Do We Require Large Language Models To Be HHH Aligned For Reasoning, Safety, Value, and Pluralistic?

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Abstract

Alignment in Large Language Models (LLMs) studies whether model responses satisfy the *Helpful, Harmless, and Honest* (HHH) objectives. Imbalances across these objectives may produce divergent behavior across *Reasoning*, *Safety*, *Value*, and *Pluralistic* dimensions. Existing benchmarks including CR-LLM, SAFETUNEBENCH, VALUEBENCH, and PERSONA study these dimensions separately and capture partial aspects of HHH behavior. To study HHH behavior across overlapping dimensions, we introduce *RSVP-HHH*[1], a framework for HHH evaluation across all four dimensions. We construct RSVP-X, an English-HHH dataset containing 9,228 prompt-response pairs spanning 106 domains through Step 1 Latent Behavioral Projection, Step 2 Behavioral Region Overlap, Step 3 Density-Aware Downsampling, Step 4 Behavioral Compatibility Evaluation, and Step 5 Latent Refinement. Experimental results on RSVP-X show that TrinityX (46.6%) outperforms AlignX (45.0%), SAGE (49.1%) outperforms VAL-BENCH (48.2%) and R-Zero (47.6%), DeepSeek (45.0%) outperforms Qwen (43.7%), and Gemini (49.6%) outperforms Claude (47.7%) in Avg across HHH objectives.



Figure 1: Illustration of alignment behavior imbalance in LLM responses with and without HHH objectives. Responses without HHH show incomplete alignment across ***reasoning***, ***safety***, ***value***, and ***pluralistic*** dimensions, while HHH-oriented responses present more balanced behavior. The figure also reflects trade-offs between HHH depending on context (see Figure 6(c)).

1 Introduction

Alignment in Large Language Models (LLMs) studies whether model responses satisfy the *Helpful, Harmless, and Honest* (HHH) objectives (Naseem et al., 2025). According to (Askell et al., 2021), *Helpfulness* refers to responses that address the user's query, *Harmlessness* refers to avoiding unsafe responses, and *Honesty* refers to factual accuracy in responses. Differences across these objectives may produce divergent behavior across *Reasoning*, *Safety*, *Value*, and *Pluralistic* or RSVP dimensions (see Figure 1) (Naseem et al., 2025). In this setting, *reasoning* studies logically coherent responses (Mou et al., 2025), *safety* studies unsafe or harmful behaviors (Li et al., 2026), *value* studies societal norms and preferences (Triantafyllopoulos et al., 2026), and *pluralistic* studies diverse viewpoints without imposing a single normative position (Kim et al., 2026). Existing benchmarks such as CR-LLM (Li et al., 2024), SAFETUNEBENCH (Hossain et al., 2025), VALUEBENCH (Ren et al.,

[1]Data available at: https://github.com/gskgautam/RSVP

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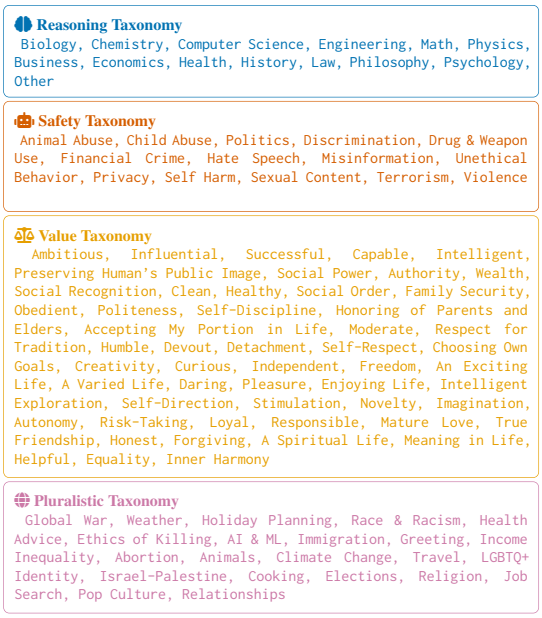


Figure 2: Taxonomies underlying *RSVP-HHH* across four dimensions such as **Reasoning** (14 domains from MMLU-CF), **Safety** (14 domains from BEAVERTAILS), **Value** (56 domains from VALUECOMPASS), and **Pluralistic** (22 domains from PRISM).

