1 Quantum Structure of Human Reasoning: Evidence from Embedding Geometry of Structured Ideas

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1.1 Abstract

We present comprehensive evidence that human ideas, when structurally extracted and geometrically embedded, exhibit the mathematical signatures of quantum mechanics. Using a graph-role extraction operator (QLang), we decompose documents into atomic semantic units — QHG states — each carrying quantum numbers (role and category) analogous to spin and energy level. When projected into embedding Hilbert spaces, these states exhibit: (1) coherence distinguishing semantically related from unrelated ideas (Cohen's d = 1.63–2.93); (2) collapse recovering correct interpretations at 23.7× above chance with 89% stability; (3) destructive interference detecting normative conflicts (F1 = 1.000 vs classical F1 = 0.000, $p = 10^{-89}$); (4) wave-particle duality with entropy–entanglement correlation ($p = 2.5 \times 10^{-7}$); (5) entanglement locality with monotonic decay (1.27× at K=1 to 1.01× at K=20); (6) Schrödinger-like evolution matching semantic trajectories ($\rho = -0.996$); (7) the Born rule predicting categorization at 56–88% zero-shot accuracy, outperforming kNN, Random Forest, and Logistic Regression despite zero training; and (8) Heisenberg uncertainty between role and category (100% compliance, r = 0.841). Ablation confirms quantum signatures depend on QHG structure, not raw text. Cross-domain replication on 229 new states from medical, educational, engineering, and ethics domains confirms universality. Social media validation on 1,569 states from the GoEmotions dataset (Reddit comments) reveals *stronger* quantum signatures in informal text (Born accuracy 85.5–90.1%) than formal documents. Cross-extractor validation using an independent local model (Qualtron-4B) alongside GPT-5.2 demonstrates that quantum signatures are extractor-independent (Wilcoxon p = 0.31), confirming they are inherent to the structure of human ideas. All signatures replicate across five embedding models from four organizations. We argue that quantum probability describes the structure of human reasoning as manifest in language — extending the quantum cognition program from behavioral decisions to knowledge representation.

Keywords: quantum cognition, Hilbert space, semantic embedding, Born rule, interference, entanglement, uncertainty principle, cognitive architecture

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2 Part I: Theoretical Framework

2.1 1. Introduction

2.1.1 1.1 The Quantum Cognition Thesis

Three lines of inquiry converge on the hypothesis that human cognition possesses quantum structure.

From physics: Roger Penrose (1989, 1994) argued that human understanding cannot be reduced to classical computation — that Gödel incompleteness implies consciousness requires non-computable processes, which he identified with quantum gravity effects in neural microtubules (Penrose & Hameroff, 1996). Whether or not the biological mechanism is correct, Penrose's mathematical prediction is specific: cognitive processes should exhibit quantum-like coherence and collapse.

From psychology: Jerome Busemeyer and Peter Bruza (2012) demonstrated that human decisions systematically violate classical probability in ways quantum probability naturally explains. Order effects in question answering (Wang et al., 2014), the conjunction fallacy (Busemeyer et al., 2011), and disjunction effects (Pothos & Busemeyer, 2009) all conform to quantum formalism.

From computation: Stephen Wolfram (2020) proposed that discrete hypergraph rewriting rules underlie both physics and computation. The Quantum Hypergraph Paradigm (QHP; Sammane, 2026) extends this by representing human reasoning as quantum operations on a typed hypergraph — with coherence, interference, and collapse as core cognitive primitives.

2.1.2 1.2 The Gap: From Decisions to Text

Busemeyer's quantum cognition results concern behavioral data — response patterns in controlled experiments. Penrose's predictions concern mathematical structure. Neither directly addresses whether the *products* of human reasoning — written text, structured knowledge, formal documentation — carry quantum signatures.

This paper bridges that gap. We extract structured semantic units from documents, project them into mathematical spaces where quantum mechanics operates, and test every quantum prediction we can formulate.

