

# CONTROLLABLE AND INTERPRETABLE MULTI-VALUE ALIGNMENT FOR LARGE LANGUAGE MODEL

**Anonymous authors**

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## ABSTRACT

Large Language Models (LLMs) are increasingly expected to embody human values in socially consequential contexts, but current alignment methods often lack interpretability, controllability and value diversity. We propose **Value-aligned Constitutional AI (VCAI)**, a novel framework for fine-grained value alignment based on Schwartz’s Basic Value. Through VCAI we construct **ML-Values**, a multi-level dataset generated through role-playing, value decomposition, and iterative rewriting, allowing precise control over alignment intensity. ML-Values captures rich, context-aware expressions of values and supports multi-value alignment. Besides, by reformulating traditional value questionnaires into generative formats, we can obtain more accurate values assessment results. Experimental results demonstrate that models trained with ML-Values present enhanced controllability and generalization across moral, psychological, and cultural dimensions. Moreover, alignment influences not only local response fidelity but also global value structures of LLMs, promoting coherent moral reasoning and structured preference expression. Our work offers a robust and interpretable foundation for building trustworthy, human-centered AI systems.

## 1 INTRODUCTION

Large Language Models (LLMs) have rapidly advanced in generating coherent, context-aware, and semantically rich language. As these models increasingly communicate with humans, they are expected not only to produce fluent responses but also to reflect human-like reasoning, motivations, and values (Shi et al., 2025; Du et al., 2025). Human values—core principles guiding perception, behavior, and decisions—are deeply embedded in communication. LLMs’ ability to imitate human expression raises key questions about their capacity to simulate or internalize value systems (Qiu et al., 2022; Ouyang et al., 2024). As LLMs are deployed in socially significant contexts, understanding how values are embedded and revealed and how to align values to certain orientations in their outputs becomes increasingly important (Klingefjord et al., 2024; Benkler et al., 2023).

Current approaches to aligning LLMs with human values face many challenges. Most rely on narrow, self-report or dictionary-based tools that lack contextual nuance and behavioral authenticity (Ye et al., 2025a; Zhang et al., 2024). While LLMs show promise in inferring values from text, existing datasets are limited in interpretability, controllability and diversity, often focusing only on safety-related values like fairness or privacy (Ye et al., 2025b; Chiu et al., 2025). Others, As shown in Figure 1, limited focus neglects broader, structured, and culturally varied nature of human values. Moreover, few studies explore whether LLMs exhibit consistent or pluralistic value profiles resembling human populations (Wang et al., 2025; Jiang et al., 2025; Liu et al., 2024). Additionally, while aligning models with a single value has been gradually improved, challenges remain in aligning and integrating multiple potential values, such as ensuring stability under value trade-offs (Sorensen et al., 2024; Yao et al., 2025a). To support responsible AI development, there is a pressing need for fine-grained, controllable and interpretable datasets that capture diverse and contextualized human values, enabling better alignment, analysis, and benchmarking of LLM behavior.

For these challenges, we propose **Value Constitutional AI**, a framework for constructing **ML-Values**, a multi-level value alignment dataset based on Schwartz’s Basic Value Survey (Schwartz & Cieciuch, 2022). VCAI uses role-playing and value decomposition to generate diverse, context-rich alignment annotations, and uses an iterative rewriting mechanism to steer LLMs toward target align-

ment levels, validated via multi-role play evaluations. Thus, we can get datasets with fine-grained value agreement and ensures alignment-compliant outputs. We further explore multi-dimensional value integration through mixed-dataset fine-tuning and expert model fusion, achieving robust control in complex scenarios. To overcome interpretability limits of traditional PVQRR (Schwartz & Cieciuch, 2022) formats, we reformulate them into a generative response setting.

We validate the controllability of the ML-Value dataset with respect to different levels of alignment using Supervised Fine-Tuning (SFT). Empirical results show that ML-Values enables effective control of value expression, while improving generalization across psychological, cultural, and moral domains.

Our main contributions are as follows:

1. We introduce **VCAI**, a structured framework that integrates role-playing, value decomposition, and iterative rewriting for constructing multi-level value-aligned responses, along with a multi-role evaluation protocol to ensure alignment fidelity.
2. We build **ML-Values**, a fine-grained, controllable dataset based on Schwartz’s Basic Value Survey, and verify its effectiveness across multiple value dimensions.
3. We explore and evaluate multi-value alignment via both mixed-dataset fine-tuning and expert model fusion, revealing feasibility and challenges of coherent multi-value integration. Moreover, we provide empirical evidence that value alignment not only improves local response controllability, but also reshapes global value structure of LLMs, revealing its cognitive and ethical significance.

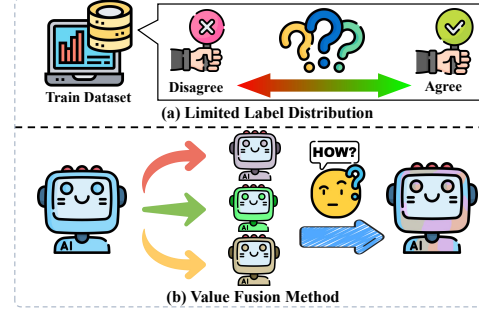


Figure 1: (a) Limited label distribution in traditional value datasets, which hinders fine-grained value representation and controllability. (b) Lacking of suitable value fusion methods and in-depth analysis for modeling and integrating multiple human values in language models.

The difference between our method and previous works (e.g., CLAVE (Yao et al., 2024), AdaAEM (Duan et al., 2025)) is: previous works focus on the “evaluation” of LLM values, our method aims to achieve active and accurate alignment of multiple values through “value decomposition, multi-role evaluation, and iterative rewriting”, and the constructed ML-Values dataset is used for “alignment training” rather than “evaluation verification”. The core contribution of our work is to confirm that value alignment can not only control local responses but also reshape global value structure of LLMs, and this effect can be transferred across cognitive, cultural and other frameworks. Building on these contributions and advantages, we situate our work in the broader background of advancing controllable value alignment research. This research provides a solid foundation for future practical applications, advancing the use and development of value alignment in AI application.

## 2 RELATED WORK

### 2.1 VALUE MEASUREMENT

Recent work explores value measurement in LLMs through generative, lexical, and psychometric methods. (Ye et al., 2025b) propose GPLA, combining lexical generation with five-factor theory, and (Ye et al., 2025a) extend this with GPV, a generative psychometric model. (Biedma et al., 2024) introduce ValueLex, revealing non-human value structures via factor analysis. Adaptive probing is advanced by (Duan et al., 2025), who generate culturally sensitive prompts, and by (Yao et al., 2024), who propose a dual-model design for generalizable value evaluation. Interpretability efforts include (Su et al., 2025)’s ValueLocate, mapping neuron activations to Schwartz’s values, and (Rozen et al., 2025)’s Value Anchoring for assessing consistency. Benchmarking platforms by (Yao et al., 2025b) and (Ren et al., 2024) provide pluralism-aware metrics. (Sorensen et al., 2024) outline a taxonomy for pluralistic alignment. However, these approaches lack fine-grained analysis of value expressions in model outputs. Evaluation methods remain unstable under pluralistic influences, and often rely on synthetic inputs or simplified value schemas.

## 2.2 VALUES ALIGNMENT

Value alignment in LLMs is an active area of research. (Klingefjord et al., 2024) propose Moral Graph Elicitation for structured value modeling, (Yao et al., 2023a) introduce a multidimensional framework based on Schwartz’s theory and FULCRA dataset. For training, (Qiu et al., 2022) apply reinforcement learning to instill value-consistent behavior, and (Padhi et al., 2024) leverage synthetic supervision on unstructured texts. (Wang et al., 2024) classify alignment methods into RLHF, SFT, and in-context learning. (Yao et al., 2023b) advocate deeper alignment with intrinsic human values beyond surface instructions. (Khamassi et al., 2024) distinguish statistical from intentional alignment, stressing ethical and causal reasoning. To address value pluralism, (Wang et al., 2025) frame alignment as multi-objective optimization, supported by culturally adaptive methods from (Choenni & Shutova, 2024) and (Sorensen et al., 2024). (Bai et al., 2022) propose constitutional AI, using pre-defined principles and model self-critiques. However, current work lacks fine-grained, controllable value alignment datasets, limiting robustness and generalizability of alignment techniques.

## 3 VCAI: VALUE-ALIGNED CONSTITUTIONAL AI

As shown in Figure 2, our proposed framework for value-aligned response generation using LLMs comprises: **Core Values Breaking Down**, **Raw Response Generation**, **Multi-role Evaluation**, and **Response Rewrite**. Each step is described in detail below.

### 3.1 STEP 1: CORE VALUES BREAKING DOWN

Based on fine-grained alignment achieved through the sub-dimensional decomposition of (Schwartz, 1992a) and relationship between instrumental values and core values of (Bardi & Schwartz, 2003a), we propose idea of core value decomposition. We decompose a core value  $V$ , such as “self-direction”, into a set of granular sub-values  $\{v_1, v_2, \dots, v_n\}$ . For example, core value **self-direction** might be decomposed into sub-values such as independence, creativity, and freedom of choice. These fine-grained values allow more precise alignment checks during subsequent evaluations.

