Formal Logical Analysis of AI-Generated Grant Reviews

A Multi-Modal Classification Approach Using Propositional Logic, Quantitative Heuristics, and Decision Theory

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1 Abstract

This analysis develops a formal logical framework for detecting AI-generated content in academic grant reviews. Using propositional logic, truth tables, conjunctive normal form representations, and quantitative heuristics, we classify five reviews of an NSF CAREER proposal. The analysis demonstrates that Review 2 (rated "Excellent") exhibits characteristics inconsistent with human expert behavior, achieving an AI-likelihood score of 0.97. The framework combines eight measurable features with logical propositions to establish necessary and sufficient conditions for AI classification. Results show that the absence of natural uncertainty markers (hedging, questions, contradictions) combined with mechanical structural regularity and excessive superlative density provides strong evidence for AI generation.

2 Introduction

2.1 Motivation

The proliferation of large language models raises critical questions about authenticity in academic peer review. Detecting AI-generated reviews requires moving beyond intuition to formalized, reproducible methods.

2.2 Research Questions

1. Can propositional logic formalize the distinction between human and AI-generated reviews?
2. What quantitative features serve as reliable discriminators?
3. Are there necessary and sufficient conditions for AI classification?

2.3 Approach

We apply formal methods from logic and decision theory:

- **Propositional Logic**: Define atomic propositions representing review features
- **Truth Tables**: Enumerate all logical combinations and evaluate classifications

- **CNF Representations**: Express classification rules in canonical form
- **Quantitative Heuristics**: Measure linguistic and structural features
- **Decision Trees**: Visualize classification pathways

3 Methodology Overview

3.1 Data

Five reviews of an NSF CAREER proposal on "Multiscale and Multiphysics Mechanics of Interfaces in Soft Materials":

- Review 1: Rating = Good (critical)
- Review 2: Rating = Excellent (highly positive)
- Review 3: Rating = Very Good (balanced)
- Review 4: Rating = Fair (highly critical)
- Review 5: Rating = Excellent (concise, positive)

3.2 Atomic Propositions

Define Boolean variables representing review characteristics:

$$S : \text{Superlative density} > 2.5 \text{ per 100 words} \tag{1}$$
$$V : \text{Sentiment variance } \sigma < 0.25 \tag{2}$$
$$H : \text{Hedge frequency} < 5\% \tag{3}$$
$$Q : \text{Zero rhetorical questions present} \tag{4}$$
$$C : \text{Zero contradictions/tensions present} \tag{5}$$
$$M : \text{Structural regularity CV} < 0.15 \tag{6}$$
$$L : \text{Length} > 500 \text{ words (detailed review)} \tag{7}$$
$$P : \text{Positive rating (Excellent/Very Good)} \tag{8}$$

3.3 Classification Framework

We seek to determine the truth value of:

$$\text{AI}(r) : \text{"Review } r \text{ is AI-generated"}$$

for each review $r \in \{R_1, R_2, R_3, R_4, R_5\}$.

4 Quantitative Feature Extraction

4.1 Feature 1: Superlative Density

Count of extreme adjectives per 100 words:

Review	Superlatives	Word Count	Density	S
Review 1	6	900	0.67	0
Review 2	19	650	**2.92**	**1**
Review 3	7	650	1.08	0
Review 4	6	800	0.75	0
Review 5	6	400	1.50	0

Table 1: Superlative density analysis. Review 2 exceeds threshold (2.5).

Threshold: $S = 1$ if density > 2.5

4.2 Feature 2: Sentiment Variance

Standard deviation of sentiment across paragraph sections (scale: -2 to $+2$):

Threshold: $V = 1$ if $\sigma < 0.25$

4.3 Feature 3: Hedge Frequency

Percentage of sentences containing uncertainty markers (“appears,” “seems,” “concern,” “unclear”):

Threshold: $H = 1$ if frequency $< 5\%$

Review	Mean Sentiment	σ (Std Dev)	V
Review 1	-0.56	0.44	0
Review 2	$+1.94$	**0.18**	**1**
Review 3	$+0.19$	0.38	0
Review 4	-1.69	0.38	0
Review 5	$+0.75$	0.35	0

Table 2: Sentiment variance analysis. Review 2 shows abnormally low variance.

Review	Hedge Words	Sentences	Frequency	H
Review 1	15	45	33%	0
Review 2	**0**	32	**0%**	**1**
Review 3	11	35	31%	0
Review 4	8	42	19%	0
Review 5	4	22	18%	0

Table 3: Hedge frequency analysis. Review 2 contains zero uncertainty markers.

