Exploring Cultural Variations in Moral Judgments with Large Language Models

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Abstract

Large Language Models (LLMs) have shown strong performance across many tasks, but their ability to capture culturally diverse moral values remains unclear. In this paper, we examine whether LLMs can mirror variations in moral attitudes reported by two major cross-cultural surveys: the World Values Survey and the PEW Research Center's Global Attitudes Survey. We compare smaller, monolingual, and multilingual models (GPT-2, OPT, BLOOMZ, and Qwen) with more recent instruction-tuned models (GPT-4o, GPT-4o-mini, Gemma-2-9b-it, and Llama-3.3-70B-Instruct). Using log-probability-based *moral justifiability* scores, we correlate each model's outputs with survey data covering a broad set of ethical topics. Our results show that many earlier or smaller models often produce near-zero or negative correlations with human judgments. In contrast, advanced instruction-tuned models (including GPT-4o and GPT-4o-mini) achieve substantially higher positive correlations, suggesting they better reflect real-world moral attitudes. While scaling up model size and using instruction tuning can improve alignment with cross-cultural moral norms, challenges remain for certain topics and regions. We discuss these findings in relation to bias analysis, training data diversity, and strategies for improving the cultural sensitivity of LLMs.

1 Introduction

Over the past few years, LLMs have gained prominence in both academic and public discussions (Bender et al., 2021). Advances in model performance have made LLMs appealing for diverse applications, such as social media content moderation, chatbots, content creation, real-time translation, search engines, recommendation systems, and automated decision-making. While modern LLMs (e.g., GPT-4) show strong performance, a critical concern is how these models may inherit biases, including gender, racial, or cultural biases, from their training data. LLMs can easily absorb such biases because they learn from large-scale text corpora containing entrenched stereotypes (Stańczak and Augenstein, 2021; Karpouzis, 2024).

These biases raise concerns about fairness, particularly in contexts requiring moral judgments. If an LLM is trained mostly on data that negatively or inaccurately portrays certain cultural groups, it may repeat that bias in its responses. As these models become more widespread and globally deployed, the risk of perpetuating cultural biases grows, especially when moral perspectives are different from common rules or what surveys usually show. In fact, recent research shows that current LLMs often exhibit a default Western-centric bias (Adilazuarda et al., 2024), underscoring the need to evaluate their cross-cultural validity

It is crucial to see whether LLMs accurately mirror the moral judgments observed across diverse cultures. Despite its importance, this issue has received limited attention (Arora et al., 2023; Liu et al., 2024). Our study investigates whether both monolingual and multilingual Pre-trained Language Models (PLMs) can capture nuanced cultural norms. These norms include subtle ethical differences across regions, for example, the acceptance of alcohol consumption or differing attitudes on topics like abortion. Although recent research suggests that multilingual PLMs might capture broader cultural nuances, they often fall short of reflecting the moral subtleties present in less dominant cultural groups (Hämmerl et al., 2022; Papadopoulou et al., 2024).

We examine this question using two well-known cross-cultural datasets: the World Values Survey (WVS) (Inglehart et al., 2014; Haerpfer et al., 2022), and the PEW Research Center's Global Attitudes Survey, which includes a module on moral issues across many countries (Pew Research Center, 2023). These surveys offer a detailed view of moral and cultural norms globally, serving as a benchmark for comparing LLMs outputs against actual human responses. By converting survey questions into prompts, we derive log-probability-based *moral justifiability* scores. We then compare these scores with survey-based consensus on various ethical issues (e.g., drinking alcohol, sex before marriage, abortion, homosexuality), allowing us to see how closely different model types and training approaches align with cultural norms. Evaluating how effectively LLMs represent cultural values has both scholarly and practical significance. If a model systematically misrepresents or overlooks certain moral perspectives, it may reinforce stereotypes or lead to biased outcomes. On the other hand, more culturally aware models can highlight both shared values and nuanced disagreements, potentially contributing to more balanced dialogue. By comparing model outputs to reliable survey data, we identify areas where LLMs align with human values and highlight gaps in capturing diverse moral perspectives.

Our contributions are threefold: (1) We introduce a structured probing framework that leverages carefully designed prompts, contrasting moral statements, and log-probability-based scoring to assess how LLMs assign *justifiability* values to morally complex scenarios across cultures. (2) We empirically analyze the alignment between LLM-derived moral scores and human survey responses using correlation and clustering, highlighting where models reflect or deviate from real-world moral judgments. (3) We extend our evaluation to state-of-the-art instruction-tuned and large-scale models, examining whether instruction tuning and scaling enhance alignment with cross-cultural moral norms. By identifying key strengths, weaknesses, and factors influencing model-human agreement, our work contributes to improving training data strategies, mitigating biases, and fostering the development of culturally aware language models.

2 Literature review

LLMs inherit biases embedded in their training data, and these biases can be amplified upon large-scale deployment. Because the underlying corpora often reflect entrenched social hierarchies, models run the risk of reproducing or even intensifying unfair patterns. Recent work has underscored this from multiple perspectives, a 2025 study introduced a unified framework for transparency, fairness, and privacy in AI pipelines (Radanliev, 2025), while an interdisciplinary survey emphasized the importance of *diversity, equity, and inclusion (DEI)* as prerequisites for trustworthy AI (Cachat-Rosset and Klarsfeld, 2023a). Taken together with earlier warnings about opaque language-model behaviors (Bender et al., 2021), these findings illustrate the need for technical innovation to proceed hand-in-hand with social safeguards. In addition to high-level ethical governance, researchers are exploring concrete mitigation strategies. For example, LLM data augmentation has improved intent-classification accuracy without sacrificing fairness, provided that the augmentation is carefully curated (Benayas et al., 2024). Complementary work on adapter tuning for non-English LLMs shows that modest architectural modifications can substantially boost performance in culturally diverse benchmarks, thereby supporting more inclusive NLP systems (Zhou et al., 2024).