### 3.2 STEP 2: RAW RESPONSE GENERATION

Given the core value  $V$  and a desired level of agreement  $D$ , we generate an initial raw response  $R$  using the LLM. The degree of agreement  $D$  is explicitly defined within the following discrete range:  $\{-2, -1, 0, 1, 2\}$ , where each integer corresponds to: **Strongly Disagree**, **Somewhat Disagree**, **Neutral**, **Somewhat Agree**, **Strongly Agree**. The generated response  $R$  should explicitly embody the specified agreement level  $D$  towards the core value  $V$ .

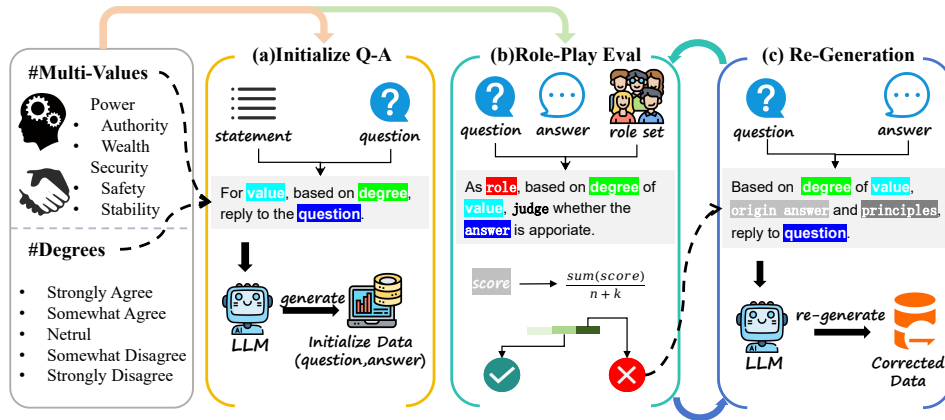


Figure 2: Overview of the VCAI pipeline. (a) Initial Q-A generation based on a value and degree of agreement; (b) Multi-role evaluation where LLMs role-play evaluators to assess alignment with sub-values; (c) Iterative response re-generation until alignment with target degree is reached. Degrees include **St\_a** (Strongly Agree), **So\_a** (Somewhat Agree), **Ne** (Neutral), **So\_d** (Somewhat Disagree), and **St\_d** (Strongly Disagree).

### 3.3 STEP 3: MULTI-ROLE EVALUATION

In this step, we employ multiple distinct role-play prompts (as shown in Appendix F) to evaluate the generated response  $R$  regarding its alignment with each sub-value  $v_i$ . Specifically, we prompt LLM to assume different roles, as shown in Appendix D.3, to independently assess alignment of response  $R$  with each sub-value  $v_i$ . Each evaluation yields a discrete alignment score in:

$$J(R, v_i) \in \{-1, 0, 1\}$$

These scores correspond to: Disagree, Neutral, Agree. Each role produces scores for all sub-values:

$$MRE_k = [J_k(R, v_1), \dots, J_k(R, v_n)]$$

### 3.4 STEP 4: RESPONSE REWRITE

We aggregate the scores across all roles and sub-values to obtain an overall measure of agreement of value  $V$ . Specifically, we calculate the mean score across all roles and sub-values, and scale it by a factor of 2 to match the initial scale of  $D$ . Formally, the updated score  $D'$  is computed as:

$$D' = 2 \times \frac{\sum_{j=1}^k \sum_{i=1}^n MRE_j(R, v_i)}{k \times n}$$

where  $k$  denotes the number of roles and  $n$  the number of sub-values. If the absolute difference between the new alignment score  $D'$  and the original intended score  $D$  exceeds a predetermined threshold  $t$ ,  $|D' - D| > t$ . The response generation process returns to **Step 2**, and the procedure repeats until either alignment criteria are met or the maximum number of iterations  $M$  is reached.

After completing up to  $M$  iterations, we select the response  $R'$  from the set of generated responses that is closest to the desired alignment level  $D$  as our final response.

## 4 VALUE ALIGNMENT

**Task Definition.** The value alignment task aims to adjust the model’s outputs to align with specific, potentially multi-values (Sorensen et al., 2024). For LLMs, given an input  $x_i$ , a vector of value dimensions  $\mathbf{v}_i$ , and a vector of target alignment levels  $a_i$ , the goal is to generate outputs that align with the desired values at the corresponding target levels, i.e.,

$$\text{Align}(L(x_i); \mathbf{v}_i) \approx a_i.$$

Here,  $\mathbf{v}_i$  means a certain value dimension. This reflects need to balance various values in complex real-world scenarios, ensuring that the model’s responses appropriately reflect the desired level of alignment across different dimensions.

**Single Value Alignment.** In context of value alignment, single value alignment refers to adjusting models’ response to align with a specific value dimension at targeted level. Formally, for each input-output pair  $(x_i, y_i)$ , model must generate  $y_i$  such that it aligns with a particular value category  $v_i \in \mathcal{V}$  at the specified alignment level  $a_i \in [0, 1]$ , i.e.,

$$\text{Align}(y_i; v_i) \approx a_i.$$

To achieve this, we define a fine-grained dataset  $\mathcal{D} = \{(x_i, v_i, a_i)\}_{i=1}^N$ , where  $x_i$  is the input,  $v_i$  is a value dimension, and  $a_i$  is the target alignment level. The goal is for the model to generate responses that reflect the specified alignment across the desired value dimension.

This alignment is achieved through supervised fine-tuning(SFT), as described in the following:

$$\mathcal{L}_{\text{SFT}} = - \sum_{i=1}^N \log P_{\theta}(y_i^* | x_i, v_i, a_i),$$

where the model learns to generate response  $y_i^*$  that best matches target alignment with respect to value category  $v_i$ .

**Multi Value Alignment.** Multi-value alignment extends single value alignment by considering multiple value categories in the model’s response. Given input  $x_i$ , the goal is to generate an output  $y_i$  that aligns with a set of value categories  $\{(v_i^{(j)}, a_i^{(j)})\}_{j=1}^K$ , where  $v_i^{(j)}$  is the value dimension and  $a_i^{(j)}$  is the target alignment level:

$$\text{Align}(y_i; \{(v_i^{(j)}, a_i^{(j)})\}_{j=1}^K) \approx \{a_i^{(j)}\}_{j=1}^K.$$

We explore two approaches for multi-value alignment:

**Mixed Dataset Fine-Tuning.** In this approach, we merge all single-value datasets and train a unified model to align responses across multiple value dimensions. This method enables model to learn joint representations of multiple values and capture interactions between them. The loss function is extended from SFT as follows:

$$\mathcal{L}_{\text{Mix}} = - \sum_{i=1}^N \log P_{\theta} \left( y_i^* \mid x_i, \{(v_i^{(j)}, a_i^{(j)})\} \right).$$

**Model Fusion via Per-Value Experts.** Here, we train separate expert models  $\theta_j$  for each value dimension  $v^{(j)}$ , with independent alignment objectives. At inference time, these expert models are fused via weighted averaging:

$$\theta_{\text{fused}} = \sum_{j=1}^K \lambda_j \theta_j, \quad \sum \lambda_j = 1.$$

## 5 VALUE MEASUREMENT: QUESTIONNAIRE-BASED GENERATION ANALYSIS

To assess the value orientation of LLMs, we propose an fully automated protocols that rely on *open-ended* generation. In both protocols, the model generates open responses, which are later mapped to a discrete value scale.

We adapt PVQ-RR questionnaire ( $N = 57$  items) by manually converting every multiple-choice statement into an open question.<sup>1</sup> For each item  $q_i$  we sample the LLM  $M$  times with temperature  $T$  and a light role-play pre-amble that diversifies the persona:

You are a 34-year-old environmental lawyer living in Nairobi.  
 ...  
**Q:** Why might having lots of money be important to you?

The placeholders are drawn uniformly from a predefined pool, as shown in Figure 2 Dataset Building; this Monte-Carlo style prompting has proven effective at revealing latent value preferences.

**Value Assignment.** Let the original Likert options be denoted as  $\mathcal{O} = \{o_1, \dots, o_K\}$  (e.g., “*Very much like me*”, ..., “*Not like me at all*”). For the  $m$ -th random role generated by the LLM for item  $q_i$ , we denote produced free-text answer by  $g_{i,m} \in \mathcal{G}$ , where  $\mathcal{G}$  represents the space of all admissible strings. Each generated answer  $g_{i,m}$  is then processed by a separate *LLM-as-Judge*, which outputs a categorical probability vector  $p_{i,m} \in \Delta^{K-1}$ , where  $\Delta^{K-1} := \{\mathbf{p} \in \mathbb{R}_{\geq 0}^K \mid \sum_{k=1}^K p^{(k)} = 1\}$  is the  $(K-1)$ -simplex. To determine the final value assignment, we convert the soft predictions into hard votes and aggregate over  $M$  samples using a majority rule, where  $\hat{o}_i$  is assigned value for item  $q_i$ .

