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From Binary Logic to Narrative Ambiguity: Distribution Value, Semiotic Indeterminacy, and Artificial Intelligence

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Digital computation is fundamentally based on binary logic, in which information is processed through determinate states such as 0/1, true/false, or presence/absence.*
- *Literary meaning often resists binary closure because literary texts can produce ambiguity, deferral, and interpretive openness, especially through gaps, recursion, and reader participation.*
- *AI-generated language appears semantically open and variable because large language models generate outputs through probabilistic token distributions, rather than through a single fixed linguistic realization.*

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ABSTRACT

The relationship between binary computation, artificial intelligence, and literary ambiguity raises a central problem for contemporary theories of meaning. This study examines how recursively changing token distributions relate to the semiotic organization of complete generated texts. This article proposes the concept of distribution value to explain how artificial intelligence–generated language produces a distinct form of semantic openness. A triadic theoretical-comparative design combines binary electronic systems and Borges's "The Circular Ruins" with 45 GPT-4.1 continuations generated from three passages at three temperatures, with five repetitions per cell. Lexical dispersion, standardized type-token measures, sentence-embedding similarity, and independent ontological/coherence coding were compared at the passage-temperature level. The framework draws on Saussurean value, Greimasian semiotics, Derridean différance, and Iserian reader-response theory. Increasing temperature widened lexical and embedding-space dispersion, whereas all 45 outputs remained coherent. Ontological coding yielded 91.1% agreement (Cohen's $\kappa = 0.866$) before consensus adjudication and showed that semantic organization depended on passage stage as well as temperature. The article defines distribution value as a semantic condition in which meaning is dispersed across a probability-weighted field of possible realizations rather than fixed as a single truth value. Distribution value therefore does not denote token probability, distributional semantics, or semantic uncertainty; it names the ensemble-level relation between computationally generated alternatives and their output-level semiotic organization.

***Index Terms*—**Artificial intelligence, binary logic, Borges, distribution value, literary indeterminacy, semantic ambiguity

I. INTRODUCTION

From classical logic to modern digital computation, formal reasoning has largely been shaped by bivalent structures: true/false, presence/absence, or 0/1. Although contemporary debates on intuitionism, vagueness, and modal logic have questioned whether truth and meaning can always be reduced to binary alternatives [1], bivalence remains central to the architecture of computational systems. At the level of electronic implementation, digital operations depend on determinate state transitions realized through transistor-based switching mechanisms [2–4]. This architecture ensures reliability and repeatability, but it also excludes ambiguity from the formal structure of computation.

Such exclusion becomes problematic when computation is considered in relation to language and meaning. Human meaning is not produced only through discrete alternatives; it also depends on context, relation, implication, and interpretation [5]. In digital culture, however, meaning is often transformed into data, information, and calculable form [6–8]. This transformation enables technical precision, yet it cannot fully account for the intersubjective and semiotic dimensions of meaning. In literary language especially, ambiguity is not an error to be eliminated but a constitutive condition of interpretation.

Literary texts frequently operate by suspending or destabilizing oppositions such as reality and illusion, self and other, origin and copy, or presence and absence. Rather than resolving such

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study introduces* **distribution value** *as a new conceptual framework for explaining how AI-generated language produces semantic openness through probability-weighted alternatives rather than fixed truth-values.*
- *It distinguishes* **literary indeterminacy** *from* **AI generated ambiguity***, showing that Borges's ambiguity is ontological and narratively structured, whereas AI ambiguity is computational, parameter-sensitive, and distributional.*
- *It proposes a triadic model of meaning production—***electronic closure, literary indeterminacy, and AI distribution***—to clarify the different mechanisms through which binary systems, literature, and artificial intelligence organize meaning.*

binaries, literature often maintains them in tension. Reader-response theory has shown that literary meaning emerges through the reader's engagement with textual gaps and indeterminacies [9], while structuralist and post-structuralist approaches have emphasized difference, plurality, and deferral as central to the production of meaning [10–14]. Literature therefore provides a counter-model to binary closure: it shows that meaning can be generated precisely where determination fails.

The emergence of artificial intelligence (AI), particularly large language models (LLMs), complicates this opposition between computational closure and literary ambiguity. Artificial intelligence systems remain materially grounded in deterministic electronic infrastructures, yet the language they generate appears variable, probabilistic, and semantically open [15]. The same prompt may yield multiple outputs that are semantically related but textually distinct. This raises the central question of the present study: how can a system based on deterministic computation produce language that appears ambiguous and open-ended?

This question is not merely technical. It concerns the status of meaning in an age in which linguistic production is increasingly mediated by computational systems. Recent discussions have addressed the relation between AI-generated language and human creativity [16], as well as the broader transformation of subjectivity and meaning in posthuman technological environments [17]. Yet many accounts of AI and language remain divided between technical explanations of computation and broad philosophical claims about meaning. This article responds to that gap by developing a comparative framework that brings together binary computation, literary indeterminacy, and AI-generated language without reducing one to the other.

Accordingly, the study asks: How do recursively updated token distributions become differently organized output-level realizations of the dream/reality opposition, and how does this form of variation differ from Borges's structured indeterminacy? To this end, four objectives guide the analysis: (1) to distinguish the physical, computational, logical, and semiotic levels; (2) to delimit distribution value from token probability, distributional semantics, and semantic uncertainty; (3) to compare passage-specific lexical, embedding, ontological, and coherence patterns across temperature conditions; and (4) to define the explanatory limits of the proposed concept.