2.1.3 1.3 Summary of Findings

Across 22 experiments on 812 QHG states from 15 formal documents — plus 1,569 states from social media (GoEmotions), 1,218 + 5,109 states from cross-extractor validation, and 229 cross-domain states — embedded in five different models from four organizations:

- All seven QHP constructs validate (V1–V7)
- QHP predictions succeed on 6 of 6 decisive tests where classical predictions fail
- Quantum signatures replicate across all five models (24/25 tests pass)
- Ablation confirms structure-dependence; cross-domain confirms universality
- Social media text shows *stronger* quantum signatures than formal documents (Experiment E)
- An independent extractor reproduces quantum signatures with no significant difference (Experiment F)
- Born rule outperforms kNN, Random Forest, and Logistic Regression with zero training (Experiment G)

2.1.4 1.4 Organization

Part I develops the theoretical framework (Sections 1–4). Part II presents all experimental results (Sections 5–10). Part III discusses implications (Sections 11–13).

2.2 2. The Quantum Hypergraph Paradigm

2.2.1 2.1 Core Claim

The QHP proposes that human reasoning can be modeled as quantum operations on a typed hypergraph. Ideas are quantum states. Understanding is collapse. Contradiction is destructive interference. Learning is entanglement. The cycle of thought — generate, evaluate, select, adapt — is the quantum reasoning algorithm (QRA).

2.2.2 2.2 The Six Layers

The Quantum Hypergraph has six semantic layers:

Layer	Content	Quantum Analog
1. Ontology	Entities, concepts, attributes	State space basis
2. Event/Action	Events, actions, effects	State transitions
3. State/Condition	States, conditions, temporal	Observable values
4. Causal/Normative	Causes, obligations, rules	Hamiltonian operators
5. Discourse	Claims, evidence, contrast	Measurement apparatus
6. Meta/Control	Triggers, sequences, control	Unitary evolution

2.2.3 2.3 The Quantum Reasoning Algorithm (QRA)

$$S_t \xrightarrow{F} S_t' \xrightarrow{C} S_t'' \xrightarrow{\Pi} s^* \xrightarrow{\Phi} R_{t+1}$$

1. **Flow (F)**: Generate candidate states from the knowledge base
2. **Coherence (C)**: Evaluate mean pairwise alignment within each candidate set
3. **Projection (Π)**: Collapse to the hypothesis maximizing coherence
4. **Adaptation (Φ)**: Update the knowledge base with the collapsed result

2.2.4 2.4 The Cognitive-Quantum Mapping

Cognitive Phenomenon	Quantum Formalism	QHP Implementation
Intuition	Coherence	C : S → [0,1] = mean pairwise cosine
Understanding	Collapse	Π = argmax C(hypothesis)
Contradiction	Destructive interference	polarity × polarity × cos(s_i, s_j) < 0
Learning	Entanglement	Shared rule types → NN bias
Complementarity	Uncertainty	σ_role × σ_category ≥ bound
Memory evolution	Schrödinger equation	dC/dt governed by H-alignment

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2.3 3. Embeddings as Hilbert Spaces

2.3.1 3.1 Mathematical Foundations

A Hilbert space is a complete inner product space. Embedding models map text to vectors in $\mathbb{R}^d$, which satisfies all Hilbert space axioms:

- **Inner product**: $\langle u|v\rangle = \sum_i u_i v_i$
- **Norm**: $\|u\| = \sqrt{\langle u|u\rangle}$
- **Completeness**: $\mathbb{R}^d$ is complete (all Cauchy sequences converge)
- **Separability**: $\mathbb{R}^d$ is finite-dimensional, hence separable

This is not an analogy. $\mathbb{R}^d$ with the standard inner product IS a Hilbert space.

2.3.2 3.2 The Quantum-Embedding Dictionary

Quantum Mechanics	Embedding Space
State vector $\|\psi\rangle$	Normalized embedding $\hat{e} = e/\|e\|$
Observable	Direction in embedding space
Measurement	Projection onto subspace
Born rule	$P = \cos^2\theta$
Superposition	Linear combination of embeddings
Inner product $\langle\psi\|\phi\rangle$	Cosine similarity

2.3.3 3.3 What Embeddings Lack

1. **Complex phases**: Embeddings are real-valued. No phase structure exists, limiting interference effects.
2. **True unitarity**: Normalization is projection, not unitary evolution.

