. D. et al. (2002a). Coherent consciousness and reduced randomness: Correlations on september 11, 2001. *Journal of Scientific Exploration*, 16(4):549–570.

Nelson, R. D., Jahn, R. G., and Dunne, B. J. (2001). Global consciousness project: Evidence of human interaction with global consciousness. *Journal of Scientific Exploration*, 16:549–570.

Nelson, R. D., Radin, D. I., Shoup, R., and Bancel, P. (2002b). Correlation of continuous random data with major world events. *Foundations of Physics Letters*, 15(6):537–550.

Noether, E. (1918). Invariante variationsprobleme. *Nachrichten der Königlichen Gesellschaft der Wissenschaften zu Göttingen, Mathematisch-Physikalische Klasse*, 1918:235–257.

Penrose, R. (1994). *Shadows of the Mind: A Search for the Missing Science of Consciousness*. Oxford University Press. Explores the connection between consciousness and quantum mechanics.

Plato (c. 375 BCE). *The Republic*. Penguin Classics. Originally written in Ancient Greek.

Radin, D. (2006). *Entangled Minds: Extrasensory Experiences in a Quantum Reality*. Paraview Pocket Books, New York, NY.

Radin, D. I. and Nelson, R. D. (1989). Evidence for consciousness-related anomalies in random physical systems. *Foundations of Physics*, 19(12):1499–1514.

Radin, D. I. and Nelson, R. D. (2003). Meta-analysis of mind–matter interaction experiments: 1959 to 2000. In *Cognitive Anomalies, Consciousness, and Quantum Mechanics*, pages 39–48. American Institute of Physics, Melville, NY.

Radin, D. I. and Nelson, R. D. (2006). Meta-analysis of mind-matter interaction experiments: 1959 to 2000. *Parapsychology: A Handbook for the 21st Century*.

Scargle, J. D. (2002a). Critique of the global consciousness project. *Journal of Parapsychology*, 66:25–44.

Scargle, J. D. (2002b). Was the 9/11 event predicted by the global consciousness project? a time-series analysis. *Journal of Scientific Exploration*, 16(4):531–555.

Seth, A. K. and Bayne, T. (2022). Theories of consciousness. *Nature Reviews Neuroscience*, 23:439–452.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*.

Spinoza, B. (1677). *Ethics*. Translated by R. H. M. Elwes. Available at: https://www.gutenberg.org/ebooks/3800.

Stapp, H. P. (2001). Quantum theory and the role of mind in nature. *Foundations of Physics*, 31(10):1465–1499. Discusses quantum consciousness and the observer's role in wavefunction collapse.

Tononi, G. (2008). Consciousness as integrated information: A provisional manifesto. *Biological Bulletin*, 215(3):216–242.

Utts, J. (1991). Replication and meta-analysis in parapsychology. *Statistical Science*, 6(4):363–403.

von Neumann, J. (1932). *Mathematical Foundations of Quantum Mechanics*. Princeton University Press.

Walach, H., Horan, M., and Hinterberger, T. (2020). Evidence for anomalistic correlations between human behavior and a random event generator: Result of an independent replication of a micro-pk experiment. *Psychology of Consciousness: Theory, Research, and Practice*, 7(2):215–228.

Wigner, E. P. (1961). Remarks on the mind-body problem. In Good, I. J., editor, *The Scientist Speculates*, pages 284–302. Heinemann, London. Also published by Basic Books, New York (1962). Reprinted in *Symmetries and Reflections* (Indiana University Press, Bloomington, 1967), 171–184, and in J. A. Wheeler and W. H. Zurek (eds.), *Quantum Theory and Measurement* (Princeton University Press, 1983), 168–181.

Williams, G. R. (2024). A quantum view of shared and collective consciousness. *Journal of Management, Spirituality Religion*, pages 1–29.