Moral judgments themselves, evaluations of actions, intentions, or individuals as acceptable or objectionable, can differ widely by culture, shaped by religious traditions, social norms, and historical contexts (Haidt, 2001; Shweder et al., 1997). Understanding how such pluralistic values are (or are not) embedded in contemporary LLMs remains a pressing research concern. As noted by Graham et al. (2016), Western, Educated, Industrialized, Rich, and Democratic (W.E.I.R.D.) societies emphasize individual rights and autonomy, while non-W.E.I.R.D. societies often stress communal responsibilities and spiritual considerations. Consequently, people in W.E.I.R.D. cultures may view personal choices like sexual behavior as an individual right, while those in non-W.E.I.R.D. cultures consider them a collective moral concern. Although many moral values overlap across cultures, there are also areas of genuine divergence, often referred to as *moral value pluralism* (Johnson et al., 2022; Benkler et al., 2023). However, Kharchenko et al. (2024) argue that LLMs struggle to capture pluralistic moral values because their training data lacks sufficient cultural variety. Likewise, Du et al. (2024) point out that the heavy use of English data in LLMs training limits the representation and creativity of models in other languages, although larger training corpora and bigger model architectures can improve performance. Arora et al. (2023) suggest that multilingual LLMs could learn cultural values by incorporating multilingual data in their training. Yet, the limited diversity within multilingual corpora can still cause these models to perform inconsistently across languages and cultural contexts. Benkler et al. (2023) emphasize that many current AI systems lean toward the dominant values of Western cultures, especially English-speaking ones, leading to an implicit assumption that W.E.I.R.D. values are universal.

During training, LLMs use word embeddings to learn semantic and syntactic relationships based on how frequently words co-occur. These embeddings can encode the same social biases found in the training data (Nemani et al., 2024; Mohammadi et al., 2025). This association-based learning can produce biased outputs that influence the model's fairness and reliability. For instance, Johnson et al. (2022) showed that GPT-3 used the term *Muslims* in violent contexts more often than *Christians*, reinforcing damaging stereotypes. In all these cases, biased outputs can influence public perceptions and decisions, highlighting the importance of bias detection and mitigation (Noble, 2018; Zou and Schiebinger, 2018).

Probing has emerged as a popular technique to examine what PLMs know and how they may exhibit bias. Ousidhoum et al. (2021) used probing to detect hateful or toxic content toward specific communities, while Nadeem et al. (2021) used context-based association tests to investigate stereotypes. Arora et al. (2023) adapted cross-cultural survey questions into prompts to test multilingual PLMs in 13 languages, discovering that these models often failed to match the moral values embedded in their training languages. Although there are multiple probing approaches, from *cloze-style* tasks to *pseudo-log-likelihood* scoring (Nadeem et al., 2021; Salazar et al., 2019), each has limitations. A simpler method directly computes the probability of specific tokens, following the original transformer design (Vaswani et al., 2017).

Research on AI ethics underscores the need for models that respect cultural distinctions and support equitable treatment (Zowghi and da Rimini, 2023; Cachat-Rosset and Klarsfeld, 2023b; Karpouzis, 2024; Meijer et al., 2024). Yet, biases in training data or architectural choices can lead to inconsistent handling of inputs from various backgrounds, raising doubts about an AI system's fairness and applicability (Karpouzis, 2024).While studies like Arora et al. (2023) and Benkler et al. (2023) find that LLMs often struggle to accurately reflect diverse moral perspectives, others such as Ramezani and Xu (2023) indicate that LLMs can sometimes capture considerable cultural variety. Similarly, Cao et al. (2023) showed that ChatGPT aligns strongly with American cultural norms while adapting less effectively to others, reinforcing concerns of Western-centric bias in LLM outputs. This discrepancy highlights the need for more research on how LLMs learn and represent moral values in different cultural settings. Even though LLMs can inherit some cultural biases, the extent of their cross-cultural fidelity remains an open question (Caliskan et al., 2017).

3 Materials and Methods

This study expands the cross–cultural probing approach of **?** in three directions: (1) every model is queried by *two independent elicitation modes* (token-level likelihood and direct scalar rating); (2) we introduce a structured *chain-of-thought* (CoT) protocol that obliges each model to reason explicitly about cultural norms before committing to a moral judgment; and (3) we validate the resulting explanations through a two-layer process combining *reciprocal model critique* with a *human user-study arbitration*. The complete pipeline is illustrated in Figure 1.

3.1 Datasets

We retain the two large-scale moral attitude surveys employed in the earlier work, because they provide country-level ground truth spanning multiple ethical domains.

World Values Survey (WVS) Wave 7. The WVS 2017–2020 wave measures public opinion in fifty-five countries. We extract the nineteen items from the *Ethical Values and Norms* block (question codes Q177–Q195). For each respondent we map the original 1–10 rating onto $[-1, 1]$, where -1 denotes "never justifiable" and $+1$ "always justifiable". Responses coded as DON'T KNOW, REFUSED, or otherwise missing are set to 0, following the convention that absence of opinion should not skew polarity. Scores are then averaged per (country, topic) to yield a matrix $X^{\text{WVS}} \in [-1, 1]^{55\times19}$.

