

The Moral Gap of Large Language Models

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ABSTRACT

Moral foundation detection is crucial for analyzing social discourse and developing ethically-aligned AI systems. While large language models excel across diverse tasks, their performance on specialized moral reasoning remains unclear.

This study provides the first comprehensive comparison between state-of-the-art LLMs and fine-tuned transformers across Twitter and Reddit datasets using ROC, PR, and DET curve analysis.

Results reveal substantial performance gaps, with LLMs exhibiting high false negative rates and systematic under-detection of moral content despite prompt engineering efforts. These findings demonstrate that task-specific fine-tuning remains superior to prompt-ing for moral reasoning applications.

1 INTRODUCTION

1.1 Motivation and Background

Moral Foundations Theory (MFT) provides a framework for understanding the psychological basis of moral reasoning and judgment across cultures (Haidt and Joseph, 2004). Developed to explain variations in moral intuitions both within and between societies, MFT proposes that moral judgments are shaped by a set of evolved moral foundations—such as care, fairness, loyalty, authority, and sanctity—which reflect underlying psychological mechanisms (Graham et al., 2013; Haidt, 2012).

MFT has found numerous applications, including analysis of political ideology (Graham et al., 2009), environmental attitudes (Feinberg and Willer, 2013), vaccine hesitancy (Amin et al., 2017), social norms (Forbes et al., 2020), news framing (Mokherian et al., 2020), social media discourse (Hoover et al., 2020), everyday moral dilemmas (Nguyen et al., 2022), and argument assessment (Kobbe et al., 2020; Landowska et al., 2024).

Social Media Post	Moral Foundation
"My heart breaks seeing children separated from families at the border"	Care
"Everyone deserves equal access to health-care regardless of income"	Fairness
"Respect your elders and follow traditional values that built this nation"	Authority
"Stand with our troops - they sacrifice everything for our freedom"	Loyalty
"Marriage is sacred and should be protected from secular corruption"	Sanctity

Table 1: Posts and Associated Moral Foundation

Computational methods for detecting moral foundations have evolved from dictionary-based approaches (Graham et al., 2009; Pennebaker and Francis, 1999) to transformer models (Nguyen et al., 2024; Preniqi et al., 2024a) and recently to large language models (Bulla et al., 2025). While LLMs from Anthropic and OpenAI offer

appealing accessibility, no study has rigorously compared their performance to specialized transformer models on moral foundation detection. This gap leaves researchers without evidence-based guidance for tool selection, making systematic evaluation essential for informed deployment in morally sensitive applications. This paper addresses this need through comprehensive empirical comparison across multiple datasets and evaluation metrics.

1.2 Contributions

The key contributions to computational moral psychology are:

- (1) **Comprehensive Evaluation:** First systematic comparison of state-of-the-art LLMs (Claude Sonnet 4, GPT-o1-mini) against fine-tuned transformers (DeBERTa, RoBERTa) for moral foundation detection across Twitter and Reddit datasets, establishing performance benchmarks for both in-domain and cross-domain scenarios.
- (2) **Rigorous Methodology:** Establishes robust evaluation framework using the spectrum of diagnosis curves (ROC, PR, and DET) to provide comprehensive performance insights and address class-imbalance limitations of prior work that relied solely on ROC analysis.
- (3) **Error Analysis and Practical Guidance:** Identifies systematic LLM limitations including high false negative rates (58-90%), foundation-specific failure patterns, and conservative prediction bias, while providing evidence-based recommendations for model selection, prompt engineering limitations, and deployment considerations in moral content analysis.

1.3 Related Work

Early computational approaches to moral foundation detection relied primarily on dictionary-based methods using manually crafted lexicons such as the Moral Foundations Dictionary (Graham et al., 2009) and its extensions (Frimer, 2019; Hopp et al., 2021). While still very popular due to interpretability and computational efficiency, these approaches suffer from very low accuracy.

The advent of deep learning and particularly transformer architectures marked a significant advancement in moral content analysis. Hoover et al. (2020) first applied deep learning models to moral foundation classification, demonstrating substantial improvements over lexicon-based approaches. Researchers have further improved accuracy by fine-tuning transformer-based models such as BERT and RoBERTa (Nguyen et al., 2024; Preniqi et al., 2024b; Trager et al., 2022), which currently achieve state-of-the-art performance.

The recent proposal of applying LLMs to moral content categorization (Bulla et al., 2025) showed promise but suffered from methodological limitations. The study used only one dataset, removed ambiguous (harder) instances, and handled annotator disagreement differently than standard practice in the field, resulting in a biased evaluation.

2 DATA AND METHODS

2.1 Datasets

We evaluate model performance on two established moral foundations datasets. The **Twitter dataset (MFTC)** (Hoover et al., 2020) contains 34,987 tweets spanning seven socially relevant topics, with trained annotators labeling moral foundations and their sentiments. We merge virtue/vice labels (positive/negative aspects of each foundation, e.g., “purity” + “degradation” → “sanctity”). The **Reddit dataset (MFRC)** (Trager et al., 2022) comprises 17,886 comments from 12 subreddits covering US politics, French politics, and everyday moral life. We merge the original equality/proportionality split back into fairness and treat “thin morality” cases as no foundation present. Both datasets use binary labels for five moral foundations (authority, care, fairness, loyalty, sanctity) with inclusive annotation scheme (positive if any annotator agrees). The data is summarized in Table 2 and Figure 1.