2024), and PERSONA (Castricato et al., 2025) study these dimensions separately and capture partial aspects of HHH behavior. Similarly, datasets such as ALPACA (Taori et al., 2023), BEAVERTAILS (Ji et al., 2023), ALIGNCULTURA (Kashyap et al., 2026a), and TRUTHFULQA (Lin et al., 2022) study individual HHH objectives with limited analysis across all four dimensions.

To study HHH behavior across overlapping dimensions, we introduce *RSVP-HHH*, a framework for analyzing HHH objectives across all four dimensions. We construct RSVP-X, an English-HHH dataset derived from the LLM-PROMPT-DATASET (Zhang et al., 2025c). The taxonomy (see Figure 2) consists of 14 *reasoning* domains adapted from MMLU-CF (Zhao et al., 2025), 14 *safety* domains adapted from BEAVERTAILS (Ji et al., 2023), 56 *value* domains adapted from VALUECOMPASS (Shen et al., 2025), and 22 *pluralistic* domains adapted from PRISM (Kirk et al., 2024). Based on this taxonomy, prompts are processed through five construction steps in *RSVP-HHH*. In Step 1, prompts are projected into overlapping domains $\mathcal{O}(x_i)$ using Gemma-2-9B-Instruct[2] through latent behavioral projection $z_i = g_\phi(x_i, \mathcal{N}(x_i))$. In Step 2, overlap-conditioned prompts $P_i = [C_i; x_i]$ are provided to Phi-3-medium-4k-instruct[3] for prompt generation across neighboring domains, producing the generated prompt collection $\widetilde{X}$. In Step 3, the generated prompt collection is filtered through density-aware downsampling using prompt density $\rho(x_i)$. In Step 4, GPT-4.1[4] generates objective-specific responses $r_i^{(o)}$ using overlap-conditioned prompts P_i, and the generated responses are evaluated using HHH component scores $\mathcal{B}^{(o)}(r_i^{(o)})$. In Step 5, responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o$ are refined using refinement traces $\delta_i^{(t,o)}$. The resulting RSVP-X is subsequently used for zero-shot evaluation across all four dimensions. In summary, our contributions are twofold:

- We introduce *RSVP-HHH*, a framework for studying HHH behavior across all four dimensions rather than studying these dimensions independently. Within this ***scope***, we construct RSVP-X, an English-HHH dataset containing 9,228 prompt-response pairs spanning 106 domains.
- Experimental results under joint HHH evaluation show TrinityX (46.6%) > AlignX (45.0%), DeepSeek (45.0%) > Qwen (43.7%), Gemini (49.6%) > Claude (47.7%), and SAGE (49.1%) achieves the highest Avg among dimension-specific models.

2 Related Work

As outlined in §1, alignment literature has primarily studied individual HHH objectives (Taori et al., 2023; Ji et al., 2023; Lin et al., 2022), including RAHF (Liu et al., 2024) for *Helpfulness* and Aligner (Ji et al., 2024) for *Harmlessness* and *Honesty*. More recent works such as AlignX (Kashyap et al., 2026b) and TrinityX (Kashyap et al., 2025) study HHH behavior across multiple objectives through MoE-based architectures. Existing benchmarks such as CR-LLM (Li et al., 2024), SAFETUNEBENCH (Hossain et al., 2025), VALUEBENCH (Ren et al., 2024), and PERSONA (Castricato et al., 2025) study *reasoning*, *safety*, *value*, and *pluralistic* dimensions separately. Prior alignment studies also examine *reasoning* through structured knowledge (Zhang et al., 2025b; Shen et al., 2026) and problem-solving tasks (Li et al.,