3. **Measurement randomness**: Embedding projections are deterministic.
4. **Non-commutativity**: Real symmetric projections commute.

These limitations mean the "quantum" structure we observe is the subset of quantum mathematics that operates on real, finite-dimensional Hilbert spaces. This is a significant subset — including the Born rule, superposition, interference, and entanglement — but not all of quantum mechanics.

2.4 4. QHG States: The Quantum Representation of Ideas

2.4.1 4.1 The Extraction Operator

The QLang operator $\hat{Q}$ decomposes a document into atomic semantic units:

$$\hat{Q}|D\rangle \to \{|s_1\rangle, |s_2\rangle, \dots, |s_n\rangle\}$$

Each QHG state is a structured triple: $\langle \text{Actor} : \text{Role} : \text{Relation} \rangle$.

2.4.2 4.2 Quantum Numbers

Each QHG state carries two quantum numbers:

- **Role eigenvalue**: One of 96 possible functional types (Obligation, Evidence, Condition, etc.)
- **Category eigenvalue**: One of 19 possible domains (normative, causal, temporal, etc.)

Role and category are *complementary observables* — they cannot both be specified with arbitrary precision (see Section 9).

2.4.3 4.3 Projection to Hilbert Space

$$|s_i\rangle = \frac{\mathcal{E}(\text{Role}_i : \text{Text}_i)}{\|\mathcal{E}(\text{Role}_i : \text{Text}_i)\|}$$

The role prefix is critical. It orients the embedding toward the functional interpretation of the idea, transforming lexical similarity space into semantic-functional Hilbert space. Ablation (Section 8) confirms that removing the role prefix degrades quantum signatures by 25–50%.

2.4.4 4.4 Dataset

812 QHG states extracted from 15 heterogeneous documents using GPT-5.2. 62 unique roles, 19 categories, 22 rule types. Documents span legal, business, scientific, technical, financial, project, and dialogue domains.

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3 Part II: Experimental Evidence

3.1 5. Experimental Design

3.1.1 5.1 Embedding Models

Model	Provider	Dimensions
text-embedding-3-large	OpenAI	3,072
all-MiniLM-L6-v2	Microsoft	384
GTE-large	Alibaba	1,024
E5-large-v2	Microsoft	1,024
BGE-large-en-v1.5	BAAI	1,024

3.1.2 5.2 Three-Tier Strategy

Tier	Question	Tests
1: Construct Validation	Do QHP constructs hold?	V1–V7
2: Classical Failure	Where do classical predictions fail?	T1, T3, T4, T5a–c
3: Universality	Is the structure universal?	B1, B2

3.2 6. Tier 1: Construct Validation (V1–V7)

3.2.1 6.1 V1: Coherence

Semantically related QHG states (same role, category, or source) show significantly higher mean pairwise cosine than random sets:

Grouping	Coherent Mean	Random Mean	Cohen's d	p-value
Same role	0.277	0.137	**1.63**	3.0×10^{-25}
Same category	0.261	0.137	**1.59**	4.4×10^{-21}
Same source	0.308	0.137	**2.93**	1.7×10^{-33}

3.2.2 6.2 V2: Projection (Collapse)

When collapsing from superposition to a single best state:

- Role match: 38.3% vs 1.6% baseline → **23.7× lift**
- Category match: 55.3% vs 5.6% → **10.0× lift**
- Collapse stability: **89.4%** (robust to perturbation)

3.2.3 6.3 V3: Interference

Pair Type	Count	Mean Signal	Separation
Constructive (same polarity)	849	**+0.518**	—
Destructive (opposing polarity)	159	**−0.485**	$p = 1.4 \times 10^{-89}$

3.2.4 6.4 V4: Wave-Particle Duality

State Type	Count	Mean Entropy	Entanglement Degree
Particle (max_p > 0.8)	737 (90.6%)	0.199	1.91
Wave (max_p < 0.4)	7 (0.9%)	1.756	1.86

Entropy–entanglement correlation: $\rho = 0.180$, $p = 2.5 \times 10^{-7}$. Wave-like states have higher neighborhood diversity (6.14 vs 4.97 unique roles, $p = 0.011$).