Table 2: Summary of datasets

Dataset	Category/Topic	Count	%
MFTC (Twitter)			
	All Lives Matter	4,988	14.3%
	Black Lives Matter	4,990	14.3%
	2016 US Presidential Election	4,987	14.3%
	Hate Speech	4,989	14.3%
	Hurricane Sandy	4,990	14.3%
	#MeToo	4,995	14.3%
	Baltimore Protests	4,985	14.2%
	MFTC Subtotal	34,924	100%
MFRC (Reddit)			
	US Politics	6,968	39.0%
	French Politics	3,984	22.3%
	Everyday Moral Life	6,933	38.7%
	MFRC Subtotal	17,885	100%
TOTAL ALL DATASETS		52,809	

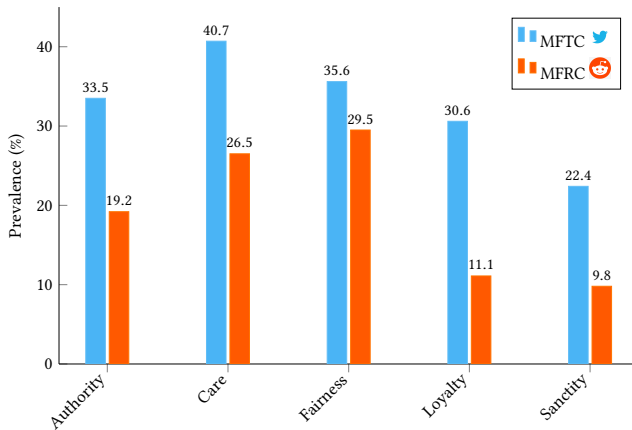


Figure 1: Moral Foundation Prevalence in Datasets

2.2 Models

Large Language Models. We selected four recent models based on cost-effectiveness and reasoning capabilities (Table 3). These include general-purpose models (Haiku, GPT-4o-mini) and reasoning-specialized models (Sonnet, GPT-o1-mini) from major vendors. Models represent state-of-the-art releases: GPT-o1-mini (April 2025), Claude Sonnet (version 3.5 from February 2025 and version 4 from May 2025). All models were accessed via Python APIs with consistent prompting strategies.

Table 3: LLM Model Specifications

Model	Vendor	Context	Output	Price (\$/1M)
Claude 3.5 Haiku	Anthropic	200K	4K	\$0.25
Claude Sonnet 4	Anthropic	200K	8K	\$3.00
GPT-4o-mini	OpenAI	128K	16K	\$0.15
GPT-o4-mini	OpenAI	128K	65K	\$3.00

Context and output in tokens. Pricing for input tokens (May 2025).

Transformer Models. While prior work established BERT models, particularly RoBERTa, as state-of-the-art for moral foundations detection, we evaluated more modern transformer architectures. For results reported in this paper, we employed DeBERTa-v3-base by Microsoft, trained with learning rate 2e-5 and the first two layers frozen for 3 epochs (throughout all results, “BERT” refers to this DeBERTa model for brevity). For in-domain evaluation, we used a 4:1 train-test split, while for out-of-domain evaluation, we trained on the full training set and evaluated on complete test sets.

2.3 Techniques

Prediction Metrics. A range of metrics for both continuous probability scores and binary predictions is used to comprehensively evaluate model performance. The abbreviations TP , FP , TN , and FN represent true positives, false positives, true negatives, and false negatives, leading to:

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

$$Precision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

and aggregated metrics

$$F1 = 2 \cdot \frac{Precision \times Recall}{Precision + Recall}, \quad BER = \frac{1}{2} \left(\frac{FN}{TP + FN} + \frac{FP}{FP + TN} \right)$$

Continuous scores are evaluated at various thresholds representing different performance tradeoffs through three complementary curves:

- **ROC curves:** Plot TPR vs. FPR with AUC ranging from 0.5 (random) to 1.0 (perfect) (Fawcett, 2006)
- **PR curves:** Plot Precision vs. Recall with AUC considered more informative for imbalanced datasets (Davis and Goadrich, 2006)
- **DET curves:** Plot (1-TPR) vs. FPR on normal deviate scale, emphasizing error rates (Martin et al., 1997)

Moral Visualization Palette. We have developed a novel colorblind-accessible color scheme that accurately reflects the theoretical structure of moral foundations as shown in Figure 2. The palette represents the gradation from individualistic foundations (cooler colours)

to collectivistic foundations (warmer colours): green for care as an inclusive, nurturing foundation; blue for fairness reflecting associations with justice and divine judgment; red for loyalty symbolizing bonds and allegiance; purple for authority representing traditional power and hierarchy; and gold for sanctity denoting the sacred and pure.



Figure 2: Novel moral foundations colour palette

3 RESULTS

3.1 Detection of Moral Content

As demonstrated in prior work, detecting whether any moral content is present, without identifying its dimensions, is relatively straightforward using text-embedding models. We reproduced (and slightly improved) results previously achieved with transformers. However, evaluation of LLMs reveals a substantial performance gap even on this simpler task. As shown in the performance curves, LLM performance is consistently inferior—they lie inside the transformer curves, indicating systematic underperformance rather than threshold-dependent differences. This evidences fundamental limitations in LLMs’ ability to detect moral content compared to fine-tuned transformers.

See Figure 3 for ROC analysis and Figure 4 for PR curves. The numerical metrics are reported as an additional "any" dimension when evaluating foundation-specific performance in the next section (Tables 4 and 5).