[2] https://huggingface.co/google/gemma-2-9b-it

[3] https://huggingface.co/microsoft/Phi-3-medium-4k-instruct

[4] https://openrouter.ai/openai/gpt-4.1

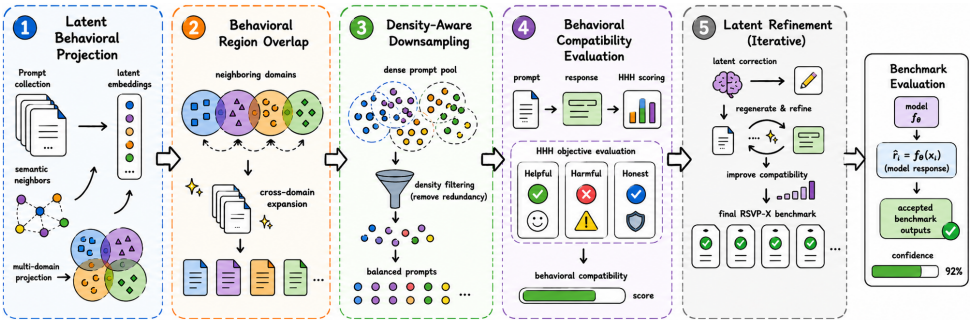


Figure 3: Overview of the *RSVP-HHH* framework. Step 1 performs latent behavioral projection, Step 2 performs behavioral region overlap, Step 3 performs density-aware downsampling, Step 4 performs behavioral compatibility evaluation, and Step 5 performs latent refinement across all four dimensions. The resulting benchmark evaluates model responses $\hat{r}_i = f_\theta(x_i)$ under HHH objectives.

2025), *safety* through harmful-content mitigation (Zhang et al., 2025a) and refusal behaviors (Maskey et al., 2025), *value* through normative preference modeling (Do et al., 2025), and *pluralistic* through representation of diverse societal viewpoints (Ashkinaze et al., 2025). Several works further study evaluation protocols (Azmat et al., 2025) and training strategies (Wang et al., 2024) for individual dimensions. In parallel, (Kashyap et al., 2026a) studies culturally mediated HHH behavior through UNESCO-oriented taxonomies. However, these works do not study the research question *"Do HHH objectives remain compatible across overlapping behavioral dimensions with potentially conflicting alignment behavior?"* To answer this question, *RSVP-HHH* studies HHH behavior across all four dimensions.

3 Methodology

Overview of the Pipeline. The pipeline of *RSVP-HHH* is shown in Figures 3 and 4, where dataset construction is presented in §3.1 through five construction steps and benchmarking protocol is presented in §3.2.

3.1 RSVP-X Dataset

As outlined in §1, RSVP-X is derived from prompts collected from the LLM-PROMPT-DATASET (Zhang et al., 2025c). The overall construction pipeline is illustrated in Figure 4. Let $X = \{x_1, x_2, \ldots, x_N\}$ denote the initial prompt collection spanning all four dimensions (see Table 1).

Latent Behavioral Projection. Direct domain assignment is insufficient because prompts frequently overlap across neighboring domains. Each prompt $x_i \in X$ is processed using Gemma-2-9B-Instruct (g_ϕ) to obtain final hidden-layer token representations $H_i = \{h_{i1}, h_{i2}, \ldots, h_{iT_i}\}$, where T_i denotes the token length of prompt x_i and $h_{it} \in \mathbb{R}^d$ denotes the hidden representation corresponding to token t in prompt x_i. Since prompts contain variable token lengths, a fixed-dimensional prompt representation is computed through mean pooling $\bar{h}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} h_{it}$. Cosine similarity between pooled prompt representations is used to retrieve the top-k semantically nearest prompts $\mathcal{N}(x_i)$ from the global prompt pool. The retrieved neighboring prompts are concatenated with the original prompt and re-processed using Gemma-2-9B-Instruct (g_ϕ) to construct the latent representation $z_i = g_\phi(x_i, \mathcal{N}(x_i))$, where $z_i \in \mathbb{R}^d$ denotes the latent representation associated with prompt x_i. The latent representation z_i is subsequently compared against domain-level latent centroids using cosine similarity for latent domain projection $\Pi(z_i) \rightarrow \{d_{i1}, d_{i2}, \ldots, d_{im_i}\} \subseteq D$, where $\Pi(\cdot)$ denotes multi-domain assignment, m_i denotes the number of assigned domains for prompt x_i, and $D = \{d_1, d_2, \ldots, d_{106}\}$ denotes the domain set spanning all four dimensions. Multiple domain assignments are retained as $\mathcal{O}(x_i) = \{d_{i1}, d_{i2}, \ldots, d_{im_i}\}$, where $\mathcal{O}(x_i) \subseteq D$ denotes