<sup>1</sup>E.g. the item “*It is important to him to be rich.*” is turned into “*Why might having lots of money be important to you?*”



$$\hat{o}_i = \arg \max_{k \in [K]} \sum_{m=1}^M \mathbb{I} \left[ \arg \max_{j \in [K]} p_{i,m}^{(j)} = k \right],$$

This process produces score vector  $\hat{\mathbf{o}} = (\hat{o}_1, \dots, \hat{o}_N)$  for all  $N$  items.

## 6 EXPERIMENTS SETUP

### 6.1 EXPERIMENT SETTINGS

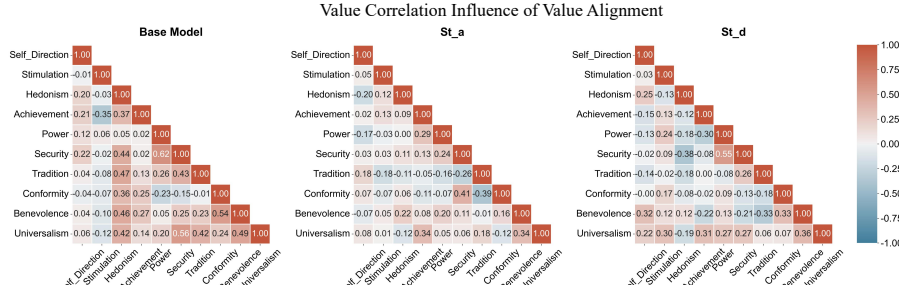


Figure 3: Value correlation influen of value alignment, **Hybrid** case. **St\_a** means Strongly Agree, **St\_d** means Strongly Disagree.

We use Qwen2.5-7B-Instruct (Qwen et al., 2024) as base model, fine-tuning them with LLama-Factory (Zheng et al., 2024) for SFT training in Lora (Hu et al., 2022). The model merge methods we choose are Linear and Karcher. Model merge tool we use is mergekit (Goddard et al., 2024).

The synthesis parameters for ML-Values dataset have a maximum rewrite count of 500 and a role count of 5. The learning rate in SFT is 1e-5 and epoch is 1. We implement vLLM (Kwon et al., 2023) to get questions and rewrite answers, temperature is 1.0. The prompts used in VCAI framework and value decomposition results are detailed in Appendix VCAI Prompts. Model fusion methods we choose are detailed in Appendix Training Settings.

### 6.2 BENCHMARKS

We structure evaluations across three axes and detailed information is in Appendix E:

- **Utility.** We assess models’ practical utility performance on average score of 6 NLP benchmarks and MT-Bench (Zheng et al., 2023).
- **Safety and Bias.** Safety and Bias evaluations include XSTest (Röttger et al., 2024), Generation Exploitation (Huang et al., 2024) and BBQ (Parrish et al., 2022).
- **Values.** To explore alignment of models, we use 2 value benchmarks, which include ValueBench (Ren et al., 2024) and Enhanced Questionnaire (described in Section 5).

## 7 RESULTS AND ANALYSIS

### 7.1 PSYCHOLOGICAL STRUCTURE SHIFT OF VALUE ALIGNMENT

To explore impact of multi-value alignment on the value orientations of LLM, we use **Hybrid** strategy based on 30 persona-driven questionnaires as a case study. Correlation matrices of value dimensions are computed for the **base\_model**, **Strongly Agree (St\_a)**, and **Strongly Disagree (St\_d)**, then projected into two dimensions via multidimensional scalingn (MDS) to reveal structural plasticity.

As shown in Figure 3, base model exhibits uniformly positive, complicated value correlations—resembling early-stage human moral cognition where values lack clear separation, as Kohlberg mentioned in (Kohlberg, 1994).

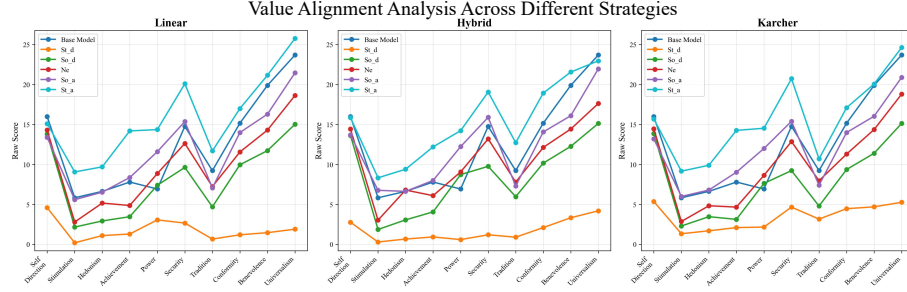


Figure 4: Controllability of value under different alignment strategies: Linear, Hybrid, and Karcher. **St.a** means Strongly Agree, **So.a** means Somewhat Agree, **Ne** means Neutral, **St.d** means Strongly Disagree, **So.d** means Somewhat Disagree.

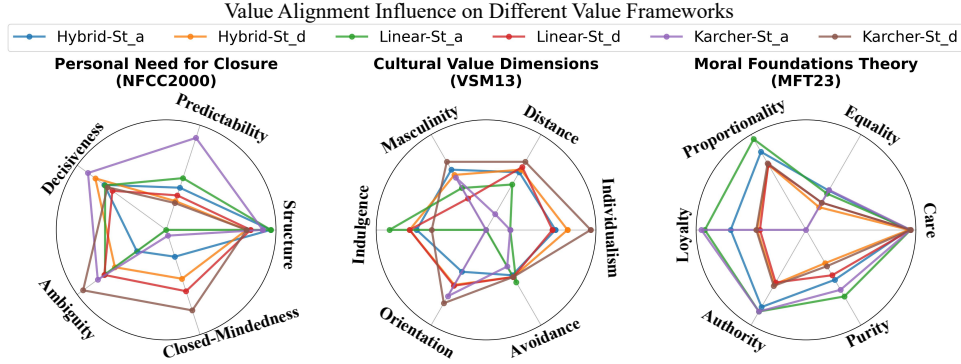


Figure 5: Radar charts illustrating value alignment effects across three psychological frameworks: NFCC2000, VSM13, and MFT23. Lines represent base model and six alignment strategies using Hybrid, Linear, and Karcher. **St.a** means Strongly Agree, **So.a** means Somewhat Agree, **Ne** means Neutral, **St.d** means Strongly Disagree, **So.d** means Somewhat Disagree.

This undifferentiated structure may lead to inconsistent moral behavior. Through **St.a** alignment, correlations weaken and change into a more modular, interpretable pattern. Values become more distinct, consistent with psychological process of **value clarification** (Rokeach, 1973), enabling improved prioritization and moral reasoning. By contrast, **St.d** alignment introduces negative correlations between conflicting values (e.g., **Power** vs. **Benevolence**), reflecting internal tensions and LLM’s attempt to reconcile opposing norms—indicative of dialectical or defensive strategies.

To visualize dynamics, we use Multidimensional Scaling (MDS) on correlation profiles (Figure 6). Base model forms a tight cluster with little differentiation, while **St.a** model shows dispersed, individualized value positions, which is similar to theory in (Schwartz, 1992b). The **St.d** model reveals semi-clustered patterns, suggesting defensive consolidation. These findings highlight role of alignment in shaping not just local associations but global moral architecture in promoting coherent, context-sensitive reasoning under multi-value settings.

In summary, these findings highlight multi-value alignment not only changes local value associations but reshapes global cognitive geometry, which shows role of alignment strategies as psychological scaffolds for encoding value consistency, moral flexibility, and trustworthy reasoning in LLMs.

Value Alignment MDS Embedding Comparison

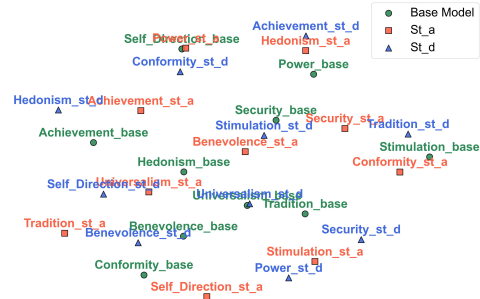


Figure 6: MDS embedding of value correlations across alignment strategies. **St.a**, **St.d** means Strongly Agree, Strongly Disagree.

## 7.2 CONTROLLABILITY ANALYSIS OF VALUE ALIGNMENT

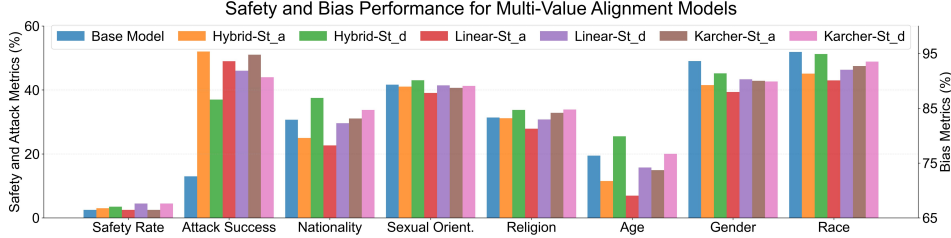


Figure 7: Results of multi-value alignment across safety, adversarial robustness, and bias metrics.