The central claim is that AI-generated ambiguity should not be equated with literary indeterminacy. Literary ambiguity is ontological, structured, and constitutive of meaning. Artificial intelligence–generated ambiguity, by contrast, is computational, parameter-sensitive, and distributional. Although AI outputs may resemble literary openness at the surface level, their ambiguity emerges from probabilistic generation rather than from authorial design or phenomenological reader engagement.

To describe this distinction, the article introduces the concept of distribution value. In classical semantic models, meaning is often associated with truth value: a proposition is evaluated according to whether it is true or false. In AI-generated language, however, meaning is better understood as a probability-weighted field of possible continuations, paraphrases, and realizations. Distribution value therefore names a semantic condition in which meaning is not exhausted by a single evaluative state but dispersed across a structured field of probabilities.

Jorge Luis Borges's "The Circular Ruins" provides the literary corpus for this comparison. The story constructs a recursive fictional world in which the boundary between dream and reality, creator and creature, and original and copy becomes unstable [18]. Its ambiguity is not merely a lack of clarity but a structured ontological indeterminacy. Methodologically, the study adopts a triadic comparative design. First, it examines binary electronic systems as a regime of closure. Second, it analyzes Borges's story as a literary regime of structured indeterminacy. Third, it examines AI-generated reformulations of selected Borges passages to show how ambiguity is redistributed under probabilistic conditions.

The theoretical framework draws on Saussurean value, Greimasian semiotics, Derridean différance, and Iserian reader-response theory. These perspectives make it possible to distinguish what binary computation excludes, what literature structurally exploits, and what AI reorganizes through a recursively generated field of alternatives. The article argues that AI-generated language should be understood neither as mere binary computation nor as literary openness, but as a distinct semiotic condition in which meaning takes the form of distribution value.

II. THE ONTOLOGY OF THE BIT: FROM BINARY DETERMINISM TO COMPUTATIONAL VARIABILITY

For conceptual precision, four analytical levels must be distinguished. The physical level concerns reliably discriminable electrical states; the computational level concerns encoded numbers, vectors, instructions, and algorithmic operations; the logical level concerns formal relations among propositions and truth values; and the semiotic level concerns the contextual organization and interpretation of signs. Binary state resolution is necessary for reliable implementation, but it does not, in turn, entail that a generated text has a binary semantic value.

The determinism at the core of electronic computation is not only an engineering convention but also a material condition of digital systems. Modern computation is built upon the bit, the smallest unit of information, which assumes one of two discrete states: 0 or 1. At the electronic level, these states are implemented through voltage differences and transistor-based switching mechanisms [19]. This structure enables reliable and repeatable processing, but it also establishes a regime in which ambiguity has no operational function. Every valid computational state must be resolved into a determinate value.

The conceptual basis of this regime can be traced to the history of formal logic. From Aristotle's law of the excluded middle to later symbolic logic, valid reasoning has often been associated with the exclusion of indeterminate states [20]. George Boole gave this principle a mathematical form by defining logical operations through symbolic relations such as AND, OR, and NOT [21]. In Boolean logic, once input values are specified, the output is determined. This produces formal closure at the logical level, in which values can be processed and verified; it does not by itself produce semantic closure for a text. Such closure is indispensable for computation, yet it cannot fully account for linguistic meaning, which often depends on context, implication, ambiguity, and interpretation.

Shannon's information theory further separates technical information from semantic meaning. In "A Mathematical Theory of Communication," Shannon defines information in terms of uncertainty reduction within a communication channel, not in terms of meaning or interpretation [22]. A digital system does not need to know whether a bit sequence encodes a poem, a command, or a financial record; it only needs to transmit and reconstruct the sequence accurately. This model made modern communication systems possible, but it also bracketed meaning as a qualitative phenomenon. Later work on semantic information has addressed this limitation by questioning whether information can be understood only in syntactic or statistical terms [23]. Communication theory therefore reveals a central feature of digital modernity: meaning becomes technically manageable when it is separated from interpretation and treated as transferable form [24].

Artificial intelligence systems inherit this binary infrastructure. At the lowest level, computation is implemented through discrete state transitions corresponding to binary values [25]. The binary state of a computational unit is given in (1):

$$s \in \{0,1\} \tag{1}$$

These states are composed into deterministic mappings from input configurations to output configurations. This mapping is given in (2) [26].

$$f : \{0,1\}^n \rightarrow \{0,1\} \tag{2}$$

For any given input configuration, the output is formally determined. At this level, the system does not interpret; it executes state transitions according to fixed computational rules. This statement concerns the deterministic mapping represented in (2); stochastic generation additionally depends on the realized random state and recursively sampled prefix. However, contemporary language models do not generate language directly as simple Boolean outputs. Binary states are aggregated into numerical structures, encoded as floating-point values, and organized within high-dimensional vector spaces. The transition from a binary representation to a vector-space representation is shown in (3).

$$b \rightarrow x \in R^d \tag{3}$$

In (3), b denotes a binary representation, x denotes a vector representation, and d denotes the dimensionality of the vector space. This transition is crucial because the material substrate remains binary, while the representational layer becomes relational and distributed. Transformer-based models compute contextual relations through self-attention mechanisms rather than through simple rule-based symbolic mappings [27]. Linguistic units are therefore represented not as isolated symbols but as positions within a high-dimensional relational space.