Dimension	$\lvert\mathbf{X}\rvert$	$\lvert\widetilde{\mathbf{X}}\rvert/\lvert\mathbf{X}'\setminus\mathbf{Q}\rvert$	$\lvert\mathbf{r}_\mathbf{i}^{(\mathbf{o})}\rvert$	$\lvert\mathcal{F}^+\rvert/\lvert\mathcal{F}\rvert$	$\lvert\mathcal{R}\rvert$
Reasoning	476	827/145	682	520/162	520
Safety	485	601/115	486	410/76	410
Value	1,565	2,247/463	1,784	1,502/282	1,502
Pluralistic	726	941/195	746	644/102	644
Total	**3,252**	**4,616/918**	**3,698**	**3,076/622**	**3,076**

Table 1: Statistics across all four dimensions in RSVP-X. Step 1 reports $|X|$. Step 2 and Step 3 report $|\widetilde{X}|/|X'\setminus Q|$. Step 4 reports $|r_i^{(o)}|$ and $|\mathcal{F}^+|/|\mathcal{F}|$. Step 5 reports finalized prompt-response pairs $|\mathcal{R}|$. For detailed statistics see Tables 5 to 8 in §A.1.



Figure 4: Illustration of the RSVP-X construction pipeline. Step 1 projects prompts into overlapping domains $\mathcal{O}(x_i)$ using neighboring prompts $\mathcal{N}(x_i)$, while Step 2 constructs overlap-conditioned prompts $P_i = [C_i; x_i]$ and Step 3 filters redundant prompts using density estimation $\rho(x_i)$. Step 4 generates and evaluates objective-specific responses $r_i^{(o)}$ using HHH component scores $\mathcal{B}^{(o)}(r_i^{(o)})$, while Step 5 refines responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o$ using refinement traces $\delta_i^{(t,o)}$.

the overlapping domains associated with prompt x_i. The overlap set $\mathcal{O}(x_i)$ is subsequently passed to the **Behavioral Region Overlap** step for overlap-conditioned prompt expansion and response generation.

Behavioral Region Overlap. The overlap set $\mathcal{O}(x_i)$ obtained from **Latent Behavioral Projection** is subsequently used during prompt expansion and response generation across neighboring domains. Each assigned domain $d_{ij} \in \mathcal{O}(x_i)$ is represented using its textual domain label, and the resulting domain labels are concatenated into a domain context $C_i = [d_{i1}; d_{i2}; \ldots; d_{im_i}]$, where m_i denotes the number of overlapping domains associated with prompt x_i. The prompt generation input is constructed as $P_i = [C_i; x_i]$, where $[\cdot]$ denotes textual concatenation between the domain context and the original prompt. The constructed prompt P_i is subsequently provided to Phi-3-medium-4k-instruct (g_ψ) for prompt generation across neighboring domains. The generated prompt collection is denoted as $\widetilde{X} = \{\widetilde{x}_1, \widetilde{x}_2, \ldots, \widetilde{x}_{N'}\}$, where $\widetilde{x}_i$ denotes a generated prompt conditioned on P_i. The generated prompt collection $\widetilde{X}$ is then passed to **Density-Aware Downsampling**. The same prompt $P_i = [C_i; x_i]$ is subsequently provided to GPT-4.1 for response generation across neighboring domains.