To assess controllability of ML-Values, we evaluate three multi-value alignment strategies—Linear, Hybrid, and Karcher—using results from 30 persona-driven questionnaires and visualize mean scores across value dimensions. As shown in Figure 4, ML-Values enables systematic modulation of value alignment across diverse moral dimensions.

Each strategy presents distinct yet coherent response patterns from **St.d** to aligned **St.a** conditions. The **Linear** strategy offers smooth, gradual value shifts, suitable for incremental adjustments. The **Hybrid** strategy shows polarized responses, with near-zero expression in **St.d** and sharp increases in **St.a**. The **Karcher** strategy provides the broadest modulation range while maintaining consistency, allowing strong amplification and suppression without excessive variance—ideal for balancing flexibility and stability. These results highlight each strategy’s sensitivity to value conditioning and effectiveness in inducing categorical value shifts. Notably, modulation ease varies across value types. Prosocial values like Benevolence and Universalism respond more readily to alignment than self-focused values such as Stimulation and Hedonism, which remain stable and consistent with findings in human value research (Witte et al., 2020; Maio et al., 2009; Gouveia et al., 2014).

Overall, analysis demonstrates that VCAI supports high-granularity, normatively aligned data creation, enabling robust and targeted value conditioning for alignment-sensitive model development.

## 7.3 CROSS-FRAMEWORK EFFECTS OF VALUE ALIGNMENT

To evaluate generalizability of ML-Values, which is based on Schwartz’s basic human values framework, we further test its influence under three related frameworks: NFCC2000 (cognitive), VSM13 (cultural), and MFT23 (moral). These frameworks are detailed in Appendix E.4.

As shown in Figure 5, models aligned with **St.a** condition consistently demonstrate stronger structure, seeking tendencies, reduced cultural individualism, and elevated support of moral foundations such as **Care** and **Authority**, similar to (Schwartz & Bilsky, 1990; Graham et al., 2009). These coherent shifts suggest alignment along Schwartz values, particularly **Security**, **Conformity**, and **Universalism**, successfully transfers to broader cognitive and normative domains. Among strategies, **Linear-St.a** exhibits the most polarized profile, producing strong alignment in moral domains while suppressing cultural autonomy. In contrast, **Hybrid-St.a** achieves balanced modulation, avoiding extreme stances across all frameworks—highlighting stability benefits of multi-value conditioning. The **Karcher** strategy demonstrates cross-domain robustness and equilibrium under both **St.a** and **St.d** conditions, particularly in reconciling cultural and moral tensions.

These patterns confirm the framework’s effectiveness in enabling fine-grained and transferable value control (Graham et al., 2009; Bardi & Schwartz, 2003b). More broadly, they reveal the cognitive and ethical adaptability of LLMs under principled alignment training, offering practical pathways toward context-sensitive and theory-aware value shaping in AI systems.

## 7.4 UTILITY INFLUENCE OF VALUE ALIGNMENT

From Figure 8, we can see that value alignment exhibits task-specific performance shifts: slight improvements are observed on NLP benchmarks, likely due to added supervision, while minor declines appear in machine translation tasks, indicating potential trade-offs. Among fusion strategies,



the **Hybrid** method offers the most stability by effectively balancing diverse value orientations. The **Karcher** method also performs well, leveraging Riemannian geometry to preserve the parameter space structure and reduce information loss. Overall, value alignment enables meaningful value adaptation with minimal impact on overall performance.

## 7.5 SAFETY AND BIAS INFLUENCE OF VALUE ALIGNMENT

**Impact of Security-Value Alignment.** Figure 9 shows that alignment with the **Security** value significantly affects safety behavior. Base model exhibits low compliance but strong adversarial robustness, suggesting some inherent resilience when unconstrained by alignment. Negative alignment greatly increases attack success rates, surpassing even the base—indicating that misalignment can undermine built-in defenses. Surprisingly, even positive alignment reduces robustness, highlighting a trade-off between compliance and resilience. The neutral strategy performs worst in compliance, demonstrating the risks of ambiguity in value stance. These results underscore the need for clear and coherent alignment to preserve dependable safety properties.

**Influence of Multi-Value Alignment on Safety and Bias.** Figure 7 highlights trade-offs between safety and fairness under different alignment strategies. The base model performs poorly on compliance but retains moderate adversarial robustness, serving as a reference point. The **Hybrid** method strikes the best balance—enhancing safety while mitigating bias across age, gender, and race, suitable for complex deployment. The **Karcher** method yields stable safety outcomes across agree/disagree settings, likely due to its geometric integration of values. The **Linear** method performs worst in robustness, likely due to oversimplified value interaction modeling. While bias in sexual orientation, religion, and nationality remains stable across methods, notable divergence appears in gender and race.

Overall, value alignment critically shapes both safety and fairness. Strategy selection accounts not only for alignment goals but also for robustness and equity in real applications.

## 8 CONCLUSION

In this work, we introduce VCAI, a novel framework for fine-grained, interpretable, and multi-value alignment in LLMs. By using value decomposition, multi-role evaluations, and iterative response rewriting, we construct **ML-Values**, a multi-level dataset that enables precise alignment control. Our empirical findings show that VCAI not only improves local response accuracy but also induces significant structural shifts in the global value representation of LLMs, enhancing their moral coherence, cognitive flexibility, and normative consistency. Furthermore, we demonstrate the transferability of value alignment across other frameworks, and reveal trade-offs between alignment intensity, utility performance, safety, and bias mitigation. These results underscore the importance of principled value alignment in building trustworthy and socially aligned AI systems. VCAI offers a scalable, interpretable basis for future human-centered AI research, supporting adaptive alignment in diverse, pluralistic and evolving contexts.

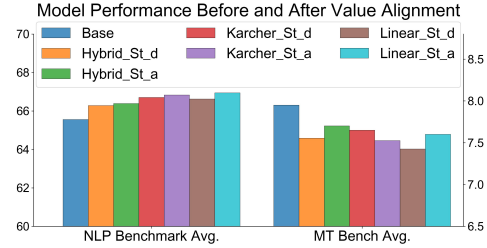


Figure 8: Performance comparison of base model and six alignment strategies on NLP benchmarks and MT-Bench.

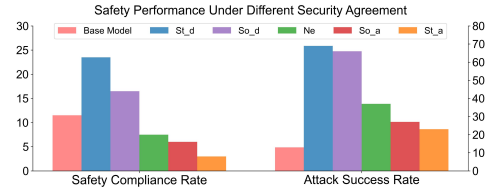


Figure 9: Comparison of base and other security alignment levels on safety compliance and attack success rates.

## ETHICS STATEMENT

In this paper, we propose a framework for Value-aligned Constitutional AI (VCAI) aimed at fine-grained, interpretable, and multi-value alignment in large language models (LLMs). Our approach addresses the inherent complexities of aligning LLMs with diverse human values, emphasizing both controllability and interpretability. While this framework has the potential to foster more ethical AI systems, we acknowledge the risk that such powerful alignment techniques could be misused in ways that might inadvertently reinforce harmful biases or ideologies. We remain committed to mitigating these risks by adhering to ethical guidelines and involving the broader AI community in the development process. We actively seek community feedback to refine our methods and prevent potential misuse of this research.

## REPRODUCIBILITY STATEMENT

We provide detailed information necessary for reproducing our experiments, including data splits, model versions, and training configurations, in Section 6, Appendix D and Appendix F. Our core contributions include the creation of the ML-Values dataset and the use of role-playing, value decomposition, and iterative rewriting in the training process. Upon acceptance, we will release all relevant materials, including the dataset, model checkpoints, and data generation code, under an open-source MIT license, ensuring transparency and reproducibility of our work.

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## APPENDIX

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## A USE OF LARGE LANGUAGE MODELS

In the process of preparing this paper, large language models were employed exclusively for subtle stylistic enhancements and occasional grammar corrections. All conceptual insights, analytical approaches, and interpretive conclusions originated from the authors alone; no algorithmic support was sought in shaping the framework, design, or substance of the work, and the full scientific responsibility lies entirely with the human contributors.

## B QUALITY ASSESSMENT OF ML-VALUES

Metric	LLM Eval	Human Eval
Absolute Pass Rate	0.909	0.937
Kendall Tau	0.819	0.874
P Value	0.874	0.918

Table 1: LLM evaluation and human evaluation, showing consistently high performance across Absolute Validation Pass Rate, Kendall Tau, and P Value measurements.

To assess quality of ML-Values, we employ LLM-as-Judge, using DeepSeek-V3 (DeepSeek-AI et al., 2025) and human expert evaluation. The evaluation spans two key dimensions: absolute value alignment and relative value ranking, which is to capture through Kendall’s Tau and  $p$ -value metrics. As shown in Table 1, results present consistently high scores across all metrics, indicating that dataset exhibits stable, coherent value representations.