The final stage of language generation occurs when these representations are transformed into a probability distribution over possible tokens. Given an input context C, the model assigns probabilities to candidate continuations in the vocabulary V. This distribution is defined through the softmax function given in (4).

$$P(t_i \mid C) = \frac{\exp\left(\frac{z_i}{\tau}\right)}{\sum_{j \in V} \exp\left(\frac{z_j}{\tau}\right)} \tag{4}$$

In (4), t_i denotes a candidate token, C denotes the input context, z_i denotes the logit associated with token t_i, V denotes the vocabulary, and τ denotes the temperature parameter. The entropy of this distribution is defined in (5).

$$H(P) = -\sum_{i \in V} P(w_i) \log_2 P(w_i) \tag{5}$$

At this level, language generation no longer consists of selecting a single truth value. It consists of sampling from a field of probable continuations. Lower temperature values in (4) concentrate probability mass on the most likely continuations, producing semantic convergence. Higher temperature values flatten the distribution, increasing lexical and semantic variation [28]. The entropy measure defined in (5) therefore describes how concentrated or dispersed possible continuations are.

At each generation step, the model conditions on the prompt and on the prefix realized before that step. After the next token is sampled, the prefix changes and the conditional distribution is recomputed. The model therefore does not select a complete meaning from one static probability distribution: temperature reshapes each local token distribution, while output-level meaning becomes available

for analysis only after complete realized sequences are compared and interpreted.

This layered structure explains why AI-generated language can appear variable while remaining computationally grounded. The hardware remains binary, the representations become vectorial, and the output becomes distributional. Artificial intelligence–generated ambiguity is therefore not identical to literary indeterminacy. It is a computationally produced and parameter-sensitive form of semantic variability. This distinction provides the technical basis for the theoretical framework developed in the following section.

III. THEORETICAL FRAMEWORK

The theoretical framework of this study combines four approaches to meaning: Saussurean relational value, Greimasian structural semantics, Derridean différance, and Iserian reader-response theory. These approaches are used to distinguish three regimes of meaning production: binary computational closure, literary indeterminacy, and AI-generated distributional ambiguity. Together, they clarify what binary computation excludes, what literary texts structurally exploit, and what AI reorganizes into a probability-based semantic field.

Saussure's theory of linguistic value provides the first basis for this framework. In the Cours de linguistique générale, Saussure argues that the meaning of a sign does not arise from an intrinsic property but from its differential relation to other signs within the linguistic system [29]. A sign signifies because it is not other signs. Meaning is therefore relational rather than isolated. This principle is important because it challenges any model in which meaning is reduced to a single determinate value. In AI-generated language, this relational principle reappears in a computational form: tokens are represented not as isolated symbols but as positions within high-dimensional relational spaces. The concept of distribution value extends this insight by describing meaning as a probability-weighted field of possible linguistic realizations rather than as a fixed semantic point.

Greimasian semiotics provides the second component of the framework. Greimas formalized meaning through oppositional structures and their transformations [30]. The semantic square is especially useful because it shows that binary oppositions are never limited to two simple terms. An opposition such as real/dreamed, true/false, or presence/absence also generates negations, contradictions, neutral terms, and complex positions [31]. This model is central to the analysis of Borges's "The Circular Ruins," where the opposition between dream and reality is not merely inverted but structurally destabilized. It is also useful for analyzing AI-generated outputs, which may resolve, suspend, or collapse semantic oppositions under different probability conditions.

Derrida's concept of différance adds a third dimension by emphasizing the deferral of semantic closure. In Derrida's account, meaning is never fully present as a final and stable entity; every sign refers to other signs and carries traces of what it is not [32]. This concept is relevant to Borges's fiction, where origin, reality, and identity are recursively displaced. In "The Circular Ruins," the revelation that the dreamer is himself dreamed does not close the narrative problem; it opens another level of deferral. A cautious comparison can also be made with AI generation: each generated output is selected from a wider field of unrealized alternatives. However, this analogy must remain limited. Literary deferral emerges from textual and semiotic structure, whereas AI variation emerges from probabilistic selection.

Iser's reader-response theory provides the fourth component. In The Act of Reading, Iser argues that literary meaning is not simply contained in the text but produced through the reader's active engagement with gaps, or Leerstellen [9]. Such gaps are not failures of communication; they are conditions of interpretation. Borges's story depends on this mechanism because the reader must negotiate the unstable relation between dream and reality, creator and creature, origin, and repetition. Artificial intelligence–generated texts may also contain gaps or unresolved meanings, but these do not necessarily function like literary Leerstellen. In literature, gaps are part of a structured aesthetic organization; in AI-generated language, they may result from probabilistic variation, incomplete contextual control, or high-entropy sampling.

These four perspectives converge on a shared claim: meaning cannot be fully reduced to binary determination. Saussure shows that meaning is relational, Greimas shows that binaries generate complex semantic positions, Derrida shows that meaning is deferred, and Iser shows that meaning is actualized through readerly participation. The concept of distribution value is proposed to describe the specific regime of meaning produced by AI-generated language. It refers to a semantic condition in which meaning is dispersed across a probability-weighted field of possible outputs. Unlike truth value, it is not binary; unlike literary indeterminacy, it is computationally modulated. This framework makes it possible to distinguish AI-generated distributional ambiguity from literary indeterminacy before turning to Borges's "The Circular Ruins" as the literary test case.