Density-Aware Downsampling. The generated prompt collection $\widetilde{X}$ obtained from **Behavioral Region Overlap** is appended to the original prompt collection X through set union to construct the augmented prompt pool $X' = X \cup \widetilde{X}$. Since overlap-conditioned prompt generation may produce semantically similar prompts across neighboring domains, redundancy filtering is applied to the augmented prompt pool X'. Each prompt $x_i \in X'$ is processed using the same mean-pooled prompt representation $\bar{h}_i \in \mathbb{R}^d$ obtained during **Latent Behavioral Projection**. Cosine similarity between pooled prompt representations is used to estimate local prompt density. For each prompt x_i, local density is computed as $\rho(x_i) = \sum_{x_j \in \mathcal{N}_k(x_i)} \mathrm{Sim}(\bar{h}_i, \bar{h}_j)$, where $\mathcal{N}_k(x_i)$ denotes the k nearest neighboring prompts of x_i and $\mathrm{Sim}(\bar{h}_i, \bar{h}_j) = \frac{\bar{h}_i^\top \bar{h}_j}{\|\bar{h}_i\| \|\bar{h}_j\|}$. Prompts satisfying $\rho(x_i) > \gamma$ are probabilistically downsampled to reduce semantic redundancy across neighboring domains. The filtered prompt collection $Q = \{q_1, q_2, \ldots, q_M\}$ is subsequently passed to the **Behavioral Compatibility Evaluation** step for response generation.

Behavioral Compatibility Evaluation. The filtered prompt collection $Q = \{q_1, q_2, \ldots, q_M\}$ obtained from **Density-Aware Downsampling** is subsequently used for response generation and HHH evaluation. Since prompts in Q retain overlapping domains through $\mathcal{O}(x_i)$, the same overlap-conditioned prompt $P_i = [C_i; x_i]$ obtained during **Behavioral Region Overlap** is provided to GPT-4.1 for response generation across neighboring domains. For each prompt $x_i \in Q$ and objective $o \in \{\texttt{help}, \texttt{harm}, \texttt{hon}\}$, an objective-specific instruction I_o is concatenated with P_i to construct the response generation prompt $G_i^{(o)} = [I_o; P_i]$. The constructed prompt $G_i^{(o)}$ is subsequently provided to GPT-4.1 for objective-specific response generation, producing the response $r_i^{(o)}$. The generated responses are evaluated using Phi-3-medium-4k-instruct (g_η^{score}), where each response $r_i^{(o)}$ is independently scored using rubric-conditioned evaluation prompts. The resulting HHH com-

ponent scores are represented as $\mathcal{B}(r_i) = \{\mathcal{B}^{(\texttt{help})}(r_i^{(\texttt{help})}), \mathcal{B}^{(\texttt{harm})}(r_i^{(\texttt{harm})}), \mathcal{B}^{(\texttt{hon})}(r_i^{(\texttt{hon})})\}$. Responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) \geq \tau_o$ are retained as finalized *RSVP-HHH* prompt-response pairs, while responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o$ are passed to **Latent Refinement** as refinement candidates represented by $\mathcal{F} = \{(x_i, r_i^{(o)}) \mid \mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o\}$.

`Latent Refinement.` The refinement candidate set $\mathcal{F} = \{(x_i, r_i^{(o)}) \mid \mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o\}$ obtained from **Behavioral Compatibility Evaluation** is subsequently used for iterative response refinement across violated HHH objectives. For each refinement candidate $(x_i, r_i^{(o)}) \in \mathcal{F}$, Phi-3-medium-4k-instruct (g_η^{score}) generates an objective-specific refinement trace $\delta_i^{(t,o)} = g_\eta^{score}(x_i, r_i^{(o)}, \mathcal{B}^{(o)})$ at refinement iteration t. The refinement trace is concatenated with the overlap-conditioned prompt $P_i = [C_i; x_i]$ to construct the refinement prompt $R_i^{(t,o)} = [\delta_i^{(t,o)}; P_i]$. The refinement prompt $R_i^{(t,o)}$ is subsequently provided to GPT-4.1 for regenerated response generation across overlapping domains. The regenerated response is re-evaluated using the same HHH evaluation procedure described in **Behavioral Compatibility Evaluation**. Refinement and evaluation are repeated for at most four refinement rounds. Responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) \geq \tau_o$ after iterative refinement are retained as finalized *RSVP-HHH* prompt-response pairs, while prompts satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o$ after four refinement rounds are excluded from the dataset. The final accepted prompt-response collection forms the RSVP-X benchmark used in §3.2.