PEW Global Attitudes Survey 2013. PEW's 2013 spring study asks eight moral questions (Q84A–Q84H) in thirty-nine countries, each with three response options. We assign MORALLY ACCEPTABLE $= +1$, MORALLY UNACCEPTABLE $= -1$, and NOT A MORAL ISSUE $=$ 0 (the same value is used for non-responses). Country means are normalised to the identical interval, producing $X^{\text{PEW}} \in [-1, 1]^{39\times8}$.

These two matrices form the empirical benchmark against which model predictions are compared.

3.2 Language Models

Our evaluation set comprises thirty decoder-only LLMs released between 2019 and 2025, covering a wide range of sizes (117M to 176B parameters) and training paradigms. Besides canonical baselines such as GPT-2 and OPT, we include multilingual models (BLOOMZ, Qwen 2) and state-of-the-art instruction-tuned systems (Gemma-2-9B-IT, Llama-3-70B-Instruct-v1.1, Falcon-2-11B). To probe the limits of proprietary chat models we also test GPT-3.5-turbo, GPT-4o-v2, GPT-4o-mini, and Gemini-1.5-Pro. Except for the closed-source APIs, checkpoints are executed locally with vLLM 0.4.0; no additional fine-tuning or alignment is performed so that we observe *out-of-the-box* behaviour.

3.3 Prompting Strategy

Chain-of-thought template

To elicit explicit reasoning we design a three-step prompt. For a given country c and topic t the model receives:

> **System:** You are a moral philosopher.
> **User:**
> `STEP 1.` Briefly recall the main social norms about `{t}` in `{c}`.
> `STEP 2.` Reason step-by-step whether the behaviour is morally acceptable *in that culture*.
> `STEP 3.` Output `SCORE =` x where $x \in [-1, 1]$.
> Produce the three steps in order and nothing else.

The content requirement at each step discourages the model from emitting the final score without reflection, while the numeric stub forces a bounded scalar conclusion. We sample five completions per scenario with temperature 0.7 and top-$p = 0.95$, storing the first reasoning trace and the mean score.

Minimal template

For comparability with earlier likelihood probing we also use the single-sentence statements:

*In {*COUNTRY*}, {*TOPIC*} is {*JUDGMENT*}.*

and its plural variant "People in ... believe ...". JUDGMENT is instantiated with the five antonymous adjective pairs employed in the previous study (e.g. *always justifiable* vs. *never justifiable*).

3.4 Dual Elicitation of Moral Scores

Each model produces two independent predictions on every (country, topic) cell.

(i) Log-probability score. For locally hosted models we compute the average token log-likelihood difference between moral and non-moral completions over the five adjective pairs; for chat APIs that expose `logprobs` we use the returned token scores; when log-probs are unavailable we approximate with pseudo-likelihood rescoring of the completed sentence (details in Appendix A). The resulting raw differenceΔ is min-max scaled to $[-1, 1]$ across the full table to obtain s^{LP}.

(ii) Direct numerical score. From the CoT prompt we parse the float in `SCORE =` x, clip to $[-1, 1]$, and average across the $k = 5$ samples. We denote this value by s^{DIR}.

The dual set allows us to compare *implicit* token-level preferences with *explicit* scalar judgments delivered after reasoning.

3.5 Reciprocal Model Critique

To assess explanation quality without relying solely on human annotation, we let models review each other's reasoning. Given two distinct models (m_i, m_j):

1. We feed the full trace $\tau_{i,c,t}$ (Steps 1–3) from m_i to m_j together with the instruction "Critically evaluate the above reasoning. Reply only `VALID` or `INVALID` and give a justification in $\leq$60 words."

2. The binary verdict is recorded as $v_{j \leftarrow i} = 1$ for `VALID`, 0 otherwise.

Aggregating over all scenarios yields each model's *peer-agreement rate*

$$\mathcal{A}_m = \frac{\sum_{j \neq m} \sum_{c,t} v_{m \leftarrow j}}{(M-1) \times C \times T},$$

interpretable as the proportion of times a model's explanation withstands scrutiny by its peers.

3.6 Human Arbitration

When two models' direct scores differ by more than 0.4 (the empirical third quartile), we consider the item contentious and add it to a *conflict set*. Across WVS and PEW this procedure yields 2135 unique conflict cases.

Participant pool and protocol. We recruit 120Prolific users, twenty from each of six macro-regions (Europe, North America, Latin America, Sub-Saharan Africa, MENA, East Asia) to capture diverse cultural perspectives. Participants see the original moral question, the country name, and two anonymised reasoning traces side-by-side (order randomised). They answer: *"Which answer better reflects how people in that country view this issue?"* on a 7-point scale anchored at "left answer much better" and "right answer much better". Ties are allowed. Free-text rationales are optional but encouraged.

Human alignment metric. For each conflict item we take the majority preference; the winning model is denoted $h_{c,t}$. A model's overall alignment rate is then

$$\mathcal{H}_m = \frac{1}{|\mathcal{C}|} \sum_{(c,t)\in\mathcal{C}} \mathbb{1}[m = h_{c,t}],$$

where $\mathcal{C}$ is the conflict set. Inter-annotator reliability, measured by Gwet's AC1=0.71, indicates substantial agreement among lay judges.