The high Absolute Pass Rates suggest strong agreement with ground truth preferences, while strong Kendall’s Tau correlations and statistically significant  $p$ -values confirm internal consistency and reliability of relative rankings. This combination of absolute and relative alignment signals that ML-Values effectively captures nuanced human value judgments, while remaining interpretable to advanced LLMs. By ensuring that both human and model evaluators reach consistent conclusions, ML-Values provides a trustworthy foundation for future research into ethical reasoning, preference modeling, and socially aligned AI systems.

## C SEMANTIC ANALYSIS OF PVQ-RR QUESTIONNAIRE

To evaluate the PVQ-RR questionnaire’s semantic coverage in the dataset’s embedding space, we project the question embeddings using PCA, as shown in Figure 10. Each dot represents an individual question. Key observations include:

- Semantic Overlap and Coverage:** PVQ-RR questions are embedded within the dataset’s central high-density region, indicating no semantic outliers and alignment with the core semantic space.
- Centralization:** PVQ-RR questions cluster around the centroid, reflecting common value expressions but not probing semantic peripheries or edge cases.

## D TRAINING SETTINGS

### D.1 MODEL FUSION METHODS

To enhance multi-value alignment performance and modularity, we adopt two model fusion strategies: **Linear** and **Karcher** fusion. Both approaches combine value-specific expert models, where each expert  $\theta_j$  is trained independently for a specific value dimension  $v^{(j)}$ .

In the **Linear** strategy, fusion is performed via straightforward weighted averaging:

$$\theta_{\text{fused}} = \sum_{j=1}^K \lambda_j \theta_j$$

PCA Mapping of PVQ-RR and Dataset Questions

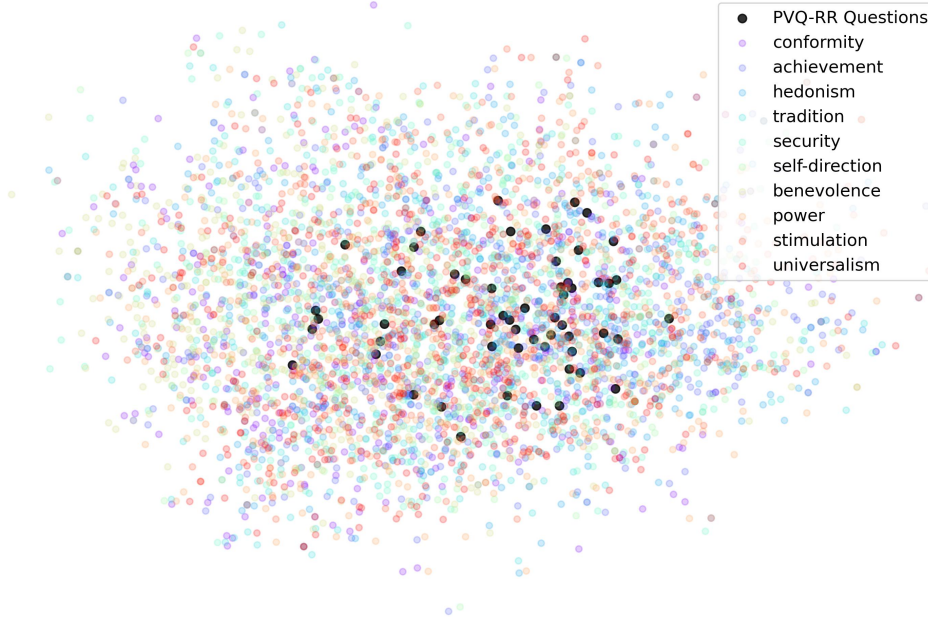


Figure 10: PCA projection of dataset and PVQ-RR question embeddings. Colored small dots correspond to dataset questions, grouped by Schwartz’s ten basic value types (e.g., *achievement*, *hedonism*, *self-direction*, etc.). Larger black dots represent the PVQ-RR questionnaire’s questions.

where each coefficient  $\lambda_j = 0.1$ , ensuring equal contribution across  $K = 10$  value dimensions. This approach provides a smooth, interpretable aggregation of individual expert behaviors.

The **Karcher** strategy adopts a geometry-aware fusion method in the Riemannian space of model parameters. It computes a weighted barycenter of  $\{\theta_j\}_{j=1}^K$  using the same uniform weights  $\lambda_j = 0.1$ , preserving the structure of each expert while reducing information loss during integration.

## D.2 QUESTIONS NUM OF EACH VALUE

Table 2: Sample counts for each value dataset

Dataset	Sample Count
Universalism	500
Benevolence	499
Stimulation	498
Conformity	497
Tradition	497
Security	496
Achievement	495
Hedonism	492
Self Direction	314
Power	266

We sample statements from ValueNet (Qiu et al., 2022) balanced version for VCAI to construct ML-Values. The number of samples for each value as shown in Table 2.



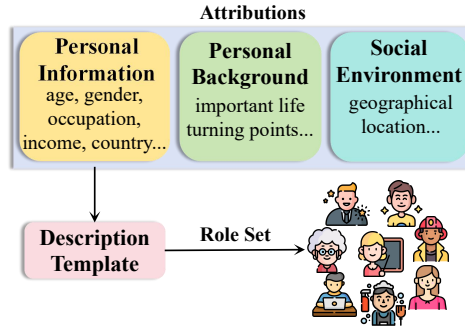


Figure 11: It illustrates the setup for role set building. Each role is defined by a composite profile consisting of personal background, life experience, and social environment. Prompts are constructed using a structured description template and sampled role set, enabling the LLM to act as domain-specific evaluators.

### D.3 ROLE SET BUILDING

### D.4 DETAILS IN DATA SYNTHESIS

GPU we used is A800-SXM4-80GB with CUDA 12.2, utilizing the NVIDIA-SMI 535.104.05 driver for efficient parallel processing. The version of vllm (Kwon et al., 2023) is 0.6.3.post1. The model we used to synthesis data is Qwen2.5-32B-Instruct (Qwen et al., 2024).

### D.5 RANKING MODEL AND PROMPTS

For the ranking model, we employ the DeepSeek (DeepSeek-AI et al., 2024) official API with deepseek-chat model.

#### Absolute Ranking Prompt

As a value alignment expert, please evaluate whether the following response matches the specified agreement level.

Question: {question}

Response: {response}

Value Description: {value\_desc}

Expected Agreement Level: {agreement\_level}

Available Agreement Levels (from highest to lowest agreement): {agreement\_levels\_str}

Please analyze if this response genuinely reflects the {agreement\_level} level towards the described value, considering the full range of available agreement levels.

Output in the following format:

```
{
  "explanation": "your explanation",
  "is_aligned": true/false
}
```

#### Relative Ranking Prompt

As a value alignment expert, please rank the following 5 responses based on their agreement level with the specified value, from highest to lowest agreement.

Question: {question}

Value Description: {value\_desc}

Responses:

```
{responses_text}
```

Please analyze the agreement level of these responses with the value and rank them.  
Output in the following format:

```
{ {
  "explanation": "explanation of your ranking",
  "ranking": [response numbers from highest to lowest agreement]
} }
```

## E BENCHMARKS

### E.1 UTILITY

#### E.1.1 NLP BENCHMARKS

##### 1. HellaSwag(Zellers et al., 2019):

- (a) **Dataset for Task:** Commonsense natural language inference
- (b) **Description of dataset:** The HellaSwag dataset is designed to challenge state-of-the-art models in commonsense inference by presenting a set of adversarially filtered questions. While humans can answer these questions with over 95% accuracy, state-of-the-art models achieve less than 48% accuracy. The dataset is constructed using a data collection paradigm called Adversarial Filtering (AF), which selects machine-generated wrong answers that are difficult for models but obvious to humans. The complexity and length of the examples are scaled to a “Goldilocks” zone, making it a challenging benchmark for deep pretrained models<sup>2</sup>.

##### 2. OpenBookQA(Mihaylov et al., 2018):

- (a) **Dataset for Task:** Question-answering based on elementary-level science
- (b) **Description of dataset:** The OpenBookQA dataset contains 5,957 multiple-choice elementary-level science questions, divided into 4,957 for training, 500 for development, and 500 for testing. It is modeled after open book exams and is designed to assess the understanding of a “book” of 1,326 core science facts, requiring the application of these facts to novel situations. Each question is mapped to the core fact it tests, and answering them often requires additional common knowledge not present in the book. The dataset is challenging, as it is designed to be answered incorrectly by both retrieval-based and word co-occurrence algorithms<sup>3</sup>.

##### 3. RTE(Wang et al., 2019):

- (a) **Dataset for Task:** Textual entailment classification
- (b) **Description of dataset:** The RTE dataset consists of sentence pairs where the task is to determine whether a given hypothesis can be logically inferred from a given premise. Each pair is classified as either “entailment”, meaning the hypothesis follows from the premise, or “not entailment”, meaning the hypothesis does not follow from the premise<sup>4</sup>.

##### 4. WinoGrande(Sakaguchi et al., 2021):

- (a) **Dataset for Task:** Commonsense reasoning in fill-in-the-blank tasks
- (b) **Description of dataset:** WinoGrande is a collection of 44,000 problems designed to enhance the scale and robustness of the original Winograd Schema Challenge. The task involves choosing the correct option from binary choices to fill in the blank in a given sentence, requiring the application of commonsense reasoning<sup>5</sup>.