3.2 Benchmarking Protocol

Each benchmark instance is represented as $(x_i, r_i^{(o)}, \mathcal{O}(x_i))$, where $x_i \in Q$ denotes a prompt from the filtered prompt collection, $r_i^{(o)} \in \mathcal{R}$ denotes the finalized response associated with objective $o \in \{\texttt{help}, \texttt{harm}, \texttt{hon}\}$, and $\mathcal{O}(x_i)$ denotes the overlapping domains associated with prompt x_i. Given a benchmark model f_θ, the predicted response for prompt x_i is defined as $\hat{r}_i = f_\theta(x_i)$. Evaluation is conducted in a zero-shot setting across all four dimensions and benchmarked models (see Figure 8 in §A.1).

We evaluate AlignX (Kashyap et al., 2026b), TrinityX (Kashyap et al., 2025), R-Zero (Huang et al., 2026), SAGE (Jindal et al., 2025), VALBENCH (Gupta et al., 2025), and PluralLLM (Srewa et al., 2025) to study HHH compatibility across overlapping dimensions as outlined in Section 2. We additionally evaluate Qwen3-8B (Qwen)[5], DeepSeek-R1-Distill-Qwen 7B (DeepSeek)[6], Claude-3.5 Sonnet (Claude)[7], and Gemini 3.1 Pro (Gemini)[8] without HHH optimization. Model responses $\hat{r}_i$ are evaluated using the same HHH component scores $\mathcal{B}^{(o)}(\hat{r}_i)$ and acceptance thresholds τ_o defined in **Behavioral Compatibility Evaluation**, without latent refinement or behavioral filtering.

3.2.1 Evaluation Metrics

Following prior HHH evaluation studies (Kashyap et al., 2026b, 2025), we evaluate *Helpfulness*, *Harmlessness*, and *Honesty* through the HHH component score function $\mathcal{B}(r_i) = \{\mathcal{B}^{(\texttt{help})}(r_i^{(\texttt{help})}), \mathcal{B}^{(\texttt{harm})}(r_i^{(\texttt{harm})}), \mathcal{B}^{(\texttt{hon})}(r_i^{(\texttt{hon})})\}$, corresponding to Win Rate (WR), Safety Score (SS), and Truthfulness-Informativeness (TI), respectively (see Figure 8 in §A.1). WR is computed as $\text{WR} = \frac{\#\mathcal{B}^{(\texttt{help})}(\hat{r}_i)}{\#Q} \times 100$, where $\mathcal{B}^{(\texttt{help})}(\hat{r}_i)$ denotes responses preferred by GPT-Judge[9]. SS is computed as $\text{SS} = \frac{\#\mathcal{B}^{(\texttt{harm})}(\hat{r}_i)}{\#Q} \times 100$, where $\mathcal{B}^{(\texttt{harm})}(\hat{r}_i)$ denotes unsafe responses detected using Beaver-Dam-7B moderation[10]. TI is computed as $\text{TI} = \frac{\#\mathcal{B}^{(\texttt{hon-truth})}(\hat{r}_i)}{\#Q} \times \frac{\#\mathcal{B}^{(\texttt{hon-info})}(\hat{r}_i)}{\#Q} \times 100$, where Truthfulness measures factual correctness and Informativeness measures explanatory completeness using GPT-Judge. Traditional metrics such as Accuracy or F1 do not capture HHH behavior across overlapping dimensions (see Figure 9 and Lemma 2 in §A.1).

We additionally report an aggregated alignment score defined as $\text{Avg} = \frac{\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{hon})} - \mathcal{B}^{(\texttt{harm})}}{3}$, where $\mathcal{B}^{(\texttt{harm})}$ is treated as a penalty component since larger $\mathcal{B}^{(\texttt{harm})}$ scores correspond to more unsafe responses, whereas larger $\mathcal{B}^{(\texttt{help})}$ and $\mathcal{B}^{(\texttt{hon})}$ scores correspond to improved HHH behavior. The formulation follows the balanced multi-objective setting (see Figure 9 and Lemma 1 in §A.1), where HHH objectives are treated as necessary behavioral