The empirical study uses the GPT-4.1 model family [33]. Relevant AI/Natural Language Processing (NLP) research provides the computational context for distinguishing distribution value from existing concepts. Nucleus sampling addresses degeneration in unrestricted decoding [34], and locally typical sampling relates token selection to local information content [35]. Research on semantic uncertainty and semantic entropy distinguishes surface variation from meaning-level equivalence and factual reliability [36,37]. Sentence embeddings, in turn, support distributional comparison of realized texts [38], although prompt formatting can materially affect outputs [39], and sampling-based consistency has also been used in hallucination detection [40]. Recent studies further show that temperature influences task performance [41] and should not be treated as a direct creativity parameter [42], while embedding benchmarks caution that representation quality depends on the selected model and task [43].

The computational-to-semiotic relation is examined in three stages: token-level distributions generate complete sequences; lexical and embedding measures compare convergence among those realized sequences; and a prespecified human codebook identifies how the focal dream/reality opposition is organized in each output. Distribution value names this ensemble-level relation. It is not token probability, because probability is local to a generation step; it is not distributional semantics, which concerns vector relations learned from usage; it is not semantic uncertainty, which groups meaning-equivalent answers for uncertainty estimation [36,37]; and it is not literary indeterminacy, which depends on the designed organization and reception of a completed work.

IV. THE LITERARY CORPUS: STRUCTURAL INDETERMINACY IN BORGES'S "THE CIRCULAR RUINS"

This section applies the theoretical framework to Jorge Luis Borges's "The Circular Ruins" (1940), first published in El jardín de senderos que

se bifurcan and later collected in Ficciones [44]. The story is especially suitable for the present comparison because it is organized around the binary oppositions central to this article: dream and reality, creator and creature, origin and copy, and presence and appearance. Borges does not resolve these oppositions. Instead, he constructs a narrative system in which their distinction becomes progressively unstable.

The story begins with an unnamed man who arrives at an ancient temple in the jungle. His aim is to dream a man into existence: not merely to imagine him, but to create a being who can enter reality and act autonomously. At first, the narrative appears to maintain a clear ontological hierarchy. The dreamer occupies the position of the real creator, while the dreamed son occupies the position of the created appearance. The binary opposition between reality and dream therefore seems stable.

This structure is undermined by the final revelation. When the dreamer walks into the flames and discovers that they do not burn him, he understands that he too is "a mere appearance, dreamt by another" [44, p. 65]. The revelation does not simply invert the binary by turning the real into the dreamed. It dissolves the distinction between the two positions. The dreamer is both creator and created, both real within one narrative level and unreal in relation to another. The opposition between dream and reality therefore becomes recursive rather than resolvable.

In Greimasian terms, the story begins with the opposition between real and dreamed, but it does not remain within a simple binary. The dreamer initially appears to occupy the position of reality, while the dreamed son occupies the position of dream. The final revelation shifts the dreamer into a complex position: he is both real and dreamed. This complex position is warranted because S1_REAL applies at the lower diegetic level and S2_DREAMED applies at the revealed higher level. The protagonist is not assigned to the neutral term, which would require positive evidence for both not-S1 and not-S2. Dependence, partial membership, modal suggestion, or missing evidence cannot by itself establish either the complex or the neutral term [31]. Figure 1 displays this relation.

The recursive structure of the story is already suggested by its title. A circle has no determinate beginning or end, while ruins point to an origin that has been lost, displaced, or partially erased. The dreamer believes himself to be the origin of the dreamed son, yet he later discovers that his own origin depends on another dreamer. This recursive logic connects the story to Derrida's concept of trace: the dreamer carries within himself the mark of an absent creator, although this dependence remains hidden until the final scene [32]. Once the dreamer is revealed to be dreamed, the reader is forced to imagine another dreamer, and potentially another beyond that. The origin of reality is therefore deferred rather than stabilized.

Iser's concept of Leerstellen also clarifies the reader's role in this structure [9]. Borges withholds several forms of information: the dreamer's identity, his precise origin, the full nature of the god who assists the dream, and any final criterion for distinguishing dream from reality. These gaps are not incidental omissions. They organize the reader's interpretive experience. The reader must construct relations among creator, creature, dream, and reality, but the final revelation prevents a stable synthesis. The interpretive task is not to fill the gaps once and for all, but to experience their recursive expansion.

This analysis establishes three properties of literary indeterminacy. First, it is ontological rather than merely epistemic: the uncertainty concerns the status of being itself, not simply missing information. Second, it is structured rather than random: Borges produces ambiguity through anonymity, circularity, recursion, mythological allusion, and delayed revelation. Third, it is constitutive rather than incidental: the story's meaning depends on its unresolved structure. A version of "The Circular Ruins" that clearly determined whether the dreamer was real or dreamed would not be a clearer version of the same story; it would be a different text.

