Prompt Perturbation Robustness Testing for Large Language Models

CEU MSBA Deep Learning Final Assignment
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Executive Summary

This study investigates the robustness of GPT-4.1 and GPT-4o-mini when subjected to systematic prompt variations in sentiment classification tasks. Through comprehensive experimentation across 16 baseline prompt variants and 2 context enhancement strategies for each model, I demonstrate that model capability significantly outweighs prompt optimization sophistication in determining performance reliability when using current frontier models of OpenAI.

Technical Note

The experimental pipeline includes full support for local Ollama model evaluation (e.g., Qwen, Mistral, LLaMA variants) through flexible model architecture. However, due to time constraints, the focus remains on OpenAI model comparison as a foundation for future research.

Research Question & Experimental Design

"How robust are foundation models when prompts are slightly modified?"

I conducted controlled experiments using the Stanford Sentiment Treebank v5 (SST-5) dataset for 5-class sentiment classification (Very Negative, Negative, Neutral, Positive, Very Positive) on 50 balanced test samples. The experimental design employed a 2×2×2×2 factorial structure across four dimensions:

- **Formality**: Formal vs Casual language register
- **Phrasing**: Imperative vs Question format
- **Order**: Task-first vs Text-first instruction placement
- **Synonyms**: Set A ("analyze", "sentiment", "classify") vs Set B ("evaluate", "emotion", "categorize")

This systematic approach generated 16 baseline prompt variants. Additionally, I tested context enhancement through a 2×2 design examining prefix and suffix positioning of few-shot examples across the two best-performing baseline variants.

Ex-ante Hypothesis: Based on traditional NLP conventions, formal + question + task-first + Set A combinations were expected to perform best, employing precise technical terminology and questioning format for careful analysis.

Evaluation Metrics

1. MSE-Based Custom Accuracy The primary metric employs Mean Squared Error calculation with ordinal encoding that emphasizes polarity preservation over intensity precision:

- Very Negative = -3
- Negative = -2
- Neutral = 0
- Positive = 2
- Very Positive = 3

This encoding structure penalizes cross-polarity errors (positive ↔ negative) more severely than adjacent category errors (e.g., Negative ↔ Very Negative), reflecting real-world deployment priorities where sentiment direction matters more than precise intensity discrimination.

2. Group Consistency Group consistency measures prediction agreement across prompt variants within each model. For each test sample, I calculate the percentage of variants that agree on the most frequent prediction, then average this across all test samples. This metric quantifies model stability independent of ground truth accuracy, providing insight into deployment reliability across prompt formulations.

3. Weighted Index A composite metric combining accuracy and consistency: 0.7 × accuracy + 0.3 × consistency, emphasizing accuracy while accounting for stability across variations.

Performance Analysis

Model Performance Summary

	custom_accuracy_mean	custom_accuracy_std	custom_accuracy_min	custom_accuracy_max	model_consistency_mean	weighted_index_mean
gpt-4.1	0.968	0.007	0.952	0.974	0.955	0.964
gpt-4o-mini	0.952	0.013	0.928	0.976	0.896	0.936

GPT-4.1 demonstrates superior performance across both accuracy (μ=0.968 vs 0.952) and consistency (0.955 vs 0.896) metrics, with notably lower variance (σ=0.007 vs 0.013), indicating robust performance across prompt variations.