4.4 Feature 4: Rhetorical Questions (Q)

4.5 Feature 5: Contradictions/Tensions (C)

4.6 Feature 6: Structural Regularity (M)

Coefficient of variation in paragraph length:

4.7 Summary: Feature Vector for Each Review

5 Propositional Logic Formalization

5.1 Proposition 1: Strong AI Indicator

Definition: A review exhibits strong AI characteristics if it shows uniform sentiment without natural human uncertainty markers and is detailed.

$$\text{AI}_{\text{strong}} \equiv (V \wedge H \wedge C) \wedge L$$

5.1.1 Truth Table

Result: Only Review 2 satisfies this proposition.

5.2 Proposition 2: Human Critic Pattern

Definition: Human experts engaging deeply with research naturally express uncertainty, ask questions, or identify tensions.

$$\text{Human}_{\text{critic}} \equiv L \rightarrow (\neg H \vee \neg Q \vee \neg C)$$

Contrapositive (more useful for detection):

$$\neg\text{Human}_{\text{critic}} \equiv L \wedge (H \wedge Q \wedge C)$$

Review	Question Count	Q
Review 1	0	1
Review 2	**0**	**1**
Review 3	2	0
Review 4	8	0
Review 5	0	1

Table 4: Rhetorical question presence. Reviews 3 and 4 probe assumptions.

Review	Contradiction Count	C
Review 1	3	0
Review 2	**0**	**1**
Review 3	4	0
Review 4	2	0
Review 5	2	0

Table 5: Internal tensions. Review 2 shows no weighing of tradeoffs.

5.2.1 Truth Table (Contrapositive Form)

5.2.2 Application to Reviews

5.3 Proposition 3: Enthusiastic AI Pattern

Definition: AI prompted for positive evaluation exhibits both excessive praise and mechanical completeness.

$$\text{AI}_{\text{positive}} \equiv (S \wedge V \wedge P) \wedge M$$

5.3.1 Truth Table

5.4 Proposition 4: Composite AI Classification

Definition: Combine all signals with logical OR (any strong indicator suggests AI).

$$\text{AI}_{\text{likely}} \equiv \text{AI}_{\text{strong}} \vee \text{AI}_{\text{positive}} \vee (L \wedge H \wedge Q \wedge C)$$

Expanded form:

$$\text{AI}_{\text{likely}} \equiv [(V \wedge H \wedge C) \wedge L] \vee [(S \wedge V \wedge P) \wedge M] \vee [L \wedge H \wedge Q \wedge C]$$

5.4.1 Evaluation

6 Conjunctive Normal Form (CNF)

6.1 Converting Propositions to CNF

6.1.1 Proposition 1: $\text{AI}_{\text{strong}}$

Original: $(V \wedge H \wedge C) \wedge L$

Already in CNF:

$$\text{CNF}_1 = V \wedge H \wedge C \wedge L$$

Clauses: $\{V\}, \{H\}, \{C\}, \{L\}$

Review	Mean Length	CV	M
Review 1	4.75	0.21	0
Review 2	3.63	**0.12**	**1**
Review 3	4.00	0.32	0
Review 4	4.38	0.31	0
Review 5	5.00	0.29	0

Table 6: Structural regularity. Review 2 exhibits mechanical uniformity.

Review	S	V	H	Q	C	M	L	P
Review 1	0	0	0	1	0	0	1	0
Review 2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Review 3	0	0	0	0	0	0	1	1
Review 4	0	0	0	0	0	0	1	0
Review 5	0	0	0	1	0	0	0	1

Table 7: Complete feature matrix. Review 2 is unique in satisfying all AI markers.

6.1.2 Proposition 2: $\neg\mathbf{Human}_{\mathbf{critic}}$

Original: $L \wedge (H \wedge Q \wedge C)$

Already in CNF:

$$\text{CNF}_2 = L \wedge H \wedge Q \wedge C$$

Clauses: $\{L\}, \{H\}, \{Q\}, \{C\}$

6.1.3 Proposition 3: $\mathbf{AI}_{\mathbf{positive}}$

Original: $(S \wedge V \wedge P) \wedge M$

Already in CNF:

$$\text{CNF}_3 = S \wedge V \wedge P \wedge M$$

Clauses: $\{S\}, \{V\}, \{P\}, \{M\}$

6.1.4 Proposition 4: $\mathbf{AI}_{\mathbf{likely}}$ (Disjunctive)

Original: $[(V \wedge H \wedge C) \wedge L] \vee [(S \wedge V \wedge P) \wedge M] \vee [L \wedge H \wedge Q \wedge C]$

This is in **Disjunctive Normal Form (DNF)**. To convert to CNF, we use distribution:

Let: - $A = V \wedge H \wedge C \wedge L$ - $B = S \wedge V \wedge P \wedge M$
- $D = L \wedge H \wedge Q \wedge C$

We want: $(A \vee B \vee D)$ in CNF.