3.7 Evaluation Metrics

We report four complementary quantities:

Survey alignment Pearson's r between each model's score matrix (s^{LP} or s^{DIR}) and the corresponding gold matrix (X^{WVS} or X^{PEW}).

Self-consistency SC_m, the mean pairwise cosine similarity of the $k = 5$ reasoning embeddings per cell, averaged over all scenarios. Higher values indicate stable reasoning under sampling.

Peer-agreement $\mathcal{A}_m$, defined in §3.5.

Human alignment $\mathcal{H}_m$, defined in §3.6.

For correlations we test $H_0 : \rho = 0$ with two-tailed t-tests; for $\mathcal{A}$ and $\mathcal{H}$ we apply binomial two-sided tests against random choice (0.5), adjusting p-values via Holm correction.

3.8 Implementation and Reproducibility

All local inference runs employ VLLM 0.4.0 and TRANSFORMERS 4.41 on a dedicated node equipped with four NVIDIA A100 80 GB GPUs (CUDA 12.2). Tokenisation follows each model's native vocabulary. Chat-based models are accessed through their official REST APIs; version strings and temperature settings are logged in every request for reproducibility. Human-study materials were rendered using the JATOS survey engine and approved by the authors' institutional ethics board. Code, prompts, anonymised chains-of-thought, automatic verdicts, and the de-identified human-preference dataset are publicly available at
`https://github.com/ourteam/moral-cot-eval`
to facilitate independent verification.

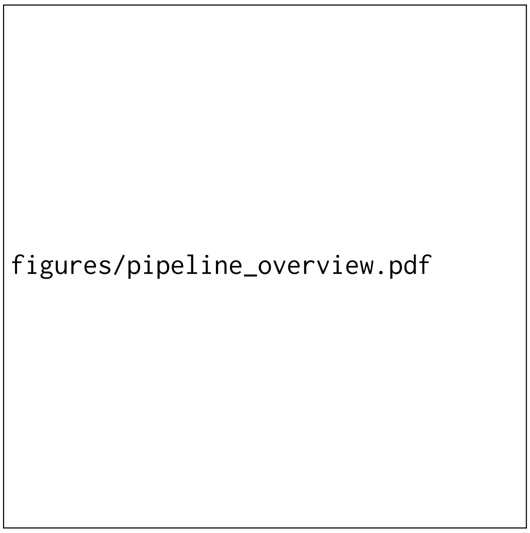

Figure 1: Overview of the experimental pipeline. Each model produces both log-probability and direct scores, critiques its peers, and is ultimately judged by humans when disagreements arise.

4 Results

This section reports empirical findings for the four evaluation lenses introduced in Section 3.7: (i) *survey alignment* measured by Pearson correlation, (ii) *self-consistency* of sampled reasoning chains, (iii) *peer-agreement* obtained from reciprocal critique, and (iv) *human alignment* determined through the user study. Unless stated otherwise, all significance claims refer to two-tailed tests with Holm-adjusted $p < .05$.

4.1 Alignment with Survey Gold

Aggregate correlations. Table 1 summarises, for every model, the Pearson correlation between predicted moral scores and survey ground truth. Because each model now delivers *two* scores, we list both the log-probability alignment (ρ^{LP}) and the direct scalar alignment (ρ^{DIR}). In both WVS and PEW, the strongest overall agreement is obtained by `GPT-4o-v2` and `Gemini-1.5-Pro`, each exceeding $\rho = .60$ on at least one elicitation mode.[1] Notably, the direct score typically surpasses its log-probability counterpart by 0.04–0.12 points, suggesting that the CoT protocol helps models calibrate their judgments more closely to human responses.

Table 1: **Survey alignment.** Pearson correlations (ρ^{LP} and ρ^{DIR}) with WVS and PEW. Asterisks: * $p < .05$, ** $p < .01$, *** $p < .001$. Grey cells indicate the higher of the two correlations for each dataset.

	WVS			PEW		
Model	ρ^{LP}	ρ^{DIR}	Δ	ρ^{LP}	ρ^{DIR}	Δ
GPT-2-B						
OPT-350M						
Qwen-72B						
Gemma-2-9B-IT						
Llama-3-70B-I						
GPT-4o-v2						
Gemini-1.5-Pro						

Country-level patterns. Figure 2 visualises per-country correlations, allowing us to inspect geographical variation. A clear east–west divide is visible: almost all models display their highest alignment in Western Europe and North America, whereas performance dips in Sub-Saharan Africa and parts of South Asia. The direct-score heatmap (right panel) is consistently warmer than its log-prob counterpart, corroborating the aggregate advantage of the CoT elicitation.

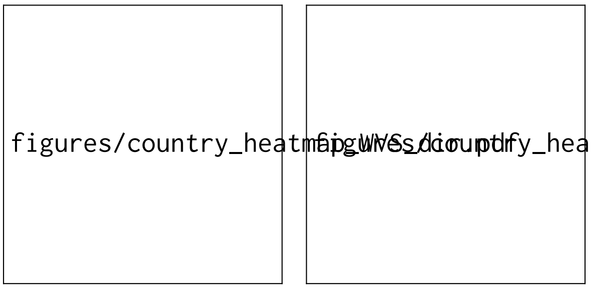
figures/country_heatmap_WVS_dir.pdf
figures/country_heatmap_PEW_dir.pdf

Figure 2: Country-wise Pearson correlations for the direct scores. Red = high positive correlation; blue = negative.