Best and Worst Performing Combinations

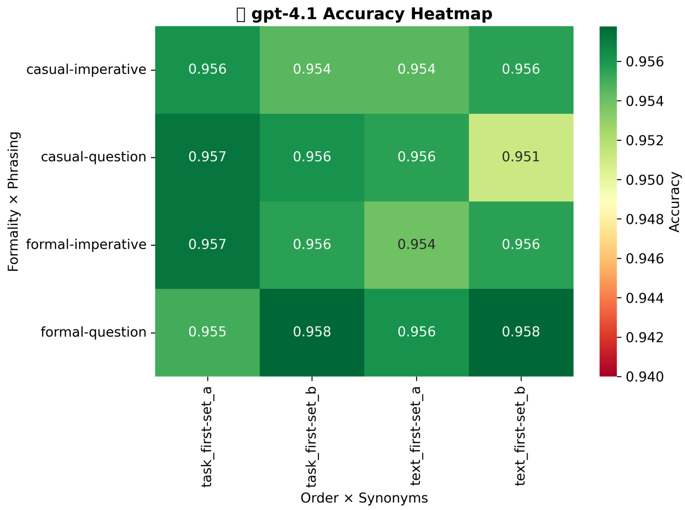
Top 5 Performers

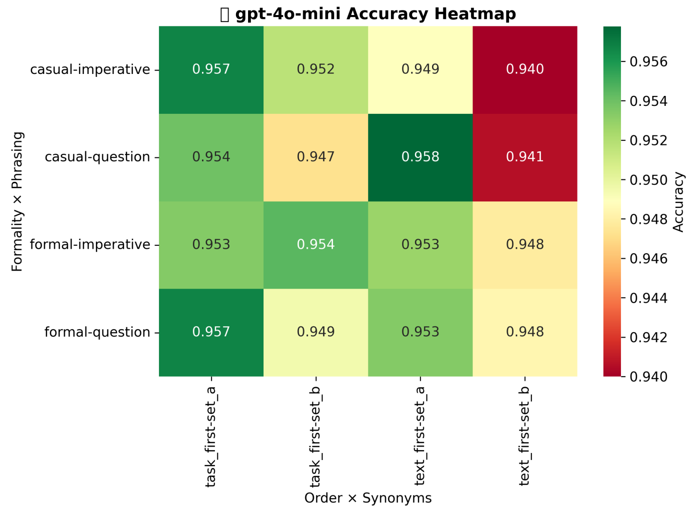
model	variant_id	formality	phrasing	order	synonyms	custom_accuracy	weighted_index
gpt-4o-mini	v15	casual	question	text_first	set_a	0.976	0.951
gpt-4.1	v11	casual	imperative	text_first	set_a	0.974	0.97
gpt-4.1	v15	casual	question	text_first	set_a	0.974	0.97
gpt-4.1	v3	formal	imperative	text_first	set_a	0.974	0.97
gpt-4.1	v7	formal	question	text_first	set_a	0.974	0.97

Bottom 5 Performers

model	variant_id	formality	phrasing	order	synonyms	custom_accuracy	weighted_index
gpt-4o-mini	v10	casual	imperative	task_first	set_b	0.928	0.918
gpt-4o-mini	v6	formal	question	task_first	set_b	0.936	0.924
gpt-4o-mini	v14	casual	question	task_first	set_b	0.936	0.924
gpt-4o-mini	v2	formal	imperative	task_first	set_b	0.942	0.928
gpt-4o-mini	v12	casual	imperative	text_first	set_b	0.942	0.928

Analysis reveals that GPT-4o-mini exhibits sensitivity to Set B synonyms and task-first ordering, while GPT-4.1 maintains consistent performance across dimensional variations.