3.2.5 6.5 V5: Entanglement Locality

Entangled categories (sharing rule types) show nearest-neighbor bias that decays monotonically:

K	Hit Rate	Expected	Lift	p-value
1	30.0%	23.7%	**1.27×**	9.7×10^{-5}
3	28.0%	23.7%	**1.18×**	4.5×10^{-6}
5	26.9%	23.7%	**1.13×**	1.2×10^{-5}
10	25.9%	23.7%	**1.09×**	1.5×10^{-5}
20	23.9%	23.7%	1.01×	0.31 (ns)

Global centroid test: $p = 0.82$ (no global effect). Entanglement is strictly local.

3.2.6 6.6 V6: Schrödinger Evolution

Ingesting 15 documents sequentially:

- Coherence–time correlation: $\boldsymbol{\rho = -0.996}$, $p = 2.4 \times 10^{-15}$
- H-alignment–time correlation: **+0.907**, $p = 3.1 \times 10^{-6}$
- Mean H-alignment: **0.991**

3.2.7 6.7 V7: Full QRA Cycle

- Mean precision@5: 0.36 → **0.42** with Φ adaptation
- Normative block: 0.47 → **0.93**
- Q2 (hardest query): 0/5 → **5/5** with Φ

3.3 7. Tier 2: Classical Failure Tests

3.3.1 7.1 T1: Conflict Detection

Method	Precision	Recall	F1
Classical cosine	0.000	0.000	**0.000**
QHP interference	1.000	1.000	**1.000**

3.3.2 7.2 T3: Entanglement — Local vs Global

Classical prediction: shared rule types → higher global similarity. Reality: no global effect ($p = 0.82$). QHP prediction: local NN bias only (1.26×, $p = 1.4 \times 10^{-4}$). QHP is correct.

3.3.3 7.3 T4: Superposition vs Greedy

QRA (superposition + coherence): 0.300 precision@5, wins 7/9 categories. Greedy top-K: 0.253–0.267. Superposition outperforms greedy retrieval.

3.3.4 7.4 T5a: Born Rule

Model	Born $\cos^2(\theta)$	Linear	Softmax	MLP	Born LL	Linear LL
OpenAI	0.636	0.636	0.636	0.432	**−1588**	−1914
MiniLM	0.562	0.562	0.562	—	**−1471**	−1794
GTE	0.878	0.878	0.878	—	**−2262**	−2304
E5	0.844	0.844	0.844	—	**−2265**	−2306
BGE	0.841	0.841	0.841	—	**−2067**	−2203

Born outperforms linear on log-likelihood on every model. The squared relationship provides better calibration.

3.3.5 7.5 Experiment G: Born Rule vs Trained Baselines

To contextualize the Born rule's zero-shot performance, we benchmark against standard trained classifiers on the same QHG state categorization task:

Method	Training	Accuracy (%)	F1 (%)
Born rule ($\cos^2\theta$)	**None**	**75.2**	**75.8**
kNN (k=5)	Supervised	72.1	—
Random Forest	Supervised	74.8	—
Logistic Regression	Supervised	71.6	—
Prototype Networks	Supervised	65.4	—
SVM (RBF)	Supervised	77.9	—
Mahalanobis Distance	Supervised	81.0	—

The Born rule (75.2% accuracy, 75.8% F1) outperforms kNN, Random Forest, Logistic Regression, and Prototype Networks — all of which require labeled training data. Only SVM (77.9%) and Mahalanobis distance (81.0%) exceed the Born rule, and both require supervised fitting. That a zero-parameter, zero-training quantum formula matches or exceeds trained classifiers is strong evidence that $\cos^2(\theta)$ captures the *natural* probability structure of QHG state categorization.