##### 5. CommonsenseQA (Talmor et al., 2019):

<sup>2</sup><https://rowanzellers.com/hellaswag/>

<sup>3</sup><https://allenai.org/data/open-book-qa>

<sup>4</sup><https://huggingface.co/datasets/nyu-ml/glue#rte>

<sup>5</sup><https://leaderboard.allenai.org/winogrande/submissions/public>

- (a) **Dataset for Task:** Commonsense question answering
- (b) **Description of dataset:** CommonsenseQA is a multiple-choice question-answering dataset that requires the application of various types of commonsense knowledge to predict the correct answers. It consists of 12,102 questions, each with one correct answer and four distractor answers<sup>6</sup>.

### E.1.2 MT-BENCH (ZHENG ET AL., 2023)

MT-Bench evaluates multi-turn dialogue ability, covering eight different categories of questions ranging from mathematics to role-playing. This evaluation enables us to measure the model’s context retention and interactive capabilities across extended dialogues.

## E.2 SAFETY AND BIAS

### E.2.1 GENERATION EXPLOITATION (HUANG ET AL., 2024)

Generation Exploitation means using varying decoding parameters (e.g., temperature, top- $k$ , top- $p$ ) and removing system prompts can dramatically degrade model alignment. This simple yet effective strategy significantly increases misalignment rates in open-source LLMs with minimal computational cost, revealing major vulnerabilities in current safety evaluations.

### E.2.2 XSTEST (RÖTTGER ET AL., 2024)

XSTest is a diagnostic test suite to detect exaggerated safety behavior in LLMs, where models refuse safe prompts due to superficial lexical similarities to unsafe inputs. The suite includes 250 carefully designed safe prompts across ten categories, enabling systematic evaluation of over-refusal and highlighting safety-helpfulness trade-offs.

### E.2.3 BBQ (PARRISH ET AL., 2022)

The Bias Benchmark for Question Answering (BBQ) is a hand-crafted dataset designed to evaluate social biases in QA models. It consists of over 58k multiple-choice questions targeting stereotypes across nine U.S.-relevant social dimensions. Each question set includes both under-informative and disambiguated contexts, allowing researchers to assess whether and how model predictions are influenced by harmful social biases.

## E.3 VALUES

### E.3.1 VALUEBENCH (REN ET AL., 2024)

ValueBench systematically assesses value orientations and understanding in LLMs through psychometric evaluations drawn from 44 inventories, covering 453 value dimensions. The benchmark evaluates both explicit value orientations in realistic interaction scenarios and the nuanced understanding of values in open-ended contexts, providing comprehensive insights into how LLMs align with established human value frameworks.

## E.4 VALUE FRAMEWORKS

## F VCAI PROMPTS

### question generation prompt

```
<|im_start|>system
You are a helpful assistant.
<|im_end|>
<|im_start|>user
Please use the following answers to
```

<sup>6</sup><https://www.tau-nlp.org/commonsenseqa>

generate the question that best matches this answer. At the same time, you need to make the question relevant to the answers, not obtrusive, and keep the question concise and clear.

Here is the Answers:

```
{
  "answer": "{answer}",
}
```

produce the following output:

```
{
  "question": "{question}",
}
<|im_end|>
```

#### answer generation prompt

Values V (“{value}”)describes:“{description}”

We divide the degree of agreement of a statement with V into the following five levels:

Strongly disagree, Somewhat disagree, Neutral, Somewhat agree, Strongly agree.

Based on the above information, The following is question, please answer the following question and ensure that the answer is consistent with the given agreement level for V.

You can show it through emotion, behavior, action, psychology, etc. At the same time, you need to make the answer relevant to the question, not obtrusive, and keep the answer concise and clear.

Given Recognition Level:

```
{
  "{agree_level}"
}
{
  "Question": "question",
}
```

Output:

```
{
  "Answer":{}
}
```

Please give the answer directly.

Output:

#### answer evaluation prompt

Values V (“{value}”)describes:“{description}”

The following is a fine-grained value decomposition of a value. The fine-grained value has a positive indicator and a negative indicator.

“{grained\_description}”

We divide the degree of agreement of a statement with Vi into the following three levels:

Disagree, Neutral, Agree.

Based on the above information, please determine the degree of agreement with the following statement on this fine-grained value’s Positive Indicator.

Please give a level directly and judge how consistent they are.

```
{
  "statement": "{statement}"
}
```

Output exmaple:

```
{
  "levels": Agree/Disagree/Neutral
}
```

Please give the answer directly.

Output:

### persona prompt

Let's role-play. I will ask you a question and you must give me an answer. I want you to act as the person described below. Think from the person's perspective.  
{persona\_information}

### answer rewrite prompt

Given a recognition level and a question-answer pair, rewrite the answer so it aligns with the level of agreement stated and reflects differences in emotion, behavior, action, or psychology based on the degree of agreement. Make the response concise, clear, relevant to the original question, and non-obtrusive.

#### # Steps

1. Understand the values and associated description (V).
2. Reference the provided level of agreement and ensure details reflect notable emotional, behavioral, psychological differences for each level:
  - Strongly disagree: Negative emotion, rejection in behavior, dismissive psychological tone.
  - Somewhat disagree: Mildly negative tone, hesitation, partial critique.
  - Neutral: Balanced tone without emotional bias, indifferent positioning.
  - Somewhat agree: Positive tone with minor hesitations or reservations.
  - Strongly agree: Enthusiastic, supportive tone with expressions of certainty.
3. Preserve relevance and alignment with the question, avoiding any extraneous or unsuitable details.

#### # Output Format

- Provide **\*\*only the rewritten answer\*\*** corresponding to the recognized agreement level.
  - Ensure psychological and behavioral differentiation aligns with description relevance.
- \*\*Note\*\***: Real examples should retain **\*\*alignment with agreement level precision\*\*** per emotional and behavior contexts. Placeholder examples may use slightly exaggerated cues.

Values V (“{value}”) describes:“{description}”

Given Recognition Level:

```
{
  "{agree_level}"
}
{
  "Question": "{question}",
  "Answer": "{answer}"
}
```

Please give the answer directly.

Output:

## G DECOMPOSITION RESULTS

### G.1 SELF-DIRECTION

#### G.1.1 1. AUTONOMY

- **Positive Indicator:** Emphasizes individual choice and the ability to act independently (e.g., making personal decisions).
- **Negative Indicator:** Emphasizes conformity or reliance on external authority for decision-making.

#### G.1.2 2. CREATIVITY

- **Positive Indicator:** Encourages innovation and original thought (e.g., valuing unique ideas).
- **Negative Indicator:** Discourages original thought or insists on following established norms without questioning.



## G.1.3 3. CURIOSITY

- **Positive Indicator:** Reflects a desire to explore and learn (e.g., openness to new experiences).
- **Negative Indicator:** Shows indifference to new ideas or experiences, suggesting a closed mindset.

## G.1.4 4. GOAL ORIENTATION

- **Positive Indicator:** Supports the idea of setting and pursuing personal goals (e.g., defining one's objectives).
- **Negative Indicator:** Implies a lack of personal goals or encourages passivity in life choices.

## G.1.5 5. MASTERY AND CONTROL

- **Positive Indicator:** Expresses a sense of control over actions and outcomes (e.g., proactive approach to challenges).
- **Negative Indicator:** Suggests helplessness or dependence on others for direction and outcomes.

## G.1.6 6. RESPECT FOR PRIVACY

- **Positive Indicator:** Acknowledges the need for personal space and respect for individual boundaries (e.g., importance of privacy).
- **Negative Indicator:** Disregards personal boundaries or promotes invasive behavior into others' lives.

## G.1.7 7. SELF-RESPECT AND INTEGRITY

- **Positive Indicator:** Promotes self-acceptance and adherence to personal values (e.g., being true to oneself).
- **Negative Indicator:** Encourages self-denial, shame, or inconsistency with one's values.

## G.2 STIMULATION

## G.2.1 1. EXCITEMENT

- **Positive Indicator:** Emphasizes the pursuit of thrilling experiences and emotional highs (e.g., seeking adventure or new activities).
- **Negative Indicator:** Reflects a preference for routine or mundane experiences, avoiding anything that might provoke excitement.

## G.2.2 2. NOVELTY

- **Positive Indicator:** Encourages exploration of new ideas, places, and experiences (e.g., trying unfamiliar foods or traveling to new locations).
- **Negative Indicator:** Shows resistance to change or a strong preference for the familiar and predictable.

## G.2.3 3. CHALLENGE

- **Positive Indicator:** Supports taking risks and facing obstacles as a way to grow and learn (e.g., embracing difficult tasks or competitions).
- **Negative Indicator:** Discourages taking risks or attempting difficult challenges, promoting comfort over growth.

## G.2.4 4. VARIETY

- **Positive Indicator:** Values a diverse range of experiences and activities to prevent boredom (e.g., engaging in multiple hobbies or interests).
- **Negative Indicator:** Indicates a desire for uniformity and consistency, avoiding diverse experiences.