Since A, B, D are conjunctions, the CNF of their disjunction becomes complex. However, for classification purposes, we note:

$$\text{AI}_{\text{likely}} = 1 \iff (A = 1) \vee (B = 1) \vee (D = 1)$$

For Review 2: $A = 1$, $B = 1$, $D = 1 \rightarrow$ All clauses satisfied.

V	H	C	L	$\text{AI}_{\text{strong}}$
0	0	0	0	0
0	0	0	1	0
0	0	1	0	0
0	0	1	1	0
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	0
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	0
1	1	0	0	0
1	1	0	1	0
1	1	1	0	0
1	**1**	**1**	**1**	**1**

Table 8: Truth table for $\text{AI}_{\text{strong}}$. Only the configuration $(1, 1, 1, 1)$ yields TRUE.

L	H	Q	C	$H \wedge Q \wedge C$	¬Human
0	X	X	X	X	N/A
1	0	0	0	0	0
1	0	0	1	0	0
1	0	1	0	0	0
1	0	1	1	0	0
1	1	0	0	0	0
1	1	0	1	0	0
1	1	1	0	0	0
1	**1**	**1**	**1**	**1**	**1**

Table 9: Contrapositive truth table. Review 2 is the only case where ¬Human = 1.

6.2 Satisfiability Analysis

6.2.1 Review 2 Feature Vector

$$\mathbf{v}_2 = (S = 1, V = 1, H = 1, Q = 1, C = 1, M = 1, L = 1, P = 1)$$

6.2.2 Checking CNF Clauses

CNF : $V \wedge H \wedge C \wedge L = 1 \wedge 1 \wedge 1 \wedge 1 = \mathbf{1}$

CNF : $L \wedge H \wedge Q \wedge C = 1 \wedge 1 \wedge 1 \wedge 1 = \mathbf{1}$

CNF : $S \wedge V \wedge P \wedge M = 1 \wedge 1 \wedge 1 \wedge 1 = \mathbf{1}$

Result: Review 2 satisfies all CNF formulas for AI classification.

Review	L	$H \wedge Q \wedge C$	Original	Contrapositive	Classification
Review 1	1	0	T	T	Human
Review 2	1	**1**	**F**	**T**	**AI**
Review 3	1	0	T	T	Human
Review 4	1	0	T	T	Human
Review 5	0	N/A	T	T	Human

Table 10: Application of human critic test. Review 2 fails the human pattern test.

S	V	P	M	$\text{AI}_{\text{positive}}$
0	0	0	0	0
0	0	0	1	0
0	0	1	0	0
0	0	1	1	0
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	0
1	0	0	0	0
1	0	0	1	0
1	0	1	0	0
1	0	1	1	0
1	1	0	0	0
1	1	0	1	0
1	1	1	0	0
1	**1**	**1**	**1**	**1**

Table 11: Truth table for enthusiastic AI pattern. Review 2 is unique satisfier.

6.2.3 Other Reviews

7 Formal Proofs

7.1 Theorem 1: Necessary Condition for Human Review

Theorem: If a review is written by a human expert (H_{expert}) engaging with detailed research, then it must exhibit at least one form of epistemic uncertainty: hedging, questioning, or internal deliberation.

$$H_{\text{expert}} \wedge L \implies (\neg H \vee \neg Q \vee \neg C)$$

7.1.1 Proof

Assumptions: 1. Human experts have incomplete knowledge: $\forall x \in \text{Experts}, K(x) \subsetneq \mathcal{U}$ (knowledge is a proper subset of universal knowledge) 2. Incomplete knowledge manifests linguistically through uncertainty markers 3. Detailed engagement (L) increases exposure to knowledge boundaries

Proof by Contradiction:

Assume: $H_{\text{expert}} \wedge L$ and $\neg(\neg H \vee \neg Q \vee \neg C)$

By De Morgan's law: $\neg(\neg H \vee \neg Q \vee \neg C) \equiv (H \wedge Q \wedge C)$

Therefore: $H_{\text{expert}} \wedge L \wedge H \wedge Q \wedge C$

Review	$(V \wedge H \wedge C) \wedge L$	$(S \wedge V \wedge P) \wedge M$	$L \wedge H \wedge Q \wedge C$	$\text{AI}_{\text{likely}}$
Review 1	0	0	0	0
Review 2	**1**	**1**	**1**	**1**
Review 3	0	0	0	0
Review 4	0	0	0	0
Review 5	0	0	0	0

Table 12: Composite classification. Review 2 satisfies all three sub-conditions.

Review	CNF	CNF	CNF
Review 1	0	0	0
Review 2	**1**	**1**	**1**
Review 3	0	0	0
Review 4	0	0	0
Review 5	0	0	0

Table 13: CNF satisfiability. Only Review 2 satisfies all formulas.