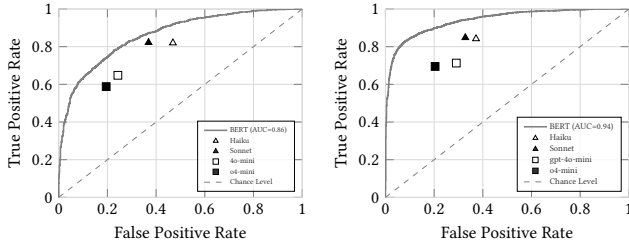


Figure 3(a) MFRC Dataset

Figure 3(b) MFTC Dataset

Figure 3: ROC Prediction Performance.

3.2 Classification of Moral Values

The results of our evaluation, presented in Table 4 and Table 5, reveal substantial performance gaps between fine-tuned transformers and LLMs. BERT consistently outperforms all LLMs with ROC-AUC scores of 0.83-0.90 and F1 scores of 0.38-0.80, while Claude-3.5-Sonnet achieves only 0.21-0.78 F1. LLMs struggle most with loyalty and sanctity, exhibiting high false negative rates (0.58-0.90) that miss most positive cases. While LLMs detect general moral content reasonably well, their inability to identify specific foundations demonstrates that task-specific fine-tuning remains superior to prompting for moral reasoning tasks.

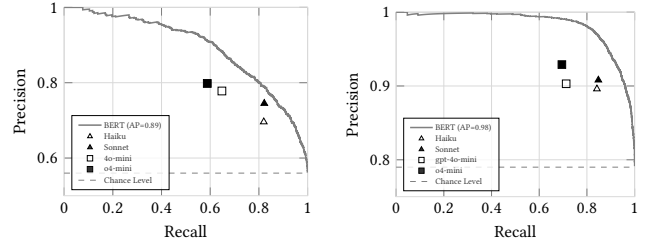


Figure 4(a) MFRC Dataset

Figure 4(b) MFTC Dataset

Figure 4: PR Prediction Performance

Table 4: Performance metrics for MFRC under simple prompt

dataset	moral dimension	model	FPR	FNR	precision	recall	f1	ROC-AUC	AP
MFRC	any	BERT	0.225	0.221	0.761	0.862	0.808	0.862	0.893
		BERT-OOD	0.247	0.306	0.691	0.892	0.779	0.800	0.829
		Haiku 3.5	0.469	0.180	0.696	0.820	0.753		
		Sonnet 3.7	0.374	0.184	0.741	0.816	0.777		
		Sonnet 4	0.369	0.178	0.745	0.822	0.782		
		gpt-4o-mini	0.243	0.352	0.778	0.648	0.707		
		o1-mini	0.195	0.412	0.798	0.588	0.677		
		BERT	0.276	0.137	0.549	0.638	0.590	0.869	0.605
		BERT-OOD	0.280	0.297	0.422	0.600	0.495	0.775	0.453
		Haiku 3.5	0.229	0.529	0.330	0.471	0.388		
	authority	Sonnet 3.7	0.143	0.523	0.444	0.477	0.460		
		Sonnet 4	0.144	0.573	0.416	0.427	0.421		
		gpt-4o-mini	0.146	0.623	0.383	0.377	0.380		
		o1-mini	0.091	0.769	0.379	0.231	0.287		
		BERT	0.217	0.156	0.691	0.720	0.706	0.896	0.775
		BERT-OOD	0.265	0.234	0.533	0.727	0.615	0.823	0.626
		Haiku 3.5	0.255	0.405	0.451	0.595	0.513		
		Sonnet 3.7	0.155	0.359	0.593	0.641	0.616		
		Sonnet 4	0.192	0.316	0.556	0.684	0.613		
		gpt-4o-mini	0.137	0.477	0.573	0.523	0.547		
	care	o1-mini	0.155	0.471	0.546	0.529	0.537		
		BERT	0.275	0.215	0.544	0.785	0.643	0.830	0.711
		BERT-OOD	0.368	0.266	0.455	0.734	0.562	0.745	0.533
		Haiku 3.5	0.362	0.416	0.419	0.584	0.488		
		Sonnet 3.7	0.264	0.387	0.509	0.613	0.556		
		Sonnet 4	0.201	0.493	0.530	0.507	0.518		
		gpt-4o-mini	0.125	0.765	0.456	0.235	0.310		
		o1-mini	0.150	0.618	0.532	0.382	0.445		
		BERT	0.194	0.202	0.471	0.639	0.542	0.878	0.563
		BERT-OOD	0.243	0.357	0.372	0.415	0.392	0.777	0.395
	fairness	Haiku 3.5	0.150	0.685	0.199	0.315	0.244		
		Sonnet 3.7	0.091	0.584	0.351	0.416	0.381		
		Sonnet 4	0.100	0.535	0.354	0.465	0.402		
		gpt-4o-mini	0.052	0.892	0.198	0.108	0.140		
		o1-mini	0.072	0.801	0.245	0.199	0.220		
		BERT	0.293	0.131	0.358	0.566	0.439	0.859	0.444
		BERT-OOD	0.283	0.258	0.305	0.531	0.388	0.804	0.376
		Haiku 3.5	0.160	0.715	0.171	0.285	0.213		
		Sonnet 3.7	0.067	0.695	0.345	0.305	0.323		
		Sonnet 4	0.064	0.695	0.353	0.305	0.327		
	loyalty	gpt-4o-mini	0.060	0.903	0.157	0.097	0.120		
		o1-mini	0.076	0.857	0.178	0.143	0.158		
		BERT	0.293	0.131	0.358	0.566	0.439	0.859	0.444
	sanctity	BERT-OOD	0.283	0.258	0.305	0.531	0.388	0.804	0.376
		Haiku 3.5	0.160	0.715	0.171	0.285	0.213		
		Sonnet 3.7	0.067	0.695	0.345	0.305	0.323		
		Sonnet 4	0.064	0.695	0.353	0.305	0.327		
		gpt-4o-mini	0.060	0.903	0.157	0.097	0.120		
		o1-mini	0.076	0.857	0.178	0.143	0.158		