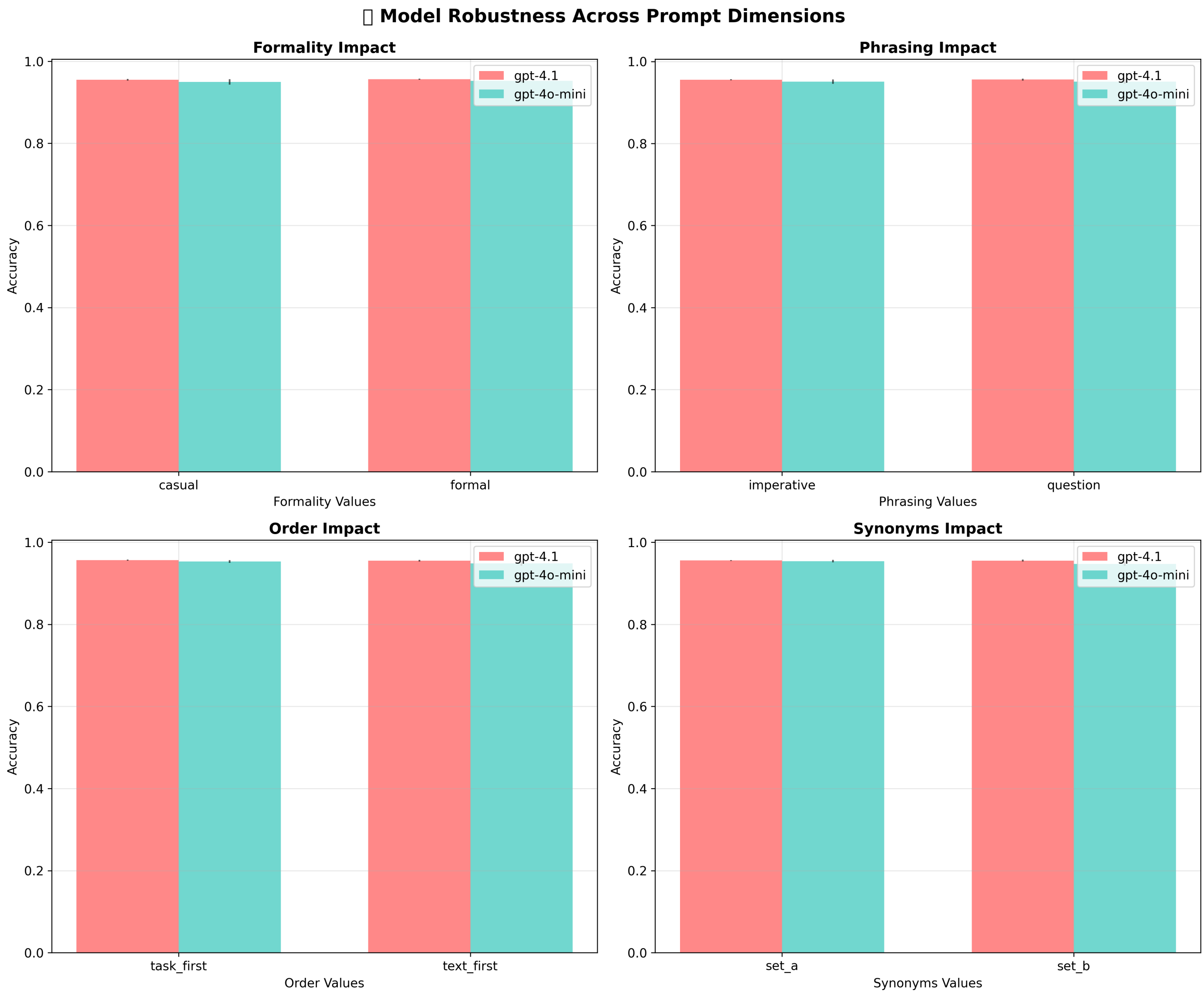


Statistical Analysis

Dimensional Impact Testing

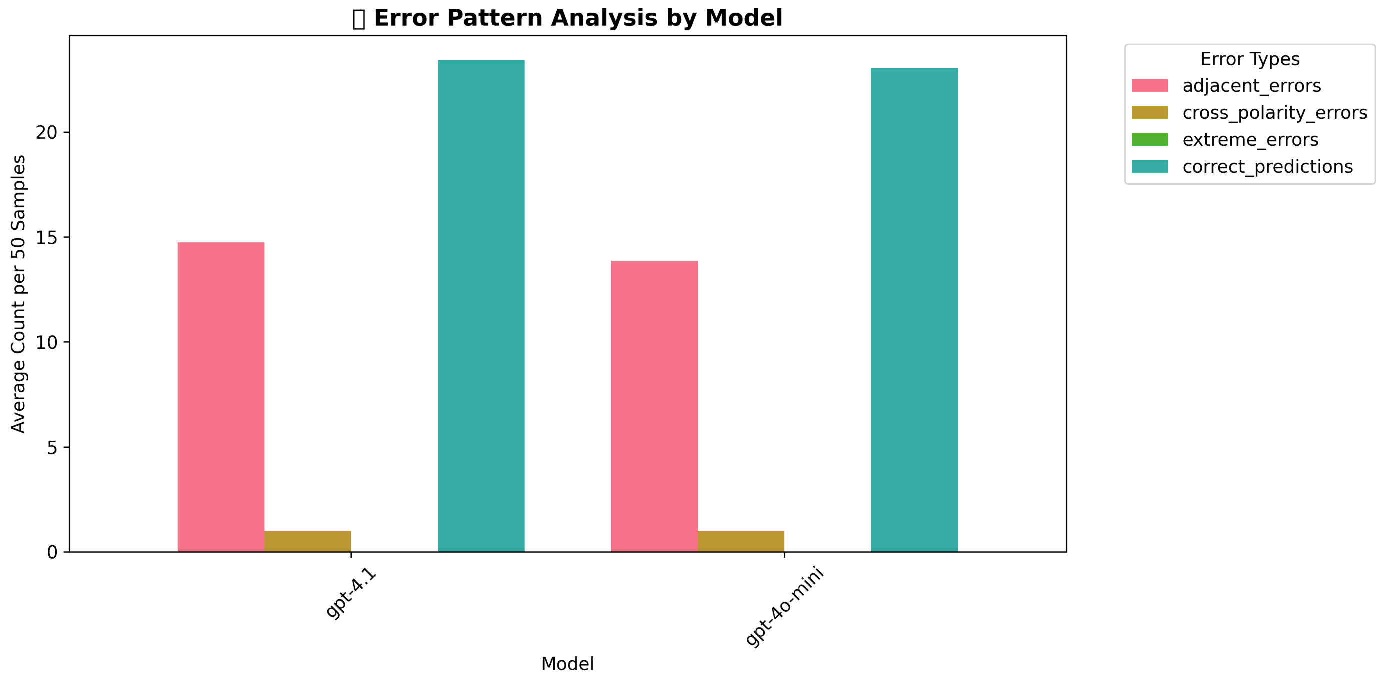
model	dimension	value1	value2	acc_mean_1	acc_mean_2	acc_std_1	acc_std_2	acc_p_value	acc_significant
gpt-4.1	formality	casual	formal	0.968	0.9685	0.0075	0.0069	0.7795	
gpt-4.1	order	task_first	text_first	0.9654	0.9715	0.0069	0.0	0.2162	
gpt-4.1	phrasing	imperative	question	0.9685	0.9684	0.0069	0.0075	0.9822	
gpt-4.1	synonyms	set_a	set_b	0.9684	0.9684	0.0072	0.0072	1.0	
gpt-4o-mini	formality	casual	formal	0.9505	0.9535	0.0154	0.011	0.6421	
gpt-4o-mini	order	task_first	text_first	0.9495	0.9545	0.0115	0.0139	0.4303	
gpt-4o-mini	phrasing	imperative	question	0.951	0.953	0.0127	0.0137	0.7516	
gpt-4o-mini	synonyms	set_a	set_b	0.9565	0.9475	0.0133	0.0067	0.0068	✓