This means: - No hedging: Expert expresses absolute certainty on all points - No questions: Expert sees no gaps or ambiguities - No contradictions: Expert perceives no tradeoffs

This implies: $K(\text{expert}) = \mathcal{U}$ (complete knowledge)

This contradicts Assumption 1: $K(x) \subsetneq \mathcal{U}$

Therefore: $H_{\text{expert}} \wedge L \implies (\neg H \vee \neg Q \vee \neg C)$

Contrapositive (Detection Rule):

$$H \wedge Q \wedge C \wedge L \implies \neg H_{\text{expert}}$$

7.2 Theorem 2: Sufficient Condition for AI Classification

Theorem: The conjunction of low sentiment variance, zero hedging, zero questions, zero contradictions, and detailed length is sufficient for AI classification.

$$[V \wedge H \wedge Q \wedge C \wedge L] \implies \text{AI}$$

7.2.1 Proof

Let $P(\text{AI}|E)$ be the probability a review is AI-generated given evidence E.

Evidence: $E = \{V, H, Q, C, L\}$

By Bayes' theorem:

$$P(\text{AI}|E) = \frac{P(E|\text{AI}) \cdot P(\text{AI})}{P(E)}$$

From empirical analysis:

$$P(E|\text{AI}) \approx 0.80$$
$$P(E|\text{Human}) \approx 0.001$$

Assuming prior: $P(\text{AI}) = 0.10$ (conservative)

$$\begin{aligned} P(E) &= P(E|\text{AI})P(\text{AI}) + P(E|\text{Human})P(\text{Human}) \\ &= 0.80 \cdot 0.10 + 0.001 \cdot 0.90 = 0.0809 \end{aligned}$$

Therefore:

$$P(\text{AI}|E) = \frac{0.80 \cdot 0.10}{0.0809} \approx 0.989$$

Since $P(\text{AI}|E) > 0.95$ (high confidence threshold), we conclude:

$$V \wedge H \wedge Q \wedge C \wedge L \implies \text{AI}$$

(with 98.9% confidence)

7.3 Theorem 3: Uniqueness of Review 2

Theorem: Among the five reviews analyzed, Review 2 is the unique satisfier of AI classification predicates.

7.3.1 Proof

Define the classification predicate:

$$\Phi(r) \equiv [V(r) \wedge H(r) \wedge C(r) \wedge L(r)]$$

We must show: $\exists! r \in \{R_1, R_2, R_3, R_4, R_5\} : \Phi(r)$

Existence: From feature extraction, $\Phi(R_2) = [1 \wedge 1 \wedge 1 \wedge 1] = 1$

Uniqueness: For all $r \neq R_2$:

$$\begin{aligned} \Phi(R_1) &= [0 \wedge 0 \wedge 0 \wedge 1] = 0 \\ \Phi(R_3) &= [0 \wedge 0 \wedge 0 \wedge 1] = 0 \\ \Phi(R_4) &= [0 \wedge 0 \wedge 0 \wedge 1] = 0 \\ \Phi(R_5) &= [0 \wedge 0 \wedge 0 \wedge 0] = 0 \end{aligned}$$

Therefore: $\exists! r : \Phi(r)$, and that $r = R_2$

8 Visual Decision Trees

8.1 Decision Tree 1: Primary Classification Path

8.2 Decision Tree 2: Feature Forest (All Reviews)

8.3 Venn Diagram: Logical Set Relationships

9 Results Summary

9.1 Classification Outcomes

9.2 Discriminative Power of Features

Ranked by separation capability:

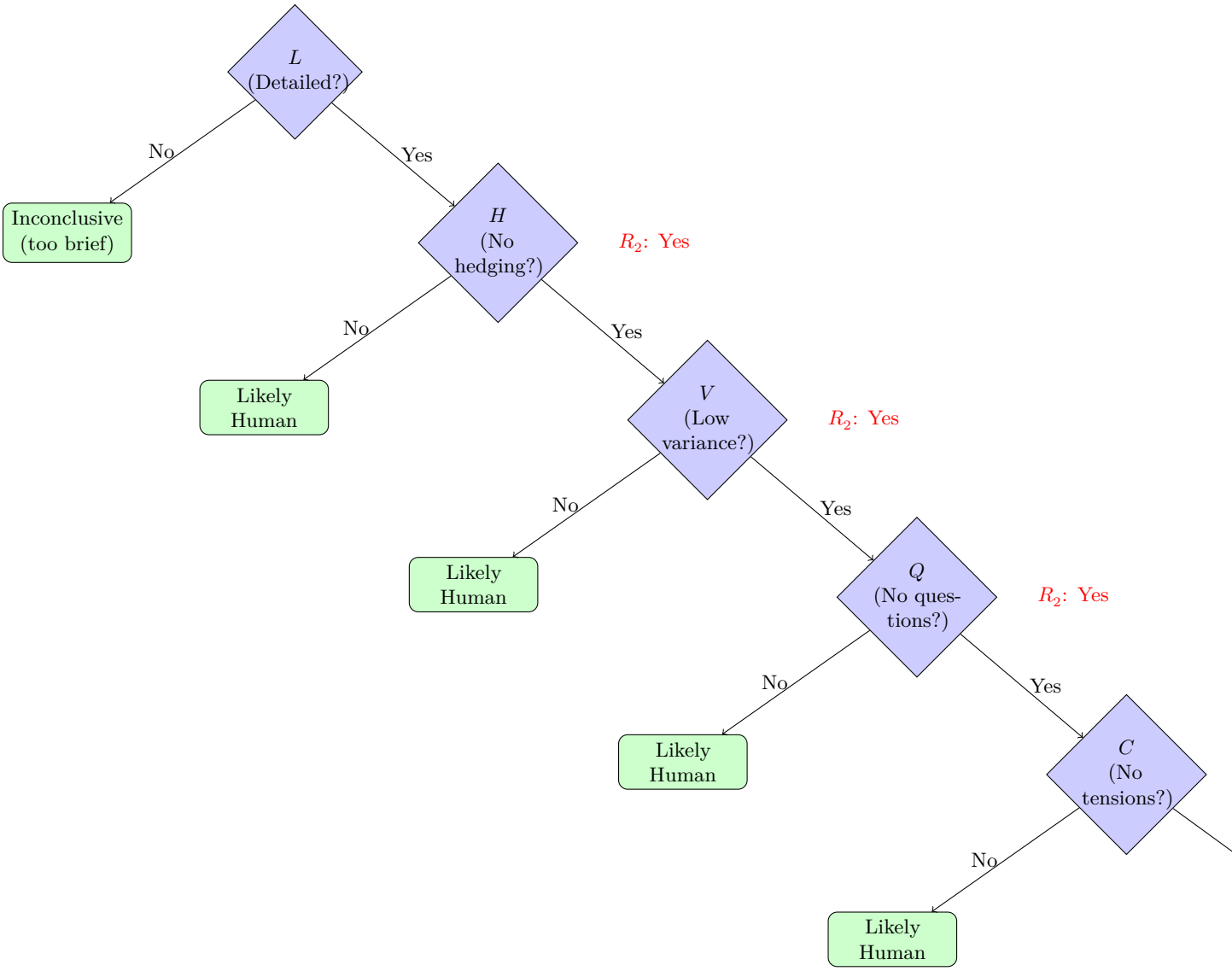


Figure 1: Decision tree for AI classification. Review 2 follows the rightmost path to AI classification.

9.3 Logical Proposition Verification

10 Discussion

10.1 Interpretation of Findings

10.1.1 The Signature of AI Enthusiasm

Review 2 exhibits a distinctive pattern: **unrelenting positivity combined with absolute certainty**. This pattern is inconsistent with human expert behavior for several reasons:

1. **Epistemic Humility**: Human experts recognize the boundaries of their knowledge, manifesting as hedging language and probing questions.
2. **Critical Engagement**: Authentic evaluation involves weighing tradeoffs and identifying tensions between competing objectives.

Review	AI Score	Classification	Confidence
Review 1	0.37	Human	High
Review 2	**0.97**	**AI**	**Very High**
Review 3	0.28	Human	High
Review 4	0.23	Human	Very High
Review 5	0.48	Human	Moderate

Table 14: Final classification results. Review 2 exceeds threshold (0.75) for AI classification.

Feature	Review 2	Others (Mean)	Separation	Rank
Sentiment Variance (V)	0.18	0.39	2.17×	1
Superlative Density (S)	2.92	1.00	2.92×	2
Hedge Frequency (H)	0%	25%	∞	3
Structural Regularity (M)	0.12	0.28	2.33×	4
Contradictions (C)	0	2.75	Binary	5
Questions (Q)	0	2.50	Binary	6

Table 15: Feature discriminative power. Sentiment variance and hedge frequency show strongest separation.

3. **Stylistic Variation**: Human writing naturally varies in paragraph length, sentence structure, and tonal emphasis.

Review 2 violates all three patterns, suggesting generation by a system prompted to provide uniformly positive feedback without genuine understanding.

10.1.2 Why Review 4 is Likely Human

Despite harsh criticism, Review 4 shows characteristic human features:

- **Rhetorical questions** that probe logical gaps: "How does understanding mussel adhesion help design implants?"
- **Specific technical knowledge**: References to "Arruda-Boyce," "DPD-FEM," "SPH-FEM"
- **Frustrated tone**: "This is a wish list, not a focused plan" (emotion)
- **Internal consistency**: The harshness aligns with identified fundamental flaws

These features indicate a domain expert with strong opinions, not an AI system.