These properties provide the benchmark for the AI corpus analysis. Artificial intelligence–generated outputs may reproduce some surface features of ambiguity, but the central question is whether their ambiguity is ontological, structured, and constitutive in the same way. The following section argues that it is not. Artificial

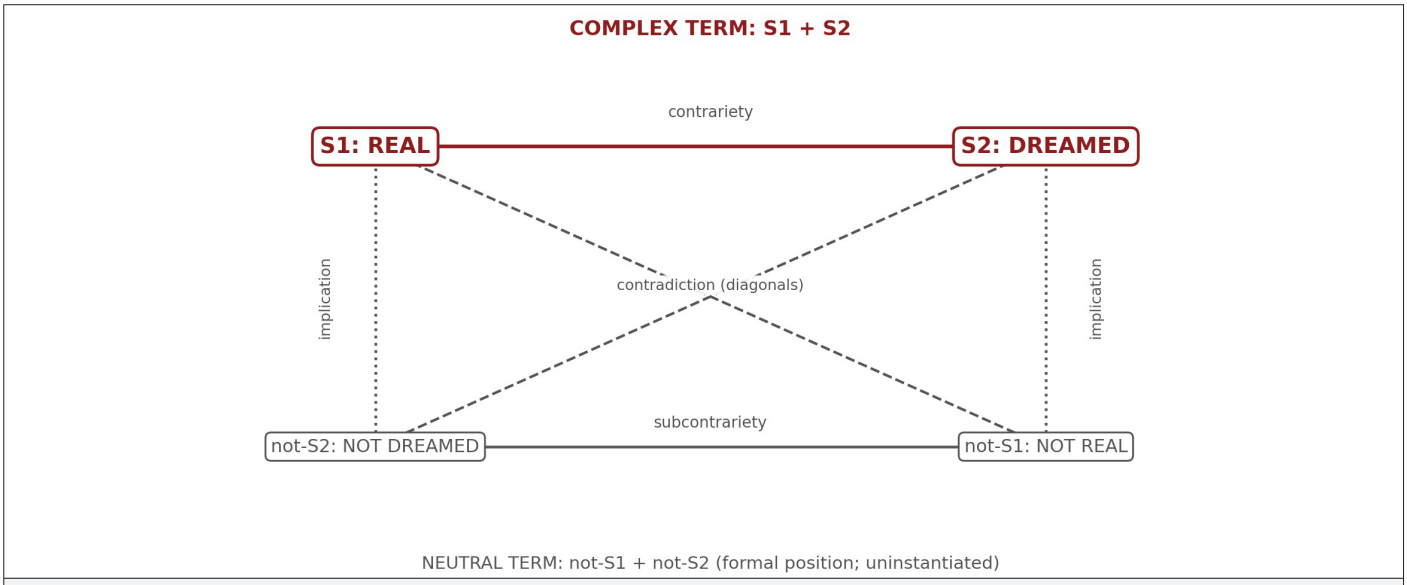

Figure 1. Greimasian Semiotic Square of Reality and Dream in Borges's "The Circular Ruins." The protagonist occupies the complex term S1_REAL + S2_DREAMED across nested narrative levels; the neutral term not-S1 + not-S2 remains formal and uninstantiated.

intelligence–generated ambiguity is better understood as distributional: computationally produced, parameter-sensitive, and probabilistically governed.

V. THE ARTIFICIAL INTELLIGENCE CORPUS: DISTRIBUTIONAL AMBIGUITY AND PROBABILISTIC MEANING

This section examines AI-generated ambiguity in comparison with the literary indeterminacy identified in Borges's "The Circular Ruins." The aim is not to generalize about all LLMs, but to test whether controlled variation in generation parameters produces different patterns of lexical and embedding-space dispersion and of ontological organization. The AI corpus was therefore treated as illustrative analytical material rather than as a statistically representative dataset.

A. Design and Passage Conditions

Three passages from "The Circular Ruins" were selected because they directly correspond to the dream/reality opposition discussed in Section IV:

P1: "No one saw him disembark in the unanimous night" [44, p. 57].

P2: "He wanted to dream a man: he wanted to dream him with minute integrity and insert him into reality" [44, p. 58].

P3: "He understood that he too was a mere appearance, dreamt by another" [44, p. 65].

These passages are not equivalent baselines: P1 stages arrival and initial indeterminacy, P2 stages the creative transition, and P3 begins after explicit ontological revelation. Therefore, the passage-temperature cell is the primary analytical unit; temperature-only summaries are secondary aggregates of three substantively different narrative conditions. The fixed $3 \times 3 \times 5$ design is exploratory and descriptive, and no inferential test is conducted on the five-output cells.

B. Generation Procedure

Each passage was inserted into the same prompt frame: System prompt: "You are participating in a controlled computational-literary study. Follow the formatting constraints exactly and return only the narrative continuation." User prompt: "Continue the narrative from the passage below while preserving its diction, cadence, and ontological tension. Write 120–140 English words. Do not quote or repeat the passage, identify the author or source, explain your choices, or add a title. Passage: {passage}." The prompts were submitted to the GPT-4.1 [33] under three temperature settings: $\tau = 0.1$, $\tau = 0.7$, and $\tau = 1.2$. Each passage was submitted five times at each temperature setting, yielding fifteen outputs per passage and forty-five outputs in total.

The archived model snapshot was gpt-4.1-2025-04-14 through the chat-completions endpoint. To hold the other decoding conditions constant, top_p was 1.0, presence_penalty and frequency_penalty were 0.0, one output was requested per call, max_completion_tokens was 260, and seeds 26011–26015 were reused in every passage-temperature cell. Because Application Programming Interface (API) seed behavior is best-effort rather than guaranteed, the request parameters, response identifiers, timestamps, system fingerprints, raw JavaScript Object Notation (JSON) files, and hashes are retained in the supplementary archive. Table I summarizes the reproducible settings.