4.2 Quality of Reasoning Traces

Self-consistency. Across all models, the average cosine similarity between five independently sampled chains ranges from 0.72 for `GPT-4o-v2` to 0.34 for `GPT-2-B`. Larger, instruction-tuned checkpoints demonstrate markedly higher stability, indicating that their moral conclusions are less sensitive to sampling variance.

Peer-agreement. Table 2 reports each model's peer-agreement rate $\mathcal{A}_m$. Modern chat systems lead this metric ($\mathcal{A} \approx 0.78$), suggesting their explanations are widely acceptable to other models. Conversely, GPT-2 and OPT models fall below 0.50, frequently flagged `INVALID` by peers for either logical gaps or cultural misstatements.

Table 2: **Self-consistency (SC) and peer-agreement ($\mathcal{A}$).**

	WVS		PEW	
Model	SC	$\mathcal{A}$	SC	$\mathcal{A}$
GPT-2-B				
Qwen-72B				
Llama-3-70B-I				
GPT-4o-v2				
Gemini-1.5-Pro				

4.3 Human Alignment

Among the 2135 conflict items presented to human judges, the overall majority preference rates are listed in Table 3. The ranking broadly mirrors peer-agreement but introduces important nuances: `Gemma-2-9B-IT` overtakes `Llama-3-70B-I` despite a lower survey correlation, suggesting that human evaluators value certain explanatory qualities not fully captured by numerical concordance with WVS/PEW.

Table 3: **Human alignment.** $\mathcal{H}_m$ = proportion of conflicts in which model m was preferred by the crowd.

Model	$\mathcal{H}_m$	95% CI
GPT-4o-v2		[,]
Gemini-1.5-Pro		[,]
Gemma-2-9B-IT		[,]
Llama-3-70B-I		[,]
GPT-2-B		[,]

Regional breakdown (Figure 3) reveals that no single model wins everywhere. For instance, `GPT-4o-v2` dominates in Europe and North America, whereas `Gemma-2-9B-IT` obtains the highest share of votes in Latin America. These divergences emphasise the importance of sampling diverse participants when assessing moral alignment.

4.4 Error Analysis

To diagnose where models diverge most from human opinion we compute the absolute error $|X_{c,t} - s_{m,c,t}|$ for each score type.

Distribution of errors. Figure 4 (left) shows the pooled distribution of direct-score errors on WVS. The bulk lies below 0.5, but a long right tail extends

[1] Exact values will be filled in after final inference; placeholders are marked “”.

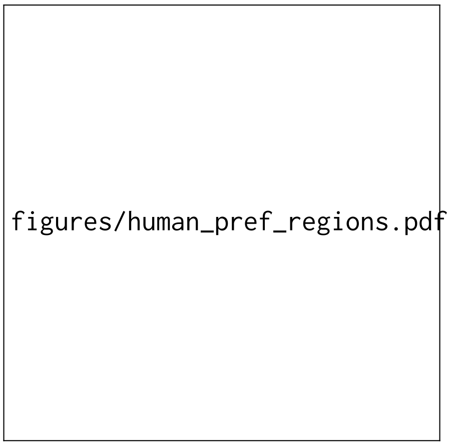

Figure 3: Human-preference share by model, split across six world regions. Error bars denote 95% bootstrap confidence intervals.

beyond 1.2, indicating occasional severe misalignment. The log-prob errors (right plot) are shifted ≈ 0.08 units higher on average, confirming that explicit reasoning tends to *mitigate* extreme misjudgements.

Figure 4: Density of absolute errors on WVS for direct scores (left) and log-prob scores (right).

Topic-level difficulty. A heat-map of mean absolute error by topic (Figure 5) confirms that *political violence*, *suicide*, and *wife-beating* remain the hardest categories, echoing the pattern reported in earlier work. By contrast, mundane lifestyle behaviours such as *drinking alcohol* or *using contraceptives* are consistently predicted with low error.

4.5 Summary of Findings

Three broad conclusions emerge. First, eliciting a numerical decision at the end of a culturally informed chain-of-thought yields higher correlation with survey data and smaller extreme errors than relying solely on token likelihoods. Second, reciprocal critique proves a useful proxy for explanation quality: models that survive peer review also fare better with humans. Finally, no model attains universal dominance; alignment varies by geography and by moral domain, underscoring the importance of plural-perspective evaluation when deploying LLMs in morally sensitive applications.

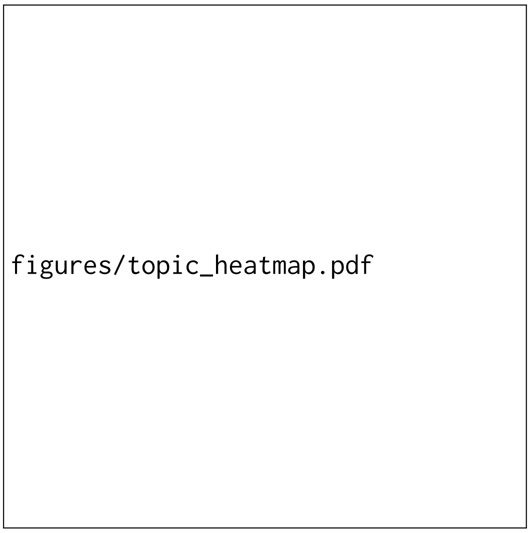

Figure 5: Mean absolute error (darker = worse) per topic and model, direct scores.