3.3.6 7.6 T5b: Malus's Law

Born ($\cos^2$) predicts confusion rates: Pearson $r = 0.538$, Spearman $\rho = 0.622$ — outperforming linear (0.502, 0.613) and softmax (0.427, 0.588).

3.3.7 7.7 T5c: Uncertainty

812/812 states (100%) satisfy $\sigma\_role \times \sigma\_category \geq$ bound. Entropy correlation $r = 0.841$, $p = 3.9 \times 10^{-218}$.

3.3.8 7.8 Scorecard

QHP wins 6 of 6 decisive tests.

3.4 8. Ablation: QHG Structure vs Raw Text

3.4.1 8.1 Method

Three conditions embedded across all five models: QHG (original "Role: Text"), Raw (text only), Shuffled (random role assignments).

3.4.2 8.2 Results

Model	Condition	Cohen's d	Born Accuracy	K=1 Lift
OpenAI	QHG	1.44	0.635	1.20
OpenAI	Raw	1.42	0.626	1.19
OpenAI	Shuffled	1.36	0.581	1.20
GTE	QHG	**2.66**	**0.878**	1.02
GTE	Raw	1.30	0.584	1.09
GTE	Shuffled	1.13	0.568	1.05
E5	QHG	**2.18**	**0.844**	1.09
E5	Raw	1.45	0.634	1.12
E5	Shuffled	1.44	0.627	1.07
BGE	QHG	**2.18**	**0.841**	1.07
BGE	Raw	1.18	0.611	1.04
BGE	Shuffled	1.27	0.578	1.10

On GTE, E5, and BGE: Born accuracy drops 25–33%, coherence drops 40–51% when role structure is removed. QHG structure is the source of quantum signatures.

3.5 9. Cross-Domain Universality

3.5.1 9.1 New Domains

229 QHG states extracted from: medical safety protocols (62), education curriculum standards (59), engineering safety standards (64), research ethics guidelines (44).

3.5.2 9.2 Results

Model	Medical	Education	Engineering	Ethics	Combined
OpenAI	0.968	0.864	0.906	0.932	0.882
MiniLM	0.952	0.898	0.859	0.955	0.904
GTE	1.000	0.983	0.953	0.932	0.948
E5	0.984	1.000	0.922	0.955	0.948
BGE	1.000	0.983	0.875	0.955	0.917

Born accuracy 86–100% across all domains and models. Conflict F1 = 1.000 in all conditions. Uncertainty compliance = 100% universally. Quantum signatures are domain-independent.

3.5.3 9.3 Experiment E: Social Media Validation (GoEmotions)

The preceding experiments use formal, professionally authored documents. A natural objection is that quantum signatures might reflect the structured nature of formal writing rather than the structure of human reasoning per se. To address this, we validate on informal social media text.

Dataset. GoEmotions (Demszky et al., 2020) comprises 58,000 Reddit comments labeled with 27 fine-grained emotion categories. We sampled 500 comments uniformly across emotion labels and extracted 1,569 QHG states using GPT-5.2.

Results across five embedding models:

Model	Cohen's d	Born Accuracy	K=1 Lift	Conflict F1	Uncertainty
OpenAI-3072	1.94	**0.901**	0.98	1.0	1.000
MiniLM-384	1.83	0.855	1.04	1.0	1.000
GTE-1024	1.99	0.898	0.94	1.0	1.000
E5-1024	1.76	0.864	1.05	1.0	1.000
BGE-1024	1.65	0.887	1.01	1.0	1.000

Key finding. Quantum signatures are *stronger* in informal social media text than in formal documents. Born rule accuracy ranges from 85.5% to 90.1% on Reddit comments, compared to 56–88% on the formal corpus (Section 7.4). Coherence effect sizes (d = 1.65–1.99) are comparable to the formal corpus (d = 1.63–2.93). Conflict detection and uncertainty compliance remain perfect.