3.2.1 ROC Analysis. Figures Figure 5(a) and Figure 5(b) show ROC curves plotting true positive rate against false positive rate across all classification thresholds. The curves visually confirm the substantial performance gaps reported in the tables, with BERT consistently achieving higher AUC values while LLM curves lie systematically inside the transformer performance envelope.

3.2.2 PR Analysis. Figures Figure 6(a) and Figure 6(b) present precision-recall curves, which are particularly informative for imbalanced datasets like moral foundation classification. These plots corroborate the tabular results, demonstrating that fine-tuned transformers maintain superior precision-recall trade-offs compared to LLMs across all moral foundations.

3.2.3 DET Curves. Results in Figure 7(a) and Figure 7(b) show Detection Error Tradeoff curves plotting false negative against false positive rates on normal deviate scales. These curves emphasize the error rate perspective and confirm the high false negative rates of LLMs documented in the tables, particularly for loyalty and sanctity foundations.

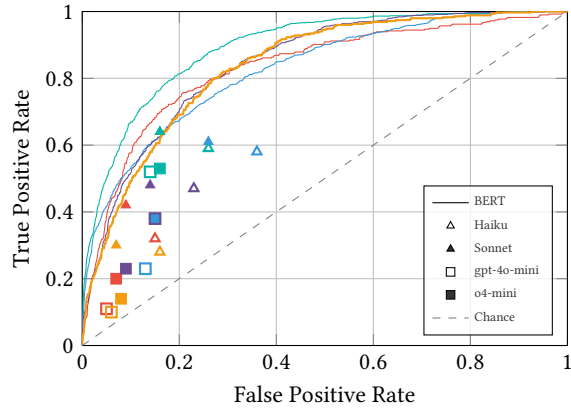


Figure 5(a) ROC curves for MFRC dataset

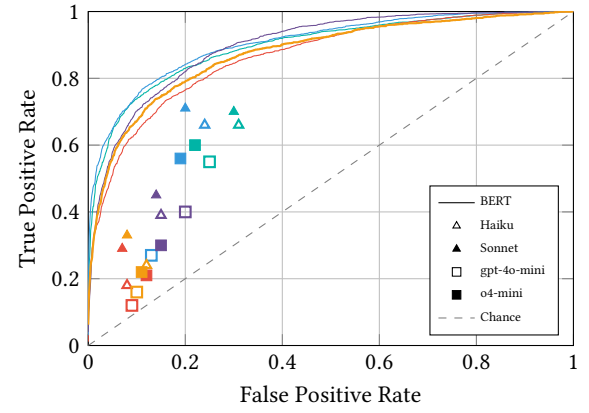


Figure 5(b) ROC curves for MFTC dataset

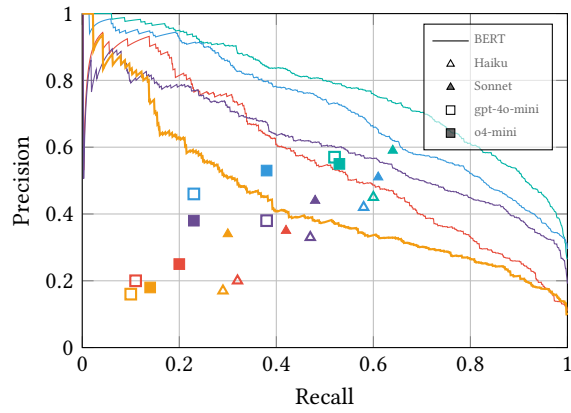


Figure 6(a) Precision-recall curves for MFRC dataset

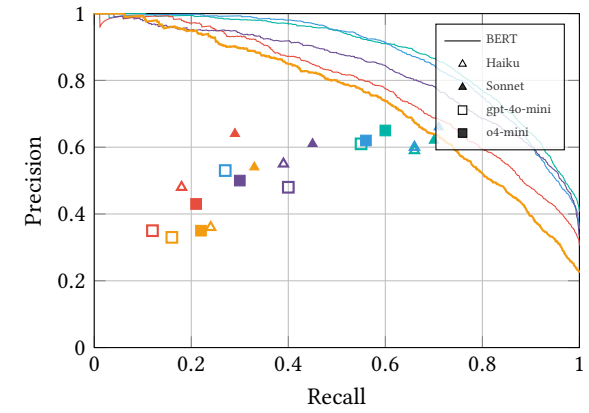


Figure 6(b) Precision-recall curves for MFTC dataset

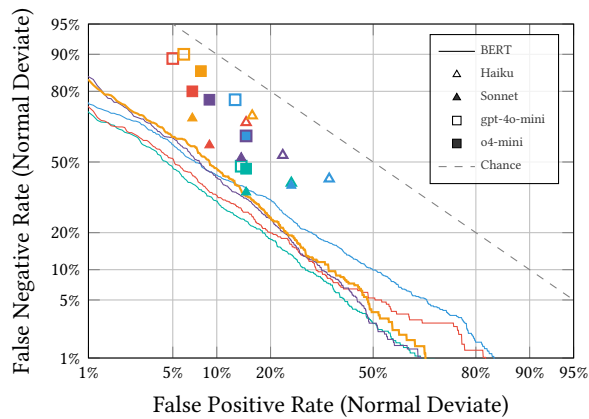


Figure 7(a) Detection error tradeoff curves for MFRC dataset

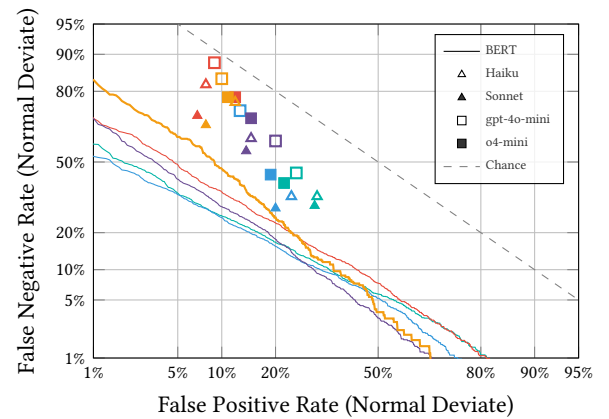


Figure 7(b) Detection error tradeoff curves for MFTC dataset

3.3 Impact of Prompt Engineering

Table 6 and Table 7 show that prompt engineering generally yields improvements, with F1 gains up to +0.078 across foundations. BERT

Table 5: Performance metrics on MFTC under simple prompt

dataset	moral dimension	model	FPR	FNR	precision	recall	f1	ROC-AUC	AP
MFTC	any	BERT	0.075	0.176	0.902	0.959	0.930	0.940	0.983
		BERT-OOD	0.189	0.238	0.867	0.934	0.899	0.860	0.957