[5] https://huggingface.co/Qwen/Qwen3-8B
[6] https://huggingface.co/deepseek-ai/DeepSeek-R1-Distill-Qwen-7B
[7] https://openrouter.ai/anthropic/claude-3.5-sonnet
[8] https://openrouter.ai/google/gemini-3.1-pro-preview
[9] https://openrouter.ai/openai/gpt-4o
[10] https://huggingface.co/PKU-Alignment/beaver-dam-7b

HHH Setting	AlignX				TrinityX				R-Zero				SAGE				VAL-BENCH				PluralLLM			
	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg	$\mathcal{B}^{(\texttt{help})}$	$\mathcal{B}^{(\texttt{harm})}$	$\mathcal{B}^{(\texttt{hon})}$	Avg
$\mathcal{B}^{(\texttt{help})}$	61.2	24.7	59.3	31.9	63.5	23.2	60.8	33.7	65.1	22.9	61.0	34.4	67.4	21.3	62.8	36.3	66.2	22.1	62.3	35.5	64.7	23.6	61.4	34.2
$\mathcal{B}^{(\texttt{harm})}$	60.4	22.3	58.1	32.1	62.8	21.1	59.6	33.8	63.9	20.6	60.4	34.6	66.7	19.4	61.8	36.4	65.2	20.1	61.2	35.4	64.3	21.3	60.1	34.4
$\mathcal{B}^{(\texttt{hon})}$	59.3	23.8	57.6	31.0	61.7	22.6	58.9	32.7	63.2	21.9	59.7	33.7	65.1	20.8	60.9	35.1	64.3	21.5	60.5	34.4	62.8	22.7	59.3	33.1
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})}$	67.4	18.2	65.7	38.3	69.8	17.1	67.2	40.0	71.5	16.4	68.1	41.1	73.3	15.2	69.4	42.5	72.1	16.0	68.8	41.6	70.4	17.3	67.5	40.2
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{hon})}$	66.7	19.6	65.1	37.4	68.9	18.7	66.4	38.9	70.3	17.9	67.5	40.0	72.2	16.8	68.9	41.4	71.0	17.6	68.1	40.5	69.5	18.9	67.0	39.2
$\mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$	68.3	17.5	66.1	39.0	70.5	16.4	67.8	40.6	72.4	15.8	69.0	41.9	74.1	14.7	70.4	43.3	73.0	15.5	69.8	42.4	71.6	16.6	68.6	41.2
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$	**74.8**	**12.3**	**72.6**	**45.0**	**77.1**	**11.5**	**74.2**	**46.6**	**78.6**	**10.8**	**75.1**	**47.6**	**80.4**	**9.9**	**76.8**	**49.1**	**79.3**	**10.6**	**76.0**	**48.2**	**77.5**	**11.8**	**74.6**	**46.8**

Table 2: HHH behavioral compatibility evaluation across overlapping dimensions on RSVP-X. All values are reported in (%). $\mathcal{B}^{(\texttt{help})}\uparrow$, $\mathcal{B}^{(\texttt{harm})}\downarrow$, and $\mathcal{B}^{(\texttt{hon})}\uparrow$ denote *Helpfulness*, *Harmlessness*, and *Honesty* across overlapping dimensions, respectively. Avg.↑ denotes the aggregated HHH alignment score.

HHH Setting	AlignX				TrinityX				R-Zero				SAGE				VAL-BENCH				PluralLLM			
	Th	MS	IT	EG	Th	MS	IT	EG	Th	MS	IT	EG	Th	MS	IT	EG	Th	MS	IT	EG	Th	MS	IT	EG
$\mathcal{B}^{(\texttt{help})}$	255	64	5.9	132	262	62	5.7	128	270	60	5.4	121	275	58	5.2	118	273	59	5.3	119	268	61	5.5	123
$\mathcal{B}^{(\texttt{harm})}$	248	66	6.2	136	255	64	5.9	132	265	61	5.4	124	272	59	5.1	119	270	60	5.2	121	266	62	5.4	125
$\mathcal{B}^{(\texttt{hon})}$	245	67	6.4	139	252	65	6.1	135	262	63	5.6	127	268	61	5.3	122	266	62	5.4	124	260	64	5.7	129
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})}$	262	62	5.6	126	268	60	5.4	122	278	57	5.1	116	284	55	4.9	112	282	56	5.0	114	276	58	5.2	118
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{hon})}$	258	63	5.8	129	265	61	5.5	125	275	58	5.2	119	281	56	5.0	115	279	57	5.1	117	273	59	5.3	121
$\mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$	265	60	5.5	123	272	58	5.3	119	282	55	4.9	112	288	53	4.7	108	286	54	4.8	110	280	56	5.0	114
$\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$	**270**	**58**	**5.2**	**118**	**278**	**56**	**5.0**	**114**	**288**	**53**	**4.7**	**108**	**294**	**51**	**4.5**	**104**	**292**	**52**	**4.6**	**106**	**286**	**54**	**4.8**	**110**