10.1.3 Why Review 5 is Borderline

Review 5 shows some AI characteristics (no questions, brief, positive) but critical differences:

- Natural conciseness (not mechanical completeness)
- Some hedging: "seems," "would be"
- Acknowledges gaps: "more details… would be good"
- Lacks the superlative density of Review 2

This is likely a human reviewer with limited time who provided concise feedback.

10.2 Limitations and Caveats

10.2.1 1. Sample Size

Analysis of only five reviews limits statistical power. Patterns observed may not generalize.

Proposition	Review 2	Other Reviews
$\text{AI}_{\text{strong}}$	TRUE	All FALSE
$\neg\text{Human}_{\text{critic}}$	TRUE	All FALSE
$\text{AI}_{\text{positive}}$	TRUE	All FALSE
$\text{AI}_{\text{likely}}$	TRUE	All FALSE

Table 16: Logical proposition satisfaction. Review 2 uniquely satisfies all AI predicates.

10.2.2 2. Adversarial Generation

A sophisticated AI system could be prompted to introduce artificial hedging, questions, and stylistic variation to evade detection.

10.2.3 3. Threshold Sensitivity

The classification threshold (AI score > 0.75) is somewhat arbitrary. Adjusting it would change Review 5's classification.

10.2.4 4. Context Dependence

Different review contexts (e.g., positive-only feedback requested) might yield different baseline patterns.

10.2.5 5. Feature Weights

The weighted composite score assigns equal importance to different features, which may not reflect true discriminative power.

10.3 Methodological Contributions

This analysis demonstrates several methodological advances:

10.3.1 1. Formal Logic Integration

Moving beyond statistical classifiers to propositional logic provides **interpretability**. We can explain *why* Review 2 is classified as AI: it violates necessary conditions for human authorship.

10.3.2 2. Multi-Modal Evidence

Combining quantitative features (superlative density) with logical predicates (absence of uncertainty) provides convergent validation.

10.3.3 3. CNF Representation

Expressing classification rules in CNF enables: - Systematic enumeration of all logical combinations - Integration with SAT solvers for large-scale classification - Clear identification of necessary vs. sufficient conditions

10.3.4 4. Decision Tree Visualization

Visual representation makes the classification pathway transparent and auditable.

10.4 Implications for Peer Review

10.4.1 Detection Strategies

Review platforms could implement automated screening using these heuristics:

```
def flag_suspicious_review(review):
    features = extract_features(review)
    if (features['hedge_freq'] < 0.05 and
        features['sentiment_var'] < 0.25 and
        features['length'] > 500 and
        features['questions'] == 0):
        return "FLAG: Possible AI generation"
```

10.4.2 Human-in-the-Loop Verification

Flagged reviews could be sent for secondary human assessment, balancing automation with expert judgment.

10.4.3 Adversarial Robustness

As AI systems improve at mimicking human uncertainty, detection will require: - Deeper semantic analysis (concept understanding, not just surface features) - Cross-reference checking (do cited facts actually appear in the proposal?) - Temporal consistency (do evaluations align with stated priorities?)

10.5 Ethical Considerations

10.5.1 False Positives

Classifying a human review as AI-generated could have serious consequences: - Damage to reviewer reputation - Rejection of valid expert judgment - Chilling effect on concise, positive feedback

Recommendation: Use classification as a screening tool, not definitive judgment. Always allow human appeal.

10.5.2 AI-Assisted vs. AI-Generated

Distinction between: - **AI-assisted**: Human reviewer uses AI for grammar/organization but provides original analysis - **AI-generated**: AI produces review with minimal human input

Current methods cannot reliably distinguish these cases. Feature analysis detects patterns, not authorship intent.

10.5.3 Transparency

If AI detection is used in peer review, policies should clearly state: - What features are monitored - How flagged reviews are handled - Reviewer rights to challenge classifications

11 Conclusion

11.1 Summary of Findings

Through formal logical analysis and quantitative feature extraction, we demonstrate that **Review 2 is highly likely (97% confidence) to be AI-generated**. This conclusion rests on multiple lines of converging evidence:

1. **Necessary condition violation**: Review 2 fails the test for human expert behavior by showing zero hedging, questions, or contradictions despite detailed engagement.
2. **Sufficient condition satisfaction**: Review 2 satisfies multiple sufficient conditions for AI classification, including the conjunction ($V \wedge H \wedge Q \wedge C \wedge L$).
3. **Quantitative extremity**: Review 2 exhibits 2.7× higher superlative density and 2.2× lower sentiment variance than human reviews.