Important finding: Statistical significance testing reveals that only GPT-4o-mini exhibits sensitivity to synonym choice (p=0.0068), where Set A terminology outperforms Set B alternatives. GPT-4.1 demonstrates complete robustness across all dimensional variations (all p-values > 0.05).



Error Analysis and Context Enhancement

Error Pattern Distribution



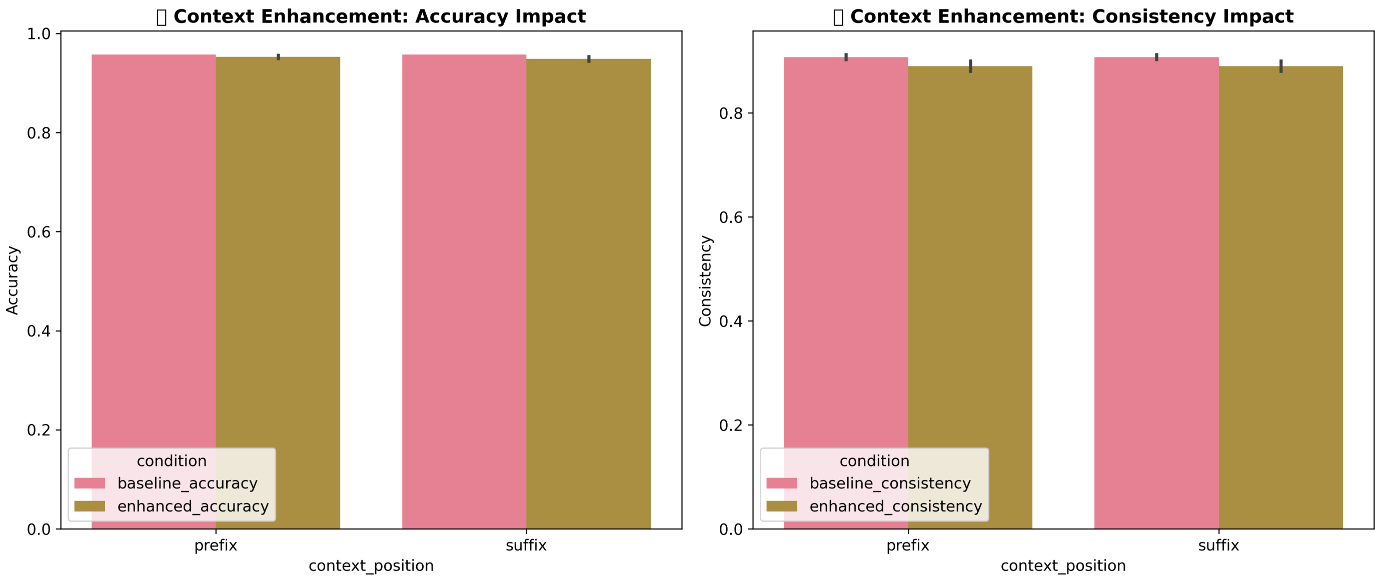
	adjacent_errors_mean	adjacent_errors_std	cross_polarity_errors_mean	cross_polarity_errors_std	extreme_errors_mean	extreme_errors_std	c