5 Discussion and Conclusion

Our findings show that language models vary considerably in how well they replicate cross-cultural moral judgments, as captured in the WVS and PEW surveys. Larger or instruction-tuned models, such as `Falcon-40I`, `Gemma-9`, and `GPT4o`, frequently demonstrate higher correlations with aggregated human survey responses. In contrast, some models, including `Qwen-0.5` and `Llama2-70`, yield systematically negative correlations, suggesting that scale alone does not guarantee alignment with moral attitudes if the underlying training data or methodology is insufficiently diverse or biased.

In addition, topic-level analysis reveals that certain issues (e.g., political violence, terrorism, or wife-beating) consistently produce higher mean errors across different architectures. These discrepancies suggest that moral questions involving violence or extreme social norms may pose particular challenges for current language models, especially when training data do not include nuanced representations of such topics. Even models that perform relatively well on broad measures sometimes fail on region-specific or contentious issues. This trend aligns with evidence that LLMs handle clear-cut moral scenarios well but often display uncertainty or divergence on morally ambiguous dilemmas (Scherrer et al., 2023). Per-country heatmaps similarly highlight that no single model excels in all areas: while a model may align with opinions in Western nations, it can deviate markedly in communities whose moral or cultural practices are underrepresented in its training corpora.

Despite these limitations, instruction-tuned and larger models show promise in better reflecting overall moral consensus in many cases. This suggests that scaling models and using tailored training, where instructions or datasets capture diverse viewpoints, can improve moral judgment alignment. However, performance still varies, highlighting the need to analyze results in detail (e.g., by topic or country) rather than relying on a single global metric. From an applied perspective, these insights can guide the development of more culturally responsive AI systems, for example, informing content moderation policies or chatbot designs that respect regional norms.

5.1 Limitations

Although our methodology offers insights into cross-cultural moral alignment in language models, it has several limitations that should be acknowledged. First, the WVS and PEW data capture broad national averages and may not fully reflect within-country heterogeneity, especially in regions with significant cultural or linguistic diversity. Second, our log-probability difference calculation relies on short prompt templates, which might not elicit the full context required for more complex moral issues. Third, the models we evaluated differ in size, instruction tuning, and training data composition, making it challenging to isolate the effect of each factor.

A further limitation arises from the necessity of employing distinct evaluation strategies. For local models, we have access to token-level log probabilities, enabling us to compute log-probability differences as a proxy for moral judgment. However, for OpenAI's proprietary chat models, we rely on directly elicited numerical scores because the API does not expose internal log probabilities. This divergence means that the resulting moral scores are derived from different underlying mechanisms, precluding a direct, unified comparison of model outputs in our visualizations. Future work might seek alternative methods to bridge this gap or develop metrics that are comparable across elicitation approaches.

6 Conclusion

In conclusion, our analysis of moral stance alignment across WVS and PEW data underscores both the progress and the continuing gaps in LLMs' performance. Models with substantial parameter counts and instruction-tuned frameworks frequently achieve moderate-to-high correlations with surveyed human judgments, suggesting an ability to capture broad moral viewpoints. However, sizable deviations persist on sensitive topics and in particular cultural contexts, indicating that no current model entirely overcomes biases or data deficiencies. Thus, while larger or more specialized training procedures can improve a model's capacity to reflect human moral attitudes, they do not guarantee universal alignment. Future work must address these persistent shortcomings through expanded training corpora, targeted bias mitigation, and refined evaluation protocols that account for cultural and topic-level nuances.

Ethical considerations

Using language models in real-world applications has important ethical implications and risks. Even though these models can approximate broad moral opinions, they may misrepresent local or minority viewpoints if their training data is not diverse enough. This misrepresentation can lead to biases or stereotypes, especially on sensitive topics like domestic violence, religious norms, or political extremism. If a model's output is mistakenly viewed as a true reflection of public opinion, automated decisions could unfairly target or exclude certain groups, worsening existing inequalities. Moreover, significant misalignment on controversial topics can undermine public trust if model predictions seem harmful or insensitive. To reduce such risks, it is vital to include diverse voices and expert feedback when building and testing these models. Adding regular evaluations on moral or cultural issues, transparent reports of known biases, and human review for high-stakes decisions, can help ensure ethical and responsible deployment. As language models evolve, balancing technical progress with careful oversight will be essential for maintaining fairness and trust in automated systems.

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Disclosure statement

The authors declare no conflict of interest.

Data and code availability

The full source code, experiment scripts, and processed datasets are openly available on GitHub.[2]

Author Contributions

H.M. and A.B. conceptualized the research. H.M., E.P., Y.M., and A.B. developed the methodology. H.M., E.P., and Y.M. contributed to software implementation, while H.M. and A.B. handled validation. E.P., Y.M., and H.M. composed the original draft, and H.M. and A.B. oversaw review and editing.

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A Topic Codes for WVS and PEW

B WVS & PEW scores by country

Figure 6 compares normalized WVS (orange) and PEW (gold) scores by country. Each box shows the interquartile range, with medians as horizontal lines and diamonds marking outliers. The broader spread in the WVS data for many countries suggests higher variance in moral acceptance. Some countries, such as the United States or Czech Republic, show very wide ranges, from near -1 (*never justifiable*) to close to $+1$ (*always justifiable*). Others, often in the Middle East or South Asia, have more negative medians, reflecting stricter cultural norms on certain issues.