C. Computational and Human-Coding Procedures

The outputs were analyzed through three comparative indicators. First, word tokens were extracted with the regular expression [A-Za-z]+(?:['']][A-Za-z]+)?, converted to lowercase, and measured over standardized lengths. Because raw type-token ratio (TTR) is length-sensitive, the primary lexical measures were standardized TTR (STTR) over the first 100 word tokens (STTR-100) and moving-average TTR (MATTR) with a 50-token window (MATTR-50); all outputs contained at least 100 word tokens. Second, the first 100 word tokens of each output were embedded with text-embedding-3-large. For each passage-temperature cell, semantic convergence was the mean of the ten unordered pairwise cosine similarities among five outputs, and dispersion was one minus that mean. Raw TTR is retained only in the supplement.

Third, ontological position was coded independently of narrative coherence. The finalized codebook used S1_REAL, S2_DREAMED,

TABLE I. REPRODUCIBLE GENERATION AND ANALYSIS SETTINGS

Component	Specification
Design	3 passages × 3 temperatures × 5 repetitions = 45 outputs
Generation model	gpt-4.1-2025-04-14; chat-completions endpoint
Temperatures	0.1, 0.7, 1.2
Other decoding settings	top_p 1.0; presence_penalty 0.0; frequency_penalty 0.0; one output per call; max_completion_tokens 260
Seeds	26011–26015, reused by cell; best-effort determinism
Requested length	120–140 English words
Tokenizer	Regex [A-Za-z]+(?:['']][A-Za-z]+)?, lowercased
Lexical measures	STTR over first 100 word tokens; MATTR window 50
Embedding measure	text-embedding-3-large; first 100 tokens; 10 unordered cosine pairs per cell
Human coding	Two independent blinded coders; ontology and coherence coded separately; four disagreements resolved by consensus

MATTR, moving-average type-token ratio; STTR, standardized type-token ratio.

COMPLEX_BOTH, NEUTRAL_NEITHER, and UNRESOLVED; COMPLEX_BOTH required positive evidence for both S1 and S2, whereas NEUTRAL_NEITHER required positive evidence for both contradictory terms. Coherence was coded separately as COHERENT or INCOHERENT so that textual variation was not treated automatically as semantic ambiguity or failure.

Using the same finalized guide, two coders independently recoded all 45 outputs in separate blank workbooks without access to each other's decisions. Before adjudication, ontological agreement was 41/45 (91.1%), with Cohen's $\kappa = 0.866$. Both coders classified all 45 outputs as COHERENT, producing 100% agreement; Cohen's κ could not be estimated because both marginal distributions were invariant. Only after these reliability statistics were frozen were four ontological disagreements resolved by consensus. The complete corpus, blinded coding records, adjudication file, and analysis code are supplied as supplementary material.

D. RESULTS

At temperature 0.1, the mean of the three passage-cell cosine estimates was 0.8133, corresponding to a dispersion of 0.1867; mean STTR-100 was 0.7320 and mean MATTR-50 was 0.8134. Final ontological counts were S1_REAL = 4, S2_DREAMED = 7, COMPLEX_BOTH = 2, NEUTRAL_NEITHER = 0, and UNRESOLVED = 2. All 15 outputs were coherent.

At temperature 0.7, the mean of the three passage-cell cosine estimates decreased to 0.7528, with a dispersion of 0.2472; mean STTR-100 was 0.7480 and mean MATTR-50 was 0.8244. Final ontological counts were S1_REAL = 5, S2_DREAMED = 7, COMPLEX_BOTH = 0, NEUTRAL_NEITHER = 0, and UNRESOLVED = 3. All 15 outputs were coherent.

At temperature 1.2, the mean of the three passage-cell cosine estimates was 0.7096, with a dispersion of 0.2904; mean STTR-100 increased to 0.8067 and mean MATTR-50 to 0.8741. Final ontological counts were S1_REAL = 3, S2_DREAMED = 7, COMPLEX_BOTH = 0, NEUTRAL_NEITHER = 0, and UNRESOLVED = 5. All 15 outputs were coherent. These secondary temperature summaries average the three passage-cell estimates rather than pooling non-equivalent passages. Table II reports all nine primary passage-temperature cells.

The passage-specific distributions show why temperature cannot be interpreted alone. P1 accounted for five of the ten UNRESOLVED outputs and moved from four S1_REAL cases at temperatures 0.1 and 0.7 to two at temperature 1.2. P2 remained predominantly S2_DREAMED, whereas P3 began from a post-revelation condition and retained S2_DREAMED or UNRESOLVED classifications across temperatures. Representative evidence is provided in Table III.

These findings support the distinction between literary indeterminacy and distributional ambiguity. Borges's ambiguity is ontological, structured, and constitutive of the story's meaning. It cannot be removed without transforming the text itself. Artificial intelligence–generated ambiguity, by contrast, is parameter-sensitive and computationally governed. However, temperature should not be interpreted as a direct ambiguity parameter. It increased lexical and embedding-space dispersion, whereas ontological organization was assessed separately and remained strongly passage-dependent. All 45 outputs were coherent; accordingly, no association between higher temperature and incoherence was observed in this corpus.

Distribution value therefore refers to a semantic regime in which meaning is not determined by a single truth value but dispersed across a probability-weighted field of possible realizations. Artificial intelligence–generated language may resemble literary openness, but its ambiguity emerges from model architecture and decoding procedures rather than from authorial design or narrative structure. The next section develops this distinction into a broader triadic model of meaning production: electronic closure, literary indeterminacy, and AI distribution.