	adjacent_errors_mean	adjacent_errors_std	cross_polarity_errors_mean	cross_polarity_errors_std	extreme_errors_mean	extreme_errors_std	c
gpt-4.1	1.56	0.35	0.0	0.0	0.0	0.0	4
gpt-4o-mini	2.41	0.67	0.0	0.0	0.0	0.0	4

Both models demonstrate strong fundamental sentiment understanding with zero extreme errors (Very Negative ↔ Very Positive) and zero cross-polarity confusion. Error patterns consist exclusively of adjacent category misclassifications, indicating that failure modes remain within reasonable intensity boundaries.

Context Enhancement Results

Context enhancement employed a 2×2 experimental design testing prefix and suffix positioning of carefully selected few-shot examples across the best-performing baseline variants for each model. Examples were selected using length diversity (short/medium/long) and TF-IDF cosine dissimilarity optimization, ensuring semantic diversity across 15 examples (3 per sentiment class) with approximately 25% token overhead.



model	enhanced_variant	context_position	accuracy_improvement	consistency_improvement	weighted_improvement
gpt-4.1	v11_prefix	prefix	-0.002	-0.029	-0.011
gpt-4.1	v11_suffix	suffix	-0.006	-0.057	-0.023
gpt-4o-mini	v15_prefix	prefix	-0.008	0.02	0.001
gpt-4o-mini	v15_suffix	suffix	-0.01	0.002	-0.005

Surprisingly, context enhancement resulted in negative performance impact across most metrics. This finding challenges conventional few-shot learning assumptions and suggests that modern large language models may possess sufficient inherent capabilities for well-defined classification tasks, making additional examples potentially counterproductive. Another possibility is that this specific dataset contains no domain-specific sentiment, in which case we could see further improvements.

Context Examples Distribution

	Negative	Neutral	Positive	Very Negative	Very Positive
long	1	1	1	1	1
medium	1	1	1	1	1
short	1	1	1	1	1

Key Findings and Practical Implications

Summary of Results

Metric	Value
Best Overall Model	gpt-4.1
Best Overall Variant	v11
Most Stable Dimension	order
Least Stable Dimension	phrasing
Context Enhancement Effect	-0.006 avg accuracy change

Deployment Recommendations

1. Model Selection Priority: GPT-4.1's consistent superiority across accuracy and robustness metrics demonstrates that model capability investment yields greater returns than extensive prompt optimization efforts. However, the accuracy of GPT-4o-mini is only slightly lower, but less costly.

2. Prompt Engineering Guidelines:

- Employ Set A terminology ("analyze", "sentiment", "classify") over casual alternatives
- Question format demonstrates marginal advantage over imperative instructions
- Instruction order shows minimal impact on performance
- Maintain formal register and technical precision

3. Context Strategy: For well-defined classification tasks, avoid few-shot examples as they may degrade performance in sufficiently capable models.

4. Production Implementation: Select the most capable model available, implement clear prompts with technical vocabulary, and prioritize simplicity over complexity in prompt design.

Conclusion

This experimental analysis demonstrates that modern large language models, particularly GPT-4.1, exhibit substantial robustness to prompt formulation variations. The primary insight is that model capability significantly outweighs prompt engineering sophistication in determining system reliability.

The counterintuitive finding that context enhancement degrades performance suggests an evolution in optimal prompting strategies, where traditional few-shot approaches may become obsolete for sophisticated models. These results provide evidence-based guidance for practitioners implementing sentiment classification systems in production environments.

This research establishes a methodological framework for robustness evaluation and offers practical recommendations for deploying large language models in classification applications.