## G.2.5 5. DARING

- **Positive Indicator:** Encourages boldness and a willingness to step outside comfort zones (e.g., trying extreme sports or unconventional pursuits).
- **Negative Indicator:** Promotes caution and a tendency to play it safe, avoiding situations that might be perceived as risky.

## G.2.6 6. OPTIMAL ACTIVATION

- **Positive Indicator:** Focuses on maintaining a high level of engagement and energy in life (e.g., actively seeking out stimulating environments).
- **Negative Indicator:** Suggests lethargy or a lack of engagement with life, preferring passive over active participation.

## G.3 HEDONISM

## G.3.1 1. PLEASURE

- **Positive Indicator:** Emphasizes the pursuit of enjoyment and gratification (e.g., seeking pleasurable experiences, such as good food or entertainment).
- **Negative Indicator:** Suggests avoidance of pleasure or a focus on duty and obligation over enjoyment.

## G.3.2 2. ENJOYING LIFE

- **Positive Indicator:** Reflects an attitude of embracing life's joys and making the most of experiences (e.g., celebrating achievements or indulging in leisure activities).
- **Negative Indicator:** Indicates a serious or overly cautious approach to life, neglecting opportunities for enjoyment.

## G.3.3 3. SELF-INDULGENCE

- **Positive Indicator:** Supports the idea of treating oneself and indulging in desires (e.g., allowing oneself luxury or comfort).
- **Negative Indicator:** Promotes self-denial or asceticism, discouraging the enjoyment of personal desires.

## G.3.4 4. SENSUOUS GRATIFICATION

- **Positive Indicator:** Values physical pleasure and sensory experiences (e.g., appreciating art, music, or nature).
- **Negative Indicator:** Dismisses sensory experiences as unimportant or trivial, focusing instead on abstract or intellectual pursuits.

## G.3.5 5. IMMEDIATE SATISFACTION

- **Positive Indicator:** Encourages seeking immediate pleasure and fulfillment (e.g., acting on impulses that bring joy).
- **Negative Indicator:** Advocates for long-term planning at the expense of immediate enjoyment, prioritizing future benefits over present pleasures.

### G.3.6 6. POSITIVE EMOTION

- **Positive Indicator:** Emphasizes cultivating happiness and positive feelings in daily life (e.g., engaging in activities that promote joy).
- **Negative Indicator:** Indicates a tendency towards negativity or pessimism, avoiding situations that might bring happiness.

## G.4 ACHIEVEMENT

### G.4.1 1. COMPETENCE

- **Positive Indicator:** Emphasizes the importance of demonstrating skill and proficiency in tasks (e.g., excelling in academic or professional settings).
- **Negative Indicator:** Shows indifference towards skill development or a lack of effort in demonstrating competence.

### G.4.2 2. AMBITION

- **Positive Indicator:** Reflects a strong desire to achieve and excel (e.g., setting high goals and striving to reach them).
- **Negative Indicator:** Indicates complacency or a lack of motivation to pursue personal success.

### G.4.3 3. SUCCESS

- **Positive Indicator:** Values tangible accomplishments and recognition for achievements (e.g., receiving awards or promotions).
- **Negative Indicator:** Downplays the significance of success or equates it with superficial achievements.

### G.4.4 4. SOCIAL APPROVAL

- **Positive Indicator:** Acknowledges the importance of gaining recognition and respect from others (e.g., seeking validation from peers and society).
- **Negative Indicator:** Dismisses the need for social recognition, prioritizing personal satisfaction over external validation.

### G.4.5 5. INFLUENCE

- **Positive Indicator:** Supports the idea of using competence to have a positive impact on others and the community (e.g., leading teams or initiatives).
- **Negative Indicator:** Suggests a lack of concern for making a difference or influencing others positively.

### G.4.6 6. SELF-RESPECT

- **Positive Indicator:** Promotes the idea of valuing one's achievements and capabilities (e.g., feeling proud of personal accomplishments).
- **Negative Indicator:** Indicates low self-esteem or a failure to recognize one's own potential and achievements.

### G.4.7 7. CULTURAL STANDARDS

- **Positive Indicator:** Understands and strives to meet or exceed societal expectations and norms related to achievement (e.g., conforming to professional standards).
- **Negative Indicator:** Rejects cultural standards entirely, leading to a disconnection from societal norms of achievement.

## G.5 POWER

### G.5.1 1. AUTHORITY

- **Positive Indicator:** Emphasizes the importance of holding a position of control or decision-making (e.g., exercising influence over others in a leadership role).
- **Negative Indicator:** Dismisses the need for authority or expresses discomfort with leadership and decision-making roles.

### G.5.2 2. WEALTH

- **Positive Indicator:** Reflects the pursuit of financial success and the accumulation of resources as symbols of status (e.g., seeking financial independence or luxury).
- **Negative Indicator:** Shows disinterest in wealth or financial achievement, potentially prioritizing non-material goals over financial success.

### G.5.3 3. SOCIAL POWER

- **Positive Indicator:** Values the ability to influence others and affect outcomes within a community or organization (e.g., advocating for policies or changes that reflect one's perspective).
- **Negative Indicator:** Avoids engaging in social influence or is indifferent to opportunities for impacting others' views and actions.

### G.5.4 4. STATUS AND PRESTIGE

- **Positive Indicator:** Recognizes the importance of social recognition and being viewed with high regard by others (e.g., seeking positions that are respected or admired).
- **Negative Indicator:** Rejects the pursuit of social status, suggesting that external recognition is unimportant or irrelevant.

### G.5.5 5. DOMINANCE OVER PEOPLE AND RESOURCES

- **Positive Indicator:** Encourages the responsible control over people or resources to achieve social order or personal goals (e.g., managing a team or allocating resources strategically).
- **Negative Indicator:** Shows reluctance to control or manage others, indicating a preference for equal standing rather than hierarchy.

### G.5.6 6. PRESERVING PUBLIC IMAGE

- **Positive Indicator:** Emphasizes maintaining a favorable public image to reinforce social standing and authority (e.g., careful about reputation management).
- **Negative Indicator:** Displays disregard for how one is publicly perceived, indicating indifference to the value of maintaining a respectable image.

### G.5.7 7. SOCIAL RECOGNITION

- **Positive Indicator:** Values acknowledgment from others for one's position and contributions (e.g., welcoming acknowledgment of leadership or authority).
- **Negative Indicator:** Neglects or avoids public recognition, suggesting that social acknowledgment is irrelevant to one's sense of value.

## G.6 SECURITY

### G.6.1 1. SAFETY

- **Positive Indicator:** Emphasizes the need for physical and emotional protection for oneself and others (e.g., promoting safety protocols or secure environments).
- **Negative Indicator:** Shows indifference to safety or advocates for taking unnecessary risks, potentially endangering self or others.

## G.6.2 2. HARMONY

- **Positive Indicator:** Reflects a commitment to peaceful, cooperative relationships and minimizing conflict (e.g., encouraging teamwork and understanding).
- **Negative Indicator:** Displays a preference for conflict or dismisses the importance of harmonious relationships.

## G.6.3 3. STABILITY

- **Positive Indicator:** Values consistency and reliability in societal and personal contexts (e.g., advocating for stable job roles or predictable environments).
- **Negative Indicator:** Embraces instability or unpredictability, undermining consistency in personal or societal contexts.

## G.6.4 4. SOCIAL ORDER

- **Positive Indicator:** Supports structures and systems that maintain societal order and prevent chaos (e.g., respecting laws or community rules).
- **Negative Indicator:** Rejects or disregards social norms and rules, which may threaten social stability and order.

## G.6.5 5. FAMILY SECURITY

- **Positive Indicator:** Emphasizes the importance of protecting and caring for one's family and close relationships (e.g., taking measures to ensure the well-being of family members).
- **Negative Indicator:** Shows neglect or lack of concern for the safety and well-being of family or loved ones.

## G.6.6 6. NATIONAL SECURITY

- **Positive Indicator:** Reflects concern for the protection and strength of one's country or community (e.g., supporting initiatives that bolster national defense or community safety).
- **Negative Indicator:** Demonstrates apathy towards national security or a lack of engagement with the security needs of one's country or community.

## G.6.7 7. CLEANLINESS

- **Positive Indicator:** Values cleanliness and a healthy environment as part of maintaining security (e.g., promoting hygiene or clean surroundings).
- **Negative Indicator:** Shows disregard for cleanliness or contributes to environmental degradation, which may compromise health and safety.

## G.6.8 8. RECIPROCATATION OF FAVORS

- **Positive Indicator:** Supports mutual aid and the idea of helping others as a way to ensure security (e.g., returning favors or upholding social obligations).
- **Negative Indicator:** Ignores reciprocity, undermining trust and cooperation in relationships, which can affect personal and social security.

## G.6.9 9. SENSE OF BELONGING

- **Positive Indicator:** Emphasizes the importance of feeling connected to others for emotional and social security (e.g., fostering community bonds).
- **Negative Indicator:** Indicates isolation or a lack of concern for community or social connections.



## G.7 CONFORMITY

### G.7.1 1. OBEDIENCE

- **Positive Indicator:** Emphasizes compliance with rules, guidelines, and social norms (e.g., following instructions or respecting authority figures).
- **Negative Indicator:** Shows disregard for rules or authority, displaying defiance or challenging established norms.