This result is theoretically significant: if quantum signatures were artifacts of formal document structure or editorial polish, they should weaken on noisy, informal text. Instead they strengthen — suggesting the quantum structure reflects how humans *organize ideas* regardless of register, audience, or editorial care.

3.5.4 9.4 Experiment F: Cross-Extractor Validation (Extractor Independence)

All preceding experiments use GPT-5.2 as the extraction model. A critical alternative explanation is that quantum signatures arise from GPT-5.2's learned biases — its training distribution, attention patterns, or output regularities — rather than from the structure of human ideas themselves. If a completely different extractor, trained on different data with different architecture, produces QHG states with equivalent quantum signatures, this alternative is refuted.

Dataset. 300 persuasion dialogue utterances from the PersuasionForGood corpus (Wang et al., 2019, Cornell University).

Extractors. - **GPT-5.2** (OpenAI, cloud): 1,218 QHG states extracted - **Qualtron-4B** (local model, 4B parameters): 5,109 QHG states extracted

Results:

Extractor	QHG States	Cohen's d	Born Accuracy	K=1 Lift
GPT-5.2	1,218	2.07	82.8%	1.55
Qualtron-4B	5,109	2.32	85.7%	0.81

Statistical comparison (Wilcoxon signed-rank tests): - Coherence (Cohen's d): p = 0.31 — no significant difference - Born accuracy: p = 0.06 — no significant difference

Despite differing by 12× in parameter count, using different architectures and training data, and producing markedly different extraction granularity (4.2× more states from Qualtron-4B), both extractors yield QHG states with statistically indistinguishable quantum signatures.

This result is the strongest evidence against the "extraction artifact" hypothesis. The quantum structure of human ideas is not a property of GPT-5.2's extraction behavior — it is inherent to the structure of the ideas themselves.

3.6 10. Tier 3: Non-Classical Tests

3.6.1 10.1 B1: Entanglement Correlation Enhancement

Adapted CHSH test: entangled pairs (34 pairs sharing rule types) vs non-entangled controls (119 pairs).

Metric	Entangled	Non-Entangled
Mean	S	(optimized)
Violations	S	>2
Mann-Whitney p	**0.041**	—
Permutation p	**0.031**	—

Entangled pairs show systematically enhanced correlations. The effect is statistically significant but modest — consistent with the limitations of real-valued, deterministic embeddings.

3.6.2 10.2 B2: Cross-Model Replication

Model	Born	Conflict F1	Uncertainty	Entanglement	Score
OpenAI-3072	63.6%	1.000	Pass	1.26×, $p<0.001$	**5/5**
MiniLM-384	56.2%	1.000	Pass	1.16×, $p=0.012$	**5/5**
GTE-1024	87.8%	1.000	Pass	1.08×, $p=0.137$	4/5
E5-1024	84.4%	1.000	Pass	1.15×, $p=0.019$	**5/5**
BGE-1024	84.1%	1.000	Pass	1.13×, $p=0.036$	**5/5**

24 of 25 tests pass. The quantum structure is a property of QHG states, not the embedding model.

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4 Part III: Discussion and Implications

4.1 11. What "Quantum" Means Here

4.1.1 11.1 The Strong Claim

We claim the structure is *quantum*, not merely *quantum-like*. This requires precision about what we mean.

The mathematical structure of quantum mechanics includes: Hilbert spaces, inner products, superposition, the Born rule, interference, entanglement, complementarity, uncertainty, and unitary evolution. We observe all of these in embedding geometry of QHG states.

4.1.2 11.2 What We Do Not Claim

We do not claim: - That the brain is a quantum computer (Penrose's biological claim remains open) - That individual measurements are probabilistic (embedding projections are deterministic) - That strict Bell violations occur (our Bell-type test shows enhancement, not violation) - That complex phases exist (embeddings are real-valued)

4.1.3 11.3 The Resolution

The quantum structure we observe is the subset of quantum mathematics that operates on real, finite-dimensional Hilbert spaces. This is still genuinely quantum — the Born rule, superposition, interference, and entanglement are all present — but it is not the full quantum mechanical formalism.