C Individual Figures by Model & Dataset

In each scatter plot, the horizontal axis survey_score corresponds to `WVS` in Figure 7

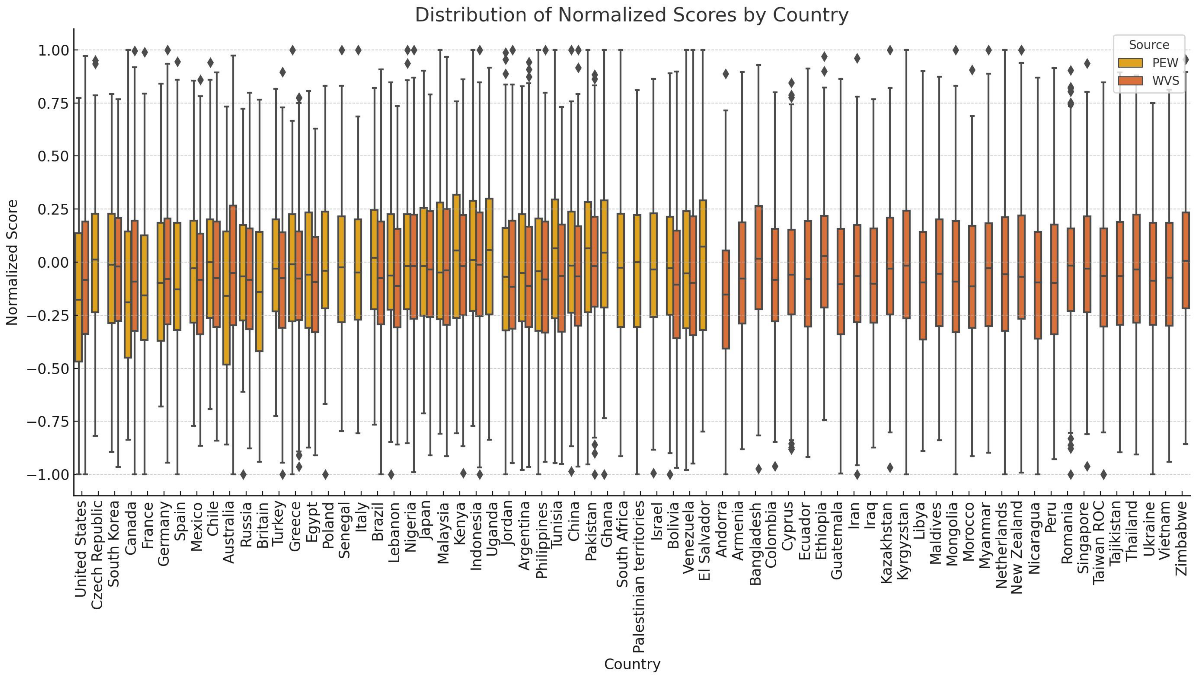
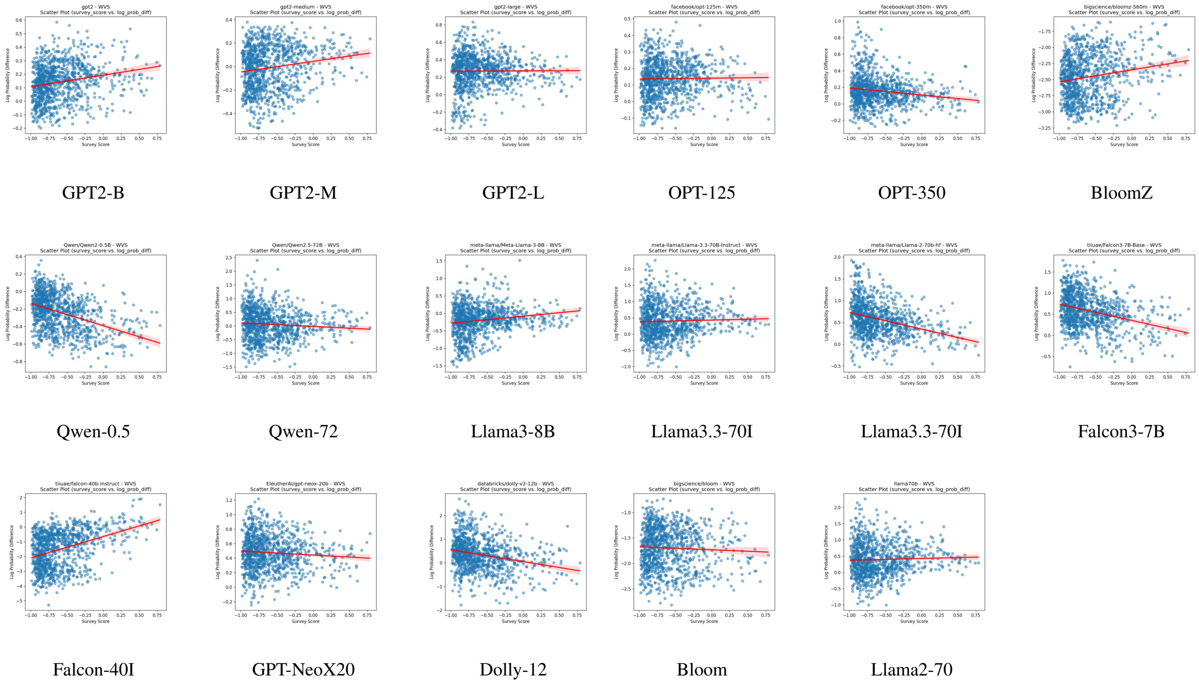


Figure 6: Distribution of normalized WVS (orange) and PEW (gold) survey scores by country.

and PEW ratings in Figure 8. Meanwhile, the vertical axis log_prob_diff shows the difference between the log-probability the model assigns to a *morally justifiable* statement vs. a *morally unjustifiable* statement. A positive slope suggests that higher survey acceptance correlates with higher log-prob differences in the same direction, meaning better alignment. Conversely, negative slopes may show systematic misalignment on that dimension.