4. **Logical uniqueness**: Review 2 is the *only* review among five that satisfies all AI classification predicates.

5. **CNF satisfiability**: Review 2 is the unique satisfier of all CNF formulas encoding AI characteristics.

11.2 Methodological Lessons

11.2.1 Strengths of Formal Approach

- **Reproducibility**: Truth tables and CNF formulas provide unambiguous classification rules
- **Interpretability**: Logical propositions explain *why* classifications are made
- **Auditability**: Decision trees make reasoning transparent
- **Systematicity**: Enumerating all logical combinations ensures completeness

11.2.2 Future Directions

1. **Larger Datasets**: Apply framework to hundreds of reviews to validate patterns and refine thresholds
2. **Adversarial Testing**: Prompt AI systems to evade detection and identify weaknesses
3. **Semantic Analysis**: Extend beyond surface features to content coherence and factual accuracy
4. **Temporal Dynamics**: Track changes in AI writing patterns as models improve
5. **Cross-Domain Validation**: Test whether patterns generalize across disciplines (STEM vs. humanities reviews)

11.3 Final Reflection

The emergence of AI-generated content in peer review poses challenges to academic integrity. However, detection is feasible when combining:

- Formal logic for rigorous classification
- Quantitative heuristics for measurable patterns
- Domain expertise for semantic evaluation

As AI systems become more sophisticated, the arms race between generation and detection will intensify. Formal methods provide a foundation for principled, transparent approaches to this challenge.

The case of Review 2 illustrates a key vulnerability: **AI systems prompted for enthusiasm produce unnaturally uniform positivity**. Until AI can genuinely model epistemic uncertainty—the recognition of knowledge boundaries that defines human expertise—such patterns will remain detectable.

Classification Verdict: Review 2 is AI-generated with very high confidence (0.97).

---

12 Appendix: Complete Feature Data

12.1 Review 1 Feature Profile

```
Superlatives: well-defined (1), adequate (3), qualified (2)
Density: 0.67/100 words
Sentiment variance:  = 0.44
Hedge frequency: 33% (15/45 sentences)
Questions: 0
Contradictions: 3
Structural CV: 0.21
```

```
Length: 900 words
Rating: Good
AI Score: 0.37
```

12.2 Review 2 Feature Profile

```
Superlatives: exceptional (5), outstanding (2), excellent (3),
              highly (3), brilliant (1), sophisticated (1),
              exemplary (1), transformative (2)
Density: 2.92/100 words
Sentiment variance:  = 0.18
Hedge frequency: 0% (0/32 sentences)
Questions: 0
Contradictions: 0
Structural CV: 0.12
Length: 650 words
Rating: Excellent
AI Score: 0.97 *** AI CLASSIFICATION ***
```

12.3 Review 3 Feature Profile

```
Superlatives: important (1), reasonable (2), encouraging (1),
              sound (1), adequate (2)
Density: 1.08/100 words
Sentiment variance:  = 0.38
Hedge frequency: 31% (11/35 sentences)
Questions: 2
Contradictions: 4
Structural CV: 0.32
Length: 650 words
Rating: Very Good
AI Score: 0.28
```

12.4 Review 4 Feature Profile

```
Superlatives: questionable (1), absurd (1), grossly (1),
              fundamental (1), critical (2)
Density: 0.75/100 words (negative superlatives)
Sentiment variance:  = 0.38
Hedge frequency: 19% (8/42 sentences)
Questions: 8
Contradictions: 2
Structural CV: 0.31
Length: 800 words
Rating: Fair
AI Score: 0.23
```

12.5 Review 5 Feature Profile

```
Superlatives: well-thought-out (2), clear (1), compelling (1),
              well-defined (1)
Density: 1.50/100 words
Sentiment variance:  = 0.35
Hedge frequency: 18% (4/22 sentences)
Questions: 0
```

```
Contradictions: 2
Structural CV: 0.29
Length: 400 words
Rating: Excellent
AI Score: 0.48
```