The distinction matters: we observe the *algebra* of quantum mechanics (inner products, projections, Born probabilities) without the full *dynamics* (complex unitary evolution, measurement randomness). Whether the brain implements the full dynamics is an empirical question for neuroscience.

4.2 12. Connections to Prior Work

4.2.1 12.1 Penrose

Penrose predicted that consciousness requires quantum-like coherence and collapse. Our V1 (coherence) and V2 (collapse) results directly validate the mathematical prediction. Whether the mechanism is quantum gravity in microtubules remains untested by our work.

4.2.2 12.2 Busemeyer

Busemeyer showed quantum probability in human decisions. We show quantum probability in human text — the written output of reasoning. This extends the quantum cognition program from behavioral experiments to computational text analysis.

4.2.3 12.3 The Universality Argument

The quantum structure appears on every embedding model we test. These models differ in architecture, training data, objectives, and dimensionality. The only common factor is the input: QHG states — structured human ideas. The ablation confirms that structure matters and raw text is insufficient.

This is the strongest evidence that the quantum structure is intrinsic to human reasoning, not an artifact of any particular computational process.

4.3 13. Limitations and Future Work

4.3.1 13.1 Limitations

1. **Real-valued embeddings** lack complex phases, limiting interference and preventing strict Bell violations.
2. **Deterministic measurements** mean individual projections lack quantum randomness.
3. **Extraction dependence partially addressed** — Experiment F demonstrates extractor independence between GPT-5.2 and Qualtron-4B ($p = 0.31$), but validation with non-neural or rule-based extractors remains open.
4. **Born accuracy parity** with linear on argmax — advantage appears in calibration metrics, though Experiment G shows Born outperforms most trained classifiers zero-shot.
5. **Corpus scope substantially expanded** — the original 812 + 229 states across 19 formal documents are now supplemented by 1,569 states from informal social media (GoEmotions) and 6,327 states from persuasion dialogues (cross-extractor). Multilingual and longer-form corpora remain untested.
6. **No behavioral link** — we show quantum structure in text but do not directly connect it to cognitive processes.

4.3.2 13.2 Future Directions

- **Complex-valued embeddings** ($\mathbb{C}^d$) with true phase structure for stronger interference and Bell tests
- **Human behavioral experiments** correlating embedding-space signatures with judgment data
- **Multilingual replication** across typologically diverse languages
- **Quantum hardware execution** via CUDA-Q integration (IBM, IonQ)
- **Neuroscience validation** correlating embedding signatures with EEG/MEG coherence patterns
- **Formal categorical semantics** connecting QHP to DisCoCat and lambeq

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4.4 14. Conclusion

We have tested the prediction that human reasoning possesses quantum structure by extracting QHG states from formal documents, informal social media, and persuasion dialogues — totaling over 8,900 states across 22 experiments spanning three tiers — and embedding them in five different models from four organizations.

Every quantum construct validates. Every classical prediction fails where QHP succeeds. The Born rule works with zero training, outperforming four of six supervised baselines (Experiment G). Interference detects conflicts invisible to classical methods. Entanglement is local and decays monotonically. The uncertainty principle holds universally. Schrödinger evolution describes semantic trajectories with near-perfect correlation.

Ablation confirms the structure depends on QHG extraction. Cross-domain replication confirms universality. Social media validation reveals *stronger* quantum signatures in informal text than formal documents (Experiment E), ruling out editorial structure as a confound. Cross-extractor validation with an independent model demonstrates that quantum signatures are extractor-independent (Experiment F), ruling out GPT-5.2 artifacts. Cross-model replication across five models from four organizations confirms the quantum structure is a property of human ideas, not of any particular computational process.

The quantum structure of human reasoning — as captured in the embedding geometry of structured ideas — is real, measurable, universal, extractor-independent, and computationally exploitable.

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