		Haiku 3.5	0.372	0.158	0.896	0.842	0.868		
		Sonnet 3.7	0.321	0.155	0.909	0.845	0.876		
		Sonnet 4	0.328	0.152	0.908	0.848	0.877		
		gpt-4o-mini	0.291	0.287	0.903	0.713	0.797		
		o4-mini	0.204	0.305	0.929	0.695	0.795		
	authority	BERT	0.204	0.173	0.743	0.742	0.742	0.899	0.830
		BERT-OOD	0.205	0.395	0.567	0.645	0.603	0.749	0.645
		Haiku 3.5	0.151	0.611	0.551	0.389	0.456		
		Sonnet 3.7	0.136	0.553	0.610	0.447	0.516		
		Sonnet 4	0.139	0.583	0.589	0.417	0.489		
		gpt-4o-mini	0.201	0.603	0.485	0.397	0.436		
care	any	BERT	0.115	0.244	0.805	0.769	0.787	0.897	0.881
		BERT-OOD	0.252	0.261	0.663	0.748	0.703	0.811	0.765
		Haiku 3.5	0.314	0.343	0.594	0.657	0.624		
		Sonnet 3.7	0.295	0.298	0.624	0.702	0.661		
		Sonnet 4	0.339	0.254	0.606	0.746	0.668		
		gpt-4o-mini	0.251	0.447	0.606	0.553	0.579		
		o4-mini	0.224	0.400	0.651	0.600	0.624		
	fairness	BERT	0.111	0.232	0.792	0.768	0.780	0.906	0.874
		BERT-OOD	0.317	0.286	0.512	0.819	0.630	0.770	0.659
		Haiku 3.5	0.243	0.338	0.601	0.662	0.630		
		Sonnet 3.7	0.204	0.287	0.659	0.713	0.685		
		Sonnet 4	0.197	0.322	0.655	0.678	0.666		
		gpt-4o-mini	0.128	0.734	0.534	0.266	0.355		
loyalty	any	BERT	0.159	0.267	0.670	0.733	0.700	0.866	0.782
		BERT-OOD	0.228	0.460	0.442	0.680	0.536	0.713	0.551
		Haiku 3.5	0.083	0.818	0.485	0.182	0.265		
		Sonnet 3.7	0.071	0.711	0.636	0.289	0.398		
		Sonnet 4	0.083	0.676	0.627	0.324	0.427		
		gpt-4o-mini	0.094	0.880	0.355	0.120	0.179		
		o4-mini	0.124	0.786	0.425	0.214	0.284		
	sanctity	BERT	0.138	0.262	0.688	0.654	0.671	0.875	0.740
		BERT-OOD	0.340	0.271	0.433	0.616	0.509	0.761	0.523
		Haiku 3.5	0.122	0.762	0.360	0.238	0.286		
		Sonnet 3.7	0.080	0.674	0.541	0.326	0.407		
		Sonnet 4	0.095	0.646	0.517	0.354	0.420		
		gpt-4o-mini	0.097	0.839	0.325	0.161	0.216		
fairness	any	BERT	0.115	0.782	0.354	0.218	0.270		

maintains substantial advantages of 0.10-0.26 F1 points even after enhanced prompting. The performance of some models in certain foundations deteriorate under prompt engineering, indicating that advanced prompting cannot reliably overcome the fundamental limitations of LLMs in moral reasoning (see [Table 8](#)).