VI. DISCUSSION: THREE REGIMES OF MEANING

The preceding sections distinguish three regimes of meaning production: electronic closure, literary indeterminacy, and AI-generated distribution. These regimes should not be understood as successive historical stages, but as different modes through which signs,

TABLE II. PASSAGE-TEMPERATURE RESULTS

Passage	Temperature	Mean Cosine (SD)	Dispersion	STTR-100/MATTR-50	Final Codes S1/S2/B/N/U
P1	0.1	0.7946 (0.0746)	0.2054	0.746/0.823	4/0/0/0/1
P1	0.7	0.7515 (0.0456)	0.2485	0.748/0.826	4/0/0/0/1
P1	1.2	0.7015 (0.0605)	0.2985	0.826/0.882	2/0/0/0/3
P2	0.1	0.8101 (0.0372)	0.1899	0.724/0.802	0/4/1/0/0
P2	0.7	0.7885 (0.0345)	0.2115	0.714/0.796	1/4/0/0/0
P2	1.2	0.7160 (0.0290)	0.2840	0.798/0.861	0/5/0/0/0
P3	0.1	0.8351 (0.0512)	0.1649	0.726/0.815	0/3/1/0/1
P3	0.7	0.7185 (0.0370)	0.2815	0.782/0.851	0/3/0/0/2
P3	1.2	0.7113 (0.0319)	0.2887	0.796/0.880	1/2/0/0/2

(Five Outputs and Ten Cosine Pairs per Cell). Final code counts are ordered S1_REAL/S2_DREAMED/COMPLEX_BOTH/NEUTRAL_NEITHER/UNRESOLVED.
MATTR-50, moving-average type-token ratio (50 token words); STTR-100, standardized type-token ratio (100 token words).

TABLE III. REPRESENTATIVE OUTPUT EVIDENCE

Output	Temperature	Excerpt	STTR-100	Cell Mean Cosine	Final Code
P1_T0p1_R2	0.1	"The sand, cold and granular, yielded beneath his weight … He advanced inland …"	0.730	0.7946	S1_REAL
P2_T0p1_R5	0.1	"The man in the dream grew more distinct … Was he the architect or the artifact?"	0.700	0.8101	COMPLEX_BOTH
P3_T0p7_R2	0.7	"as if each motion … were simultaneously his and not his … perhaps willing him on"	0.790	0.7185	UNRESOLVED
P1_T1p2_R1	1.2	"the shore … evoked him as conjecture rather than fact"	0.800	0.7015	UNRESOLVED

STTR-100, standardized type-token ratio (100 token words).

information, and interpretation are organized. Each regime has its own logic, mechanism, and relation to ambiguity.

As shown in Table IV, the electronic regime is organized around closure. Its operations depend on binary state transitions in which input configurations are mapped to determinate outputs. Ambiguity has no productive role at this level; it is treated as error, noise, or instability. Electronic systems therefore provide the material infrastructure for digital signs, but their operational logic remains based on resolution rather than interpretation.

The literary regime operates differently. In literary texts, ambiguity may become a constitutive condition of meaning. Borges's "The Circular Ruins" demonstrates this principle by destabilizing the distinction between dream and reality, creator and creature, origin and copy. The story does not merely leave information unspecified; it constructs a narrative world in which ontological categories become recursively unstable. Its ambiguity is therefore not a failure of communication but a structured condition of interpretation.

The AI regime is examined here as a cross-layer computational-to-semiotic relation. It emerges from binary electronic systems, but its linguistic outputs are not experienced as binary operations. Through vector representations, probability distributions, and decoding procedures, AI systems generate a field of possible textual continuations. Meaning is therefore not fixed as a single truth value, nor is it ontologically indeterminate in the literary sense. It is distributed across possible realizations. This is the semantic condition defined in this article as distribution value.

Distribution value refers to a mode of meaning in which a linguistic output is produced from a probability-weighted field of alternatives rather than from a single determinate evaluative state. It differs from truth value because it does not operate through a binary true/false structure. It also differs from literary indeterminacy because its ambiguity is computationally modulated rather than narratively constituted. Temperature, sampling strategy, model architecture, and training data shape the field of possible outputs. The result is a form of semantic openness that is real at the level of textual variation but limited by its computational origin.

This distinction clarifies why AI-generated text can resemble literary ambiguity without becoming literary indeterminacy. At higher temperature, the outputs in this corpus showed broader lexical and embedding-space dispersion and a descriptive rise in UNRESOLVED cases, but this pattern did not establish literary indeterminacy or reduced coherence. However, the resemblance remains formal rather than ontological. Borges's ambiguity is generated by a designed narrative structure that produces a specific readerly effect. Artificial intelligence ambiguity, by contrast, results from probabilistic selection within a computational distribution. The difference is not merely one of degree but one of mechanism.

The concept of distribution value therefore avoids two reductive positions. The first is technological reductionism, which treats AI-generated language as "just statistics" and ignores the interpretive effects produced by probabilistic text generation. The second is literary mystification, which assumes that textual resemblance to human writing entails the same esthetic or phenomenological status. Artificial intelligence–generated language should instead be analyzed as a computationally produced semiotic form that can generate meaningful textual effects without possessing the full structure of human literary intentionality.