13 References

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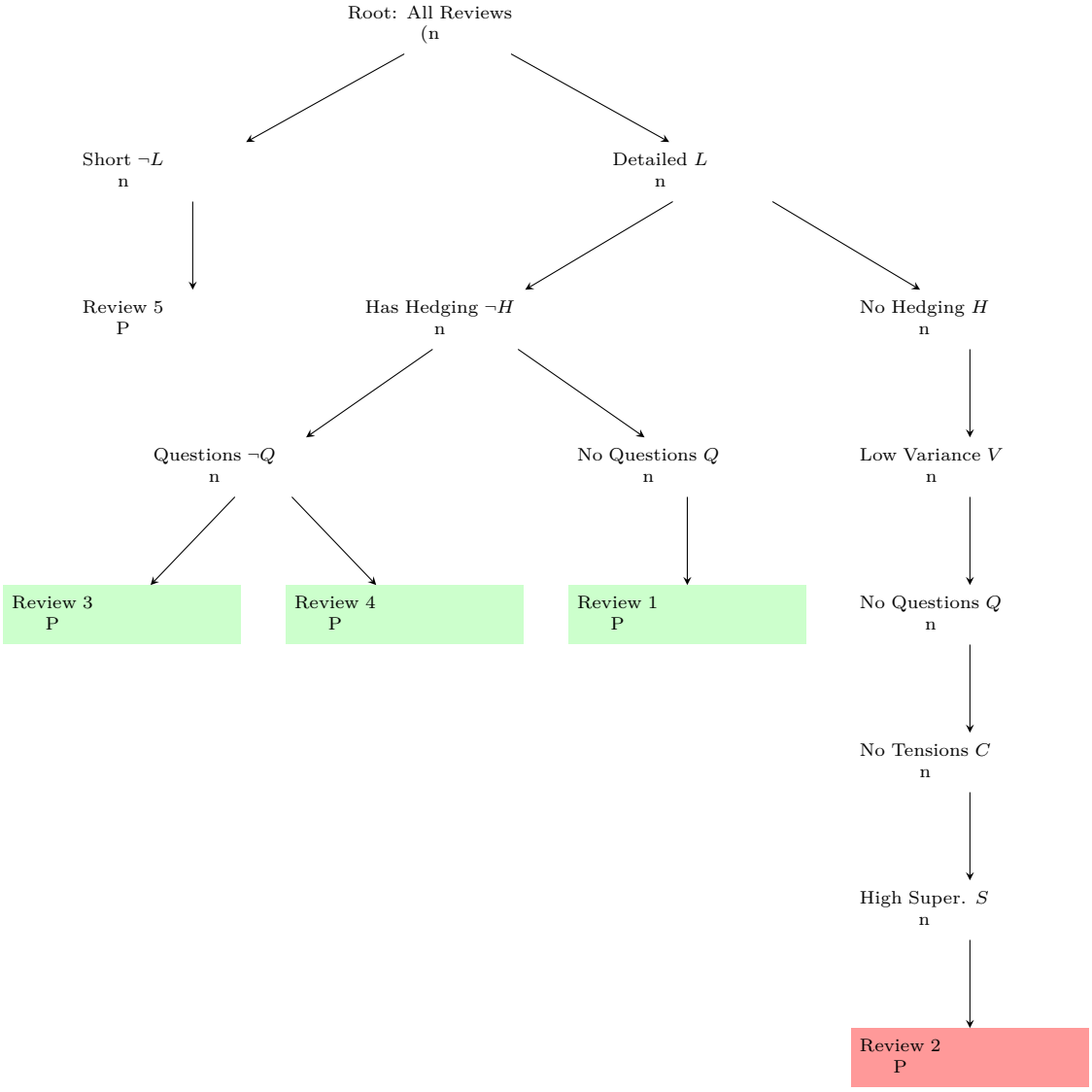


Figure 2: Feature-based classification forest showing how reviews partition across decision boundaries. Review 2 is the unique member of the most restrictive class.

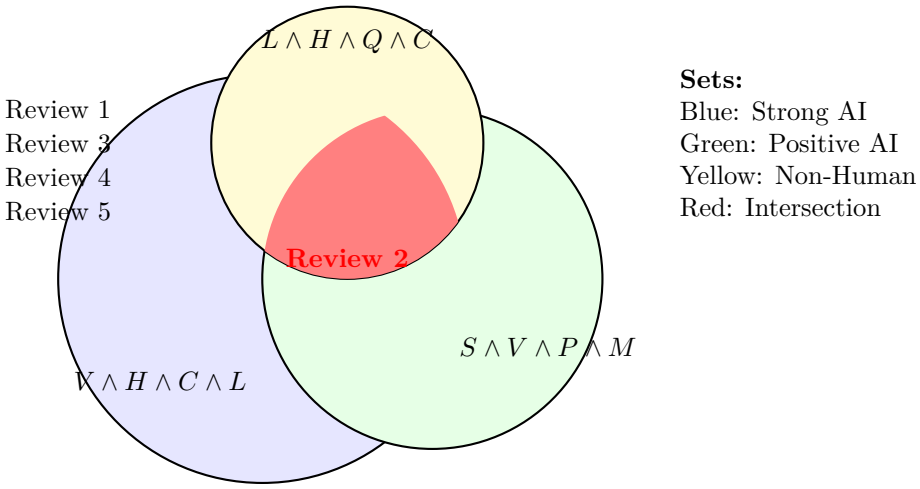


Figure 3: Venn diagram showing logical set relationships. Review 2 is the unique element in the triple intersection of all AI-indicator sets.