Table 6: Performance on MFRC under prompt engineering

dataset	moral dimension	model	FPR	FNR	precision	recall	f1	ROC-AUC	AP
MFRC	any	BERT	0.225	0.221	0.761	0.862	0.808	0.862	0.893
		BERT-OOD	0.247	0.306	0.691	0.892	0.779	0.800	0.829
		Haiku 3.5	0.622	0.102	0.655	0.898	0.757		
		Sonnet 3.7	0.793	0.017	0.619	0.983	0.760		
		Sonnet 4	0.626	0.067	0.662	0.933	0.774		
		gpt-4o-mini	0.339	0.310	0.728	0.690	0.708		
		o4-mini	0.622	0.102	0.655	0.898	0.757		
	authority	BERT	0.276	0.137	0.549	0.638	0.590	0.869	0.665
		BERT-OOD	0.280	0.297	0.422	0.600	0.495	0.775	0.453
		Haiku 3.5	0.195	0.565	0.349	0.435	0.387		
		Sonnet 3.7	0.378	0.245	0.324	0.755	0.453		
		Sonnet 4	0.222	0.453	0.372	0.547	0.443		
		gpt-4o-mini	0.096	0.763	0.372	0.237	0.290		
care	any	BERT	0.217	0.156	0.691	0.720	0.706	0.896	0.775
		BERT-OOD	0.265	0.234	0.533	0.727	0.615	0.823	0.626
		Haiku 3.5	0.225	0.364	0.499	0.636	0.559		
		Sonnet 3.7	0.291	0.210	0.488	0.790	0.603		
		Sonnet 4	0.244	0.256	0.517	0.744	0.610		
		gpt-4o-mini	0.089	0.500	0.665	0.500	0.571		
		o4-mini	0.225	0.364	0.499	0.636	0.559		
	fairness	BERT	0.275	0.215	0.544	0.785	0.643	0.830	0.711
		BERT-OOD	0.368	0.266	0.455	0.734	0.562	0.745	0.533
		Haiku 3.5	0.440	0.269	0.426	0.731	0.539		
		Sonnet 3.7	0.434	0.220	0.446	0.780	0.567		
		Sonnet 4	0.255	0.429	0.500	0.571	0.533		
		gpt-4o-mini	0.160	0.627	0.510	0.373	0.431		
loyalty	any	BERT	0.194	0.202	0.471	0.639	0.542	0.878	0.563
		BERT-OOD	0.243	0.357	0.372	0.415	0.392	0.777	0.395
		Haiku 3.5	0.187	0.607	0.199	0.393	0.265		
		Sonnet 3.7	0.348	0.256	0.202	0.744	0.318		
		Sonnet 4	0.183	0.446	0.264	0.554	0.357		
		gpt-4o-mini	0.066	0.786	0.277	0.214	0.241		
		o4-mini	0.187	0.607	0.199	0.393	0.265		
	sanctity	BERT	0.293	0.131	0.358	0.566	0.439	0.859	0.444
		BERT-OOD	0.283	0.258	0.305	0.531	0.388	0.804	0.376
		Haiku 3.5	0.065	0.857	0.202	0.143	0.167		
		Sonnet 3.7	0.200	0.430	0.247	0.570	0.345		
		Sonnet 4	0.116	0.605	0.283	0.395	0.330		
		gpt-4o-mini	0.036	0.840	0.341	0.160	0.218		
fairness	any	BERT	0.065	0.857	0.202	0.143	0.167		

3.3.1 Impact. Performance curves under prompt engineering (Figures [Figure 8\(a\)](#), [Figure 8\(b\)](#), [Figure 9\(a\)](#), [Figure 9\(b\)](#), [Figure 10\(a\)](#),

Table 7: Performance on MFTC under prompt engineering

dataset	moral dimension	model	FPR	FNR	precision	recall	f1	ROC-AUC	AP
MFTC	any	BERT	0.075	0.176	0.902	0.959	0.930	0.940	0.983
		BERT-OOD	0.189	0.238	0.867	0.934	0.899	0.860	0.957
		Haiku 3.5	0.346	0.162	0.902	0.838	0.869		
		Sonnet 3.7	0.643	0.042	0.850	0.958	0.901		
		Sonnet 4	0.598	0.055	0.858	0.945	0.899		
		gpt-4o-mini	0.189	0.283	0.935	0.717	0.812		
		o4-mini	0.295	0.174	0.915	0.826	0.868		
	authority	BERT	0.204	0.173	0.743	0.742	0.742	0.899	0.830
		BERT-OOD	0.205	0.395	0.567	0.645	0.603	0.749	0.645
		Haiku 3.5	0.140	0.620	0.565	0.380	0.454		
		Sonnet 3.7	0.272	0.340	0.537	0.660	0.592		
		Sonnet 4	0.173	0.520	0.570	0.480	0.521		
		gpt-4o-mini	0.055	0.769	0.666	0.231	0.343		
care	any	BERT	0.115	0.244	0.805	0.769	0.787	0.897	0.881
		BERT-OOD	0.252	0.261	0.663	0.748	0.703	0.811	0.765
		Haiku 3.5	0.334	0.322	0.586	0.678	0.629		
		Sonnet 3.7	0.436	0.173	0.570	0.827	0.675		
		Sonnet 4	0.376	0.218	0.592	0.782	0.674		
		gpt-4o-mini	0.164	0.473	0.691	0.527	0.598		
		o4-mini	0.243	0.341	0.654	0.659	0.656		
	fairness	BERT	0.111	0.232	0.792	0.768	0.780	0.906	0.874
		BERT-OOD	0.317	0.286	0.512	0.819	0.630	0.770	0.659
		Haiku 3.5	0.289	0.280	0.580	0.720	0.642		
		Sonnet 3.7	0.307	0.193	0.592	0.807	0.683		
		Sonnet 4	0.232	0.301	0.624	0.699	0.659		
		gpt-4o-mini	0.140	0.518	0.655	0.482	0.556		
loyalty	any	BERT	0.159	0.267	0.670	0.733	0.700	0.866	0.782
		BERT-OOD	0.228	0.460	0.442	0.680	0.536	0.713	0.551
		Haiku 3.5	0.129	0.703	0.498	0.297	0.372		
		Sonnet 3.7	0.268	0.441	0.473	0.559	0.513		
		Sonnet 4	0.156	0.612	0.516	0.388	0.443		
		gpt-4o-mini	0.075	0.732	0.606	0.268	0.371		
		o4-mini	0.148	0.613	0.529	0.387	0.447		
	sanctity	BERT	0.138	0.262	0.688	0.654	0.671	0.875	0.740
		BERT-OOD	0.340	0.271	0.433	0.616	0.509	0.761	0.523
		Haiku 3.5	0.059	0.731	0.570	0.269	0.366		
		Sonnet 3.7	0.213	0.419	0.441	0.581	0.502		
		Sonnet 4	0.219	0.417	0.435	0.583	0.498		
		gpt-4o-mini	0.030	0.776	0.687	0.224	0.338		
fairness	any	BERT	0.067	0.663	0.591	0.337	0.429		