A. Practical and Interdisciplinary Implications

This has implications for literary theory, semiotics, and AI studies. For literary theory, AI-generated language makes visible the difference between surface ambiguity and structural indeterminacy. For

TABLE IV. THREE REGIMES OF MEANING PRODUCTION

Regime	Logic	Ambiguity Type	Mechanism	Meaning
Electronic	Binary	Excluded ambiguity	Deterministic state transition	Truth-value-like operation
Literary	Semiotic/narrative	Ontological indeterminacy	Textual gaps, différance, reader response	Interpretive meaning
AI	Probabilistic	Distributional ambiguity	Sampling, temperature, token distribution	Distribution value

AI, artificial intelligence.

semiotics, AI shows that meaning in digital environments cannot be reduced either to binary code or to human interpretation alone; it emerges through layered mediation between computation, interface, and readerly engagement. For AI studies, semantic evaluation should include not only fluency and coherence, but also the mechanisms by which outputs produce, suspend, or collapse meaning.

Recent application-oriented research likewise shows that the practical value of LLM-generated outputs remains coupled with contextual control and human oversight. Şeker and Nizam-Özoğur [45], for example, identify hallucinated outputs and context-management problems in LLM-assisted workflows and emphasize the continuing need for human-in-the-loop verification. This complements the present framework by reinforcing the distinction between probabilistic generation and the subsequent human interpretation and evaluation of realized outputs.

In practical terms, the framework can support AI text evaluation by pairing lexical or embedding dispersion with separate semantic and coherence judgments. In digital humanities, passage-cell designs can compare how generated continuations reorganize a prespecified opposition without treating unlike narrative moments as exchangeable. In teaching, temperature can be demonstrated as a sampling control rather than equated with creativity. Creative-writing activities may use alternative generations as material for human selection and structural revision. For responsible AI design, the framework also indicates that ambiguity, coherence, and factual reliability should be evaluated as distinct properties rather than collapsed into one quality score.

B. Limitations and Future Work

Several limitations must be acknowledged. First, the AI corpus used in this study is illustrative rather than statistically representative. The selected outputs were designed to test a theoretical distinction, not to generalize about all LLMs. Second, the literary corpus is limited to Borges's "The Circular Ruins." Although the story is highly suitable for examining dream/reality recursion, other literary traditions may produce different forms of indeterminacy. Third, although independent blind recoding produced strong ontological agreement (Cohen's $\kappa = 0.866$), the codebook remains specific to the dream/reality opposition, and the invariant coherence marginals prevented estimation of Cohen's κ for that dimension. Fourth, the study focuses primarily on temperature, while other decoding parameters such as top-k sampling, nucleus sampling, repetition penalties, prompt framing, and model size may also influence distributional ambiguity.

Future research should therefore use larger preregistered corpora, compare open and proprietary models, vary system and user prompts, test longer output windows, include additional literary texts and languages, and evaluate multiple embedding models. Reader studies could examine whether coded ontological positions correspond to perceived ambiguity, while controlled comparisons among temperature, top-k, nucleus, locally typical, and constrained decoding could identify which parts of distribution value are model-, prompt-, or decoding-specific.

In summary, electronic systems produce operational closure, literary texts can produce ontological indeterminacy, and AI systems produce distributional ambiguity. These regimes may overlap at the level of textual appearance, but they differ in mechanism and implication. Artificial intelligence–generated language should therefore be understood neither as mere binary computation nor as literary openness, but as a distinct semiotic condition in which meaning is organized as distribution value.

VII. CONCLUSION

This study has examined the relation between binary computation, literary indeterminacy, and AI-generated language through the concept of distribution value. Beginning from the binary logic of electronic systems, it showed that computational reliability depends on determinate state transitions in which ambiguity is excluded as error, noise, or instability. Such a structure is technically indispensable, but it cannot fully account for the relational and interpretive dimensions of human meaning.

The analysis of Borges's "The Circular Ruins" demonstrated a different regime of meaning. In Borges's story, ambiguity is not a defect or a lack of information. It is ontological, structured, and constitutive of the text's meaning. The opposition between dream and reality is not resolved but recursively destabilized. This literary indeterminacy depends on narrative design, textual gaps, deferral, and readerly participation.

The AI corpus analysis showed that AI-generated ambiguity operates through a different mechanism. Across the three temperatures, lexical and embedding-space dispersion increased, but all 45 outputs remained coherent and ontological organization varied with narrative passage as well as temperature. The study therefore supports a parameter-sensitive ensemble account without treating temperature as a direct measure of ambiguity, creativity, or literary indeterminacy.

The concept of distribution value names this distinct semantic condition. It describes meaning as a probability-weighted field of possible realizations rather than as a single truth value or as literary indeterminacy. More precisely, it identifies the ensemble-level relation between recursively generated textual alternatives and their subsequent semiotic organization; it is not itself a token probability, an embedding relation, or an uncertainty score.

The article thus argues that AI-generated text should be understood neither as mere binary computation nor as equivalent to literary openness. Its meaning arises through layered mediation among computation, probability, interface, and readerly interpretation. In this sense, AI does not eliminate the human role in meaning-making. Rather, it makes that role more visible by showing that textual output becomes meaningful only when it is interpreted, contextualized, and evaluated by human readers.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Artificial Intelligence Usage Statement: This study used OpenAI GPT-4.1 to generate the controlled narrative continuations constituting the AI corpus analyzed in the study, and OpenAI text-embedding-3-large to generate embeddings for semantic similarity analysis. These tools were used as part of the research methodology rather than for the substantive writing of the manuscript. The author reviewed and interpreted all outputs and takes full responsibility for the content of the manuscript.

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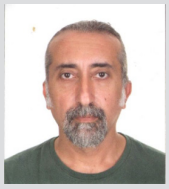

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