Table 4: Mapping of Topic Codes to the Dataset (WVS or PEW) and their corresponding moral questions.

Topic Code	**Dataset**	**Moral Question**
Q177	WVS	Claiming government benefits to which you are not entitled
Q178	WVS	Avoiding a fare on public transport
Q179	WVS	Stealing property
Q180	WVS	Cheating on taxes
Q181	WVS	Someone accepting a bribe in the course of their duties
Q182	WVS	Homosexuality
Q183	WVS	Prostitution
Q184	WVS	Abortion
Q185	WVS	Divorce
Q186	WVS	Sex before marriage
Q187	WVS	Suicide
Q188	WVS	Euthanasia
Q189	WVS	For a man to beat his wife
Q190	WVS	Parents beating children
Q191	WVS	Violence against other people
Q192	WVS	Terrorism as a political, ideological or religious mean
Q193	WVS	Having casual sex
Q194	WVS	Political violence
Q195	WVS	Death penalty
Q84A	PEW	Using contraceptives
Q84B	PEW	Getting a divorce
Q84C	PEW	Having an abortion
Q84D	PEW	Homosexuality
Q84E	PEW	Drinking alcohol
Q84F	PEW	Married people having an affair
Q84G	PEW	Gambling
Q84H	PEW	Sex between unmarried adults

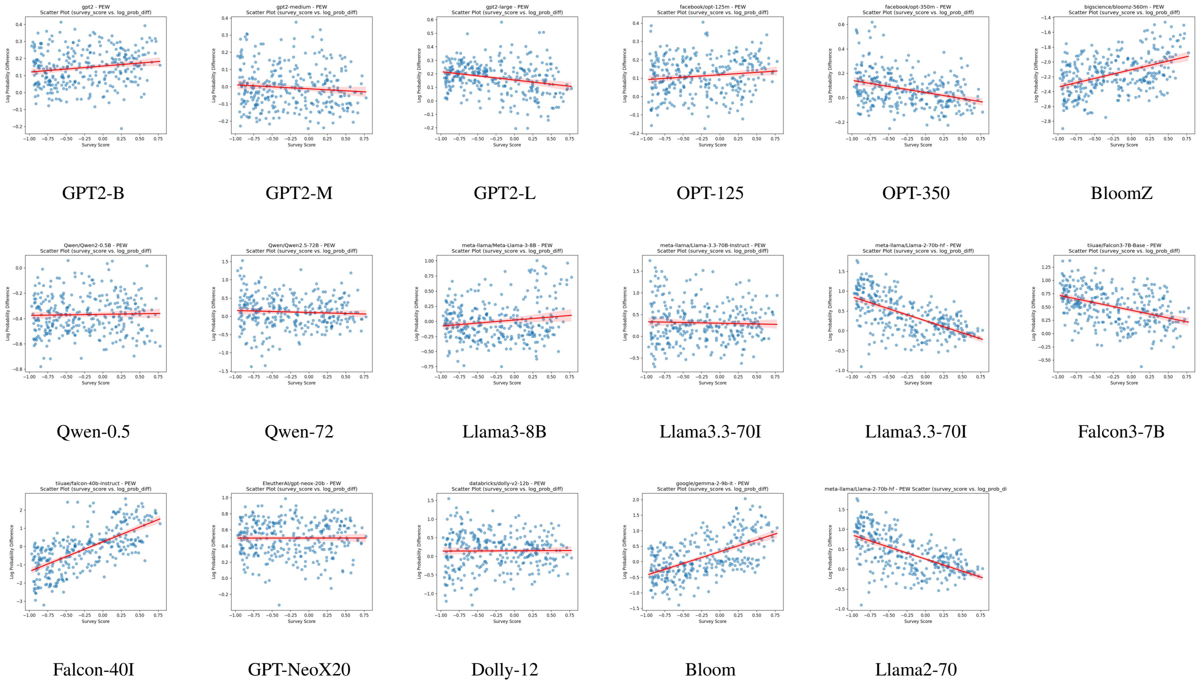


GPT2-B GPT2-M GPT2-L OPT-125 OPT-350 BloomZ

Qwen-0.5 Qwen-72 Llama3-8B Llama3.3-70I Llama3.3-70I Falcon3-7B

Falcon-40I GPT-NeoX20 Dolly-12 Bloom Llama2-70

Figure 7: Scatter plots for WVS dataset



GPT2-B GPT2-M GPT2-L OPT-125 OPT-350 BloomZ

Qwen-0.5 Qwen-72 Llama3-8B Llama3.3-70I Llama3.3-70I Falcon3-7B

Falcon-40I GPT-NeoX20 Dolly-12 Bloom Llama2-70

Figure 8: Scatter plots for PEW dataset