Table 8: Prompt engineering performance delta comparison

Dataset	Moral Dimension	Model	Δ FPR	Δ FNR	Δ Prec	Δ Rec	Δ F1
MFTC	any	Haiku 3.5	-0.03	0.00	0.01	0.00	0.00</

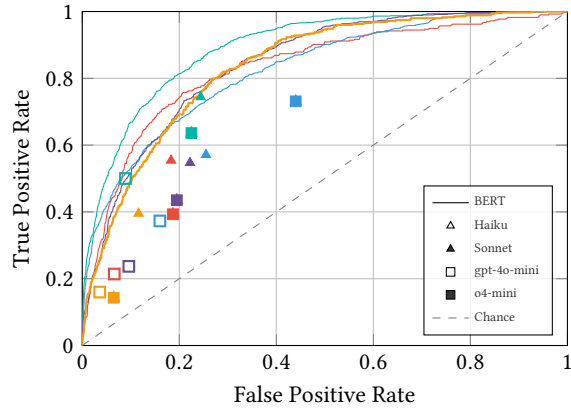


Figure 8(a) ROC curves for MFRC dataset.

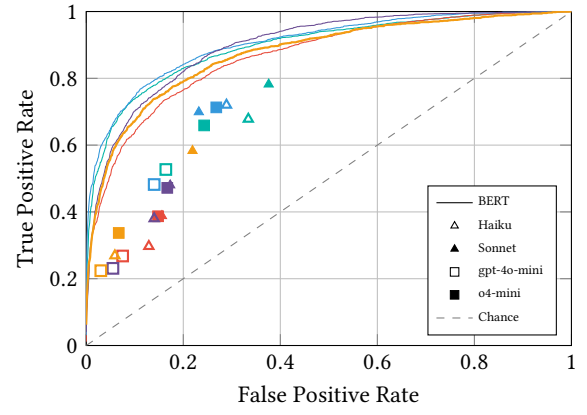


Figure 8(b) ROC curves for MFTC Dataset

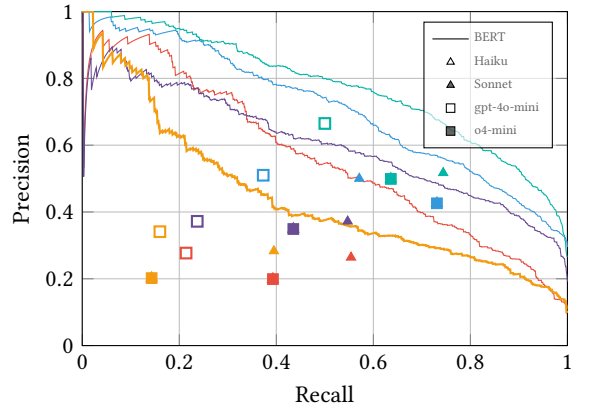


Figure 9(a) Precision-recall curves for MFRC dataset

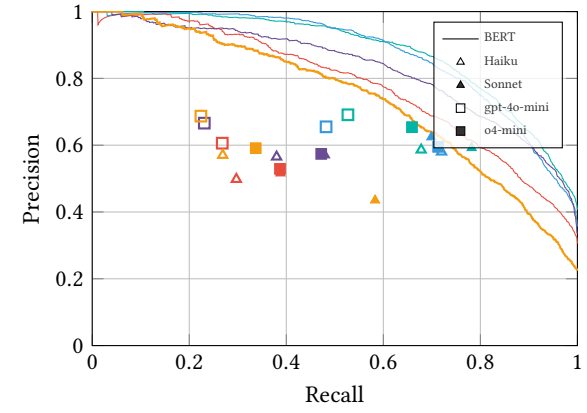


Figure 9(b) Precision-recall curves for MFTC dataset

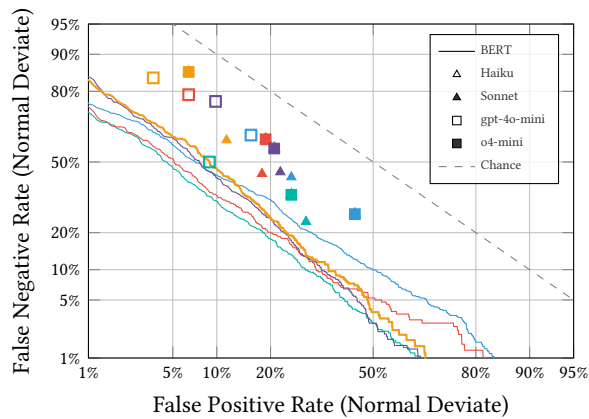


Figure 10(a) DET curves for MFRC dataset

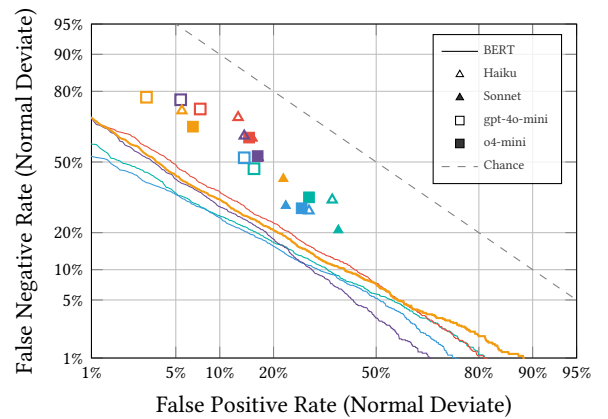


Figure 10(b) DET curves for MFTC dataset

dominates the precision-recall space, while LLM curves remain

largely within the transformer envelope with inconsistent gains and unchanged high false negative rate patterns.

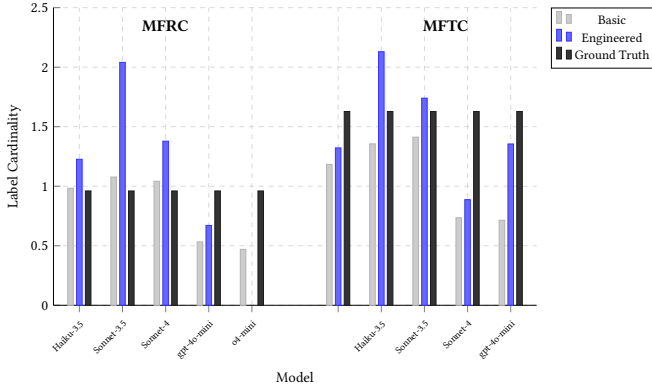


Figure 11: Label cardinality by model and prompt type

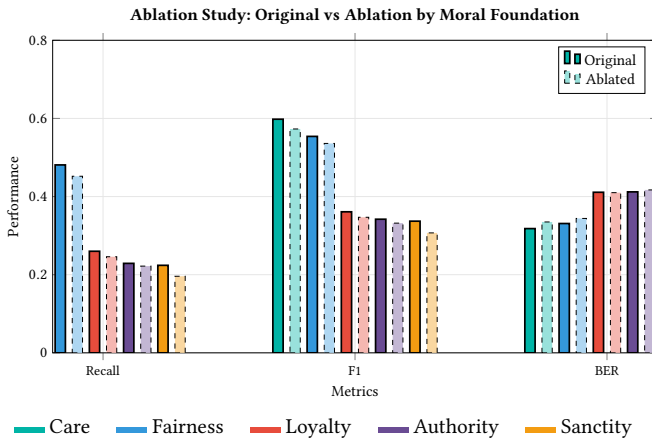


Figure 12: Impact of Removed Recall-Improving Instructions

3.4 Under-Detection of Moral Content

Our ablation study reveals fundamental limitations in LLMs’ moral reasoning approach. Figure 12 demonstrates that LLMs require explicit recall-increasing instructions to identify moral foundations, suggesting they inherently under-detect moral content. Even with enhanced prompting that reinforces multi-label classification requirements, Figure 11 shows LLMs consistently predict lower label cardinality than ground truth, indicating systematic under-prediction of moral dimensions. This conservative bias explains their high false negative rates and suggests that LLMs lack the nuanced understanding necessary to recognize the complex, overlapping nature of moral foundations in text.