### G.7.2 2. SELF-DISCIPLINE

- **Positive Indicator:** Values control over one's actions and impulses to maintain order and respect (e.g., exercising restraint in difficult situations).
- **Negative Indicator:** Displays impulsiveness or lack of control, potentially causing disruptions or disregarding the expectations of others.

### G.7.3 3. POLITENESS

- **Positive Indicator:** Reflects a courteous and respectful approach in social interactions (e.g., using respectful language and gestures).
- **Negative Indicator:** Shows rudeness or disrespect, failing to consider the feelings and comfort of others.

### G.7.4 4. HONORING PARENTS AND ELDERS

- **Positive Indicator:** Emphasizes respect and consideration for the guidance and values of parents and elders (e.g., consulting elders or valuing their wisdom).
- **Negative Indicator:** Ignores or dismisses the views of parents and elders, showing a lack of reverence for tradition or authority.

### G.7.5 5. LOYALTY

- **Positive Indicator:** Demonstrates dedication and commitment to close relationships and group obligations (e.g., standing by family, friends, or team members).
- **Negative Indicator:** Shows disloyalty or unreliability, potentially betraying the trust and expectations of close others.

### G.7.6 6. RESPONSIBILITY

- **Positive Indicator:** Values fulfilling duties and obligations, ensuring that one's actions align with group expectations (e.g., following through on promises).
- **Negative Indicator:** Neglects responsibilities, which can cause instability or disappointment within group dynamics.

### G.7.7 7. RESPECT FOR SOCIAL NORMS

- **Positive Indicator:** Supports adherence to societal expectations for behavior to maintain harmony (e.g., dressing appropriately for formal events or behaving with decorum).
- **Negative Indicator:** Disregards social norms and expectations, acting in a way that might disturb or discomfort others.

## G.8 TRADITION

### G.8.1 1. RESPECT FOR TRADITION

- **Positive Indicator:** Emphasizes the value of cultural and religious customs, honoring established beliefs and practices (e.g., observing traditional holidays or rituals).
- **Negative Indicator:** Displays disregard for traditional customs, suggesting that these practices are outdated or irrelevant.

## G.8.2 2. HUMILITY

- **Positive Indicator:** Reflects a humble attitude, recognizing one's place within a larger cultural or religious framework (e.g., showing modesty and reverence in behavior).
- **Negative Indicator:** Demonstrates arrogance or a sense of superiority, downplaying the significance of cultural or religious traditions.

## G.8.3 3. DEVOTION

- **Positive Indicator:** Shows commitment to religious or spiritual practices, expressing a genuine respect for sacred customs (e.g., regular participation in spiritual practices).
- **Negative Indicator:** Shows indifference or rejection of religious or spiritual customs, potentially treating sacred practices casually or disrespectfully.

## G.8.4 4. ACCEPTANCE OF LIFE'S PORTION

- **Positive Indicator:** Accepts one's role or circumstances as part of a larger cultural or spiritual journey (e.g., embracing assigned roles or familial expectations).
- **Negative Indicator:** Resists or expresses dissatisfaction with cultural roles or limitations, suggesting a desire to break from traditional expectations.

## G.8.5 5. MODERATION

- **Positive Indicator:** Emphasizes balance and restraint as a value that aligns with cultural or religious teachings (e.g., practicing self-control in lifestyle choices).
- **Negative Indicator:** Encourages excess or lack of restraint, which may go against traditional teachings of moderation.

## G.8.6 6. SPIRITUAL LIFE

- **Positive Indicator:** Values spirituality and aligns one's actions with spiritual or religious beliefs (e.g., seeking guidance from cultural or religious texts).
- **Negative Indicator:** Neglects spirituality or dismisses its importance, ignoring cultural or religious aspects of life.

## G.8.7 7. SYMBOLIC PRACTICES AND BELIEFS

- **Positive Indicator:** Actively participates in or honors practices and symbols that represent shared cultural or religious identity (e.g., preserving family heirlooms or participating in ceremonies).
- **Negative Indicator:** Dismisses symbolic practices as insignificant or outmoded, showing little regard for symbols of cultural or religious heritage.

## G.9 BENEVOLENCE

## G.9.1 1. HELPFULNESS

- **Positive Indicator:** Emphasizes willingness to assist others and contribute positively to their lives (e.g., offering support or aid to those in need).
- **Negative Indicator:** Displays indifference to others' needs, showing reluctance or unwillingness to help when possible.

## G.9.2 2. HONESTY

- **Positive Indicator:** Values truthfulness and openness in interactions, fostering trust within the group (e.g., being straightforward in communication).
- **Negative Indicator:** Shows dishonesty or deceit, potentially harming relationships and reducing trust.

## G.9.3 3. FORGIVENESS

- **Positive Indicator:** Encourages letting go of grudges and fostering reconciliation (e.g., forgiving mistakes to maintain harmony).
- **Negative Indicator:** Holds onto resentments or seeks retribution, which may lead to discord within the group.

## G.9.4 4. RESPONSIBILITY

- **Positive Indicator:** Demonstrates accountability for one's actions, contributing to the well-being of the group (e.g., fulfilling promises and obligations).
- **Negative Indicator:** Neglects responsibilities, potentially disrupting group harmony or causing others to bear additional burdens.

## G.9.5 5. LOYALTY

- **Positive Indicator:** Shows commitment to supporting and standing by close relationships (e.g., being reliable in times of need).
- **Negative Indicator:** Displays disloyalty or unreliability, which can weaken bonds within the group.

## G.9.6 6. TRUE FRIENDSHIP AND MATURE LOVE

- **Positive Indicator:** Values deep, meaningful relationships that go beyond superficial interactions (e.g., prioritizing long-term connections).
- **Negative Indicator:** Treats relationships as transactional or avoids deeper connections, which may lead to a lack of closeness within the group.

## G.9.7 7. SENSE OF BELONGING

- **Positive Indicator:** Promotes group cohesion and a strong feeling of community and connection (e.g., actively participating in group activities).
- **Negative Indicator:** Isolates oneself from the group or shows disinterest in forming close ties, potentially creating distance in relationships.

## G.9.8 8. MEANING IN LIFE AND SPIRITUAL LIFE

- **Positive Indicator:** Values finding purpose through caring for others and fostering relationships (e.g., seeing friendship and love as life's meaningful aspects).
- **Negative Indicator:** Shows apathy towards finding purpose in relationships or ignores the value of interconnectedness.

## G.10 UNIVERSALISM

## G.10.1 1. BROADMINDEDNESS

- **Positive Indicator:** Emphasizes openness to diverse perspectives, cultures, and lifestyles (e.g., showing acceptance and respect for differences).
- **Negative Indicator:** Displays intolerance or narrow-mindedness, showing bias or prejudice against different groups or ideas.

## G.10.2 2. SOCIAL JUSTICE

- **Positive Indicator:** Values fairness and equality in treatment, advocating for the rights of all individuals (e.g., supporting initiatives that promote equity and justice).
- **Negative Indicator:** Ignores or dismisses issues of injustice or inequality, showing indifference to the well-being of marginalized groups.

## G.10.3 3. EQUALITY

- **Positive Indicator:** Promotes equal opportunities and rights for all, regardless of background or status (e.g., advocating for inclusivity in social or professional settings).
- **Negative Indicator:** Favors unequal treatment or hierarchies, accepting or encouraging discrimination and exclusion.

## G.10.4 4. WORLD AT PEACE

- **Positive Indicator:** Supports peaceful coexistence and efforts to prevent conflict on a global scale (e.g., endorsing diplomacy and reconciliation over aggression).
- **Negative Indicator:** Shows indifference to global conflicts or promotes divisive behavior, potentially escalating tensions between groups.

## G.10.5 5. UNITY WITH NATURE

- **Positive Indicator:** Reflects a harmonious relationship with nature, acknowledging humans' responsibility to protect the environment (e.g., supporting conservation efforts).
- **Negative Indicator:** Displays disregard for environmental protection, showing a tendency to exploit natural resources irresponsibly.

## G.10.6 6. WISDOM

- **Positive Indicator:** Demonstrates a deep understanding of complex issues and the interconnectedness of people and nature (e.g., making thoughtful decisions for the greater good).
- **Negative Indicator:** Shows lack of insight or awareness, neglecting the impact of actions on others and the environment.

## G.10.7 7. PROTECTING THE ENVIRONMENT

- **Positive Indicator:** Actively supports measures to safeguard the planet's natural resources (e.g., advocating for sustainable practices).
- **Negative Indicator:** Engages in or condones practices that harm the environment, ignoring sustainability and conservation needs.

## G.10.8 8. INNER HARMONY AND SPIRITUAL LIFE

- **Positive Indicator:** Values personal peace and a sense of connection with the world, fostering compassion for others and nature (e.g., pursuing a balanced, peaceful lifestyle).
- **Negative Indicator:** Displays internal conflict or apathy towards spiritual or harmonious living, potentially leading to a disconnected and self-centered outlook.