4 CONCLUSION

This study presents the first comprehensive comparison between fine-tuned transformer models and state-of-the-art LLMs for moral foundation classification. Despite their flexibility and accessibility, LLMs significantly underperform across multiple evaluation metrics, exhibiting excessive false negatives on complex moral dimensions such as loyalty and sanctity. Fine-tuned transformers such as DeBERTa and RoBERTa outperform LLMs by substantial margins, particularly on nuanced foundation-level classification.

Critically, prompt engineering yielded inconsistent and minimal improvements, with some models actually degrading, demonstrating that prompting general-purpose LLMs cannot reliably substitute for task-specific fine-tuning. These findings reveal fundamental limitations in LLMs’ moral reasoning capabilities and systematic under-detection of moral content.

Given LLMs’ increasing integration into ethically sensitive applications—chatbots, content moderation, decision aids—these accuracy limitations raise serious deployment concerns. The AI community must prioritize specialized models for moral analysis, implement mandatory human oversight for LLM moral applications, and develop hybrid approaches combining LLM accessibility with transformer precision. Future research should focus on culturally diverse moral datasets, systematic error analysis, and embedding explicit moral reasoning into training protocols rather than relying on post-hoc prompting strategies.

Bridging the gap between technical performance and moral responsibility requires acknowledging current limitations and investing in purpose-built solutions—ensuring language technologies serve society both intelligently and ethically.

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