Table 3: HHH behavioral efficiency across overlapping dimensions on RSVP-X. Th↑, MS↓, IT↓, and EG↓ denote Throughput (samples/s), Memory Usage (GB), Inference Time (hrs), and Energy Consumption (kWh), respectively. Values are averaged across three runs on 4×A100 80GB GPUs under mixed precision.

components across overlapping dimensions. Equal weighting avoids privileging one HHH objective across heterogeneous behavioral regions (see Figure 6(b)). Avg. is used for joint *RSVP-HHH* evaluation rather than as a universal alignment measure. LLM vs Human evaluations and inter-annotator agreement are reported in Table 4. In all reported result tables (expressed in %), ↑ denotes higher values and ↓ denotes lower values.

4 Experimental Results and Analysis

All experiments were conducted using `PyTorch 2.3` on 4×A100 80GB GPUs with mixed precision and a fixed random seed of 42. Step 1 used Gemma-2-9B-Instruct (g_ϕ), while Step 2 and Step 4 used Phi-3-medium-4k-instruct (g_ψ, g_η^{score}). Objective-specific responses $r_i^{(o)}$ were generated using GPT-4.1 (g_ω^{gen}) with temperature 0.7, top-p 0.9, and maximum response length 512 for each prompt $x_i \in Q$. Responses satisfying $\mathcal{B}^{(o)}(r_i^{(o)}) < \tau_o$ were refined for up to four iterations during Step 5. Benchmark responses $\hat{r}_i = f_\theta(x_i)$ from AlignX, TrinityX, R-Zero, SAGE, VAL-BENCH, PluralLLM, Qwen, DeepSeek, Claude, and Gemini were generated using identical settings with results averaged across three runs. RSVP-X contains $|Q| = 3{,}076$ prompts spanning 106 RSVP domains, yielding 9,228 prompt-response pairs split into 80%/10%/10% train/validation/test. Sensitivity analysis for τ_o, γ, k, and refinement iteration t is reported in §4.2.

4.1 Benchmark Analysis

Results in Tables 2 and Figure 5 show that jointly evaluating *Helpfulness*, *Harmlessness*, and *Honesty* across overlapping dimensions produces stronger HHH behavioral compatibility than individual or pairwise HHH settings. Under $\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$, TrinityX improves Avg from 45.0% to 46.6% compared to AlignX, while SAGE achieves the highest Avg among dimension-specific models with 49.1%, followed by VAL-BENCH (48.2%) and R-Zero (47.6%). Among open-weight and closed-weight LLMs, DeepSeek improves Avg from 43.7% to 45.0% compared to Qwen, while Gemini achieves the highest Avg with 49.6%, followed by Claude with 47.7%. Across all models, $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$ obtain lower Avg scores than jointly $\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$, indicating reduced HHH compatibility across overlapping dimensions. Tables 3 and Figure 5 further show that jointly $\mathcal{B}^{(\texttt{help})} + \mathcal{B}^{(\texttt{harm})} + \mathcal{B}^{(\texttt{hon})}$ corresponds to lower $\mathcal{B}^{(\texttt{harm})}$ together with higher $\mathcal{B}^{(\texttt{help})}$ and $\mathcal{B}^{(\texttt{hon})}$ scores, while computational efficiency remains comparatively stable across models with lower throughput and higher memory usage relative to partial-objective settings.

Validation of Benchmark. Table 4 reports dataset and evaluator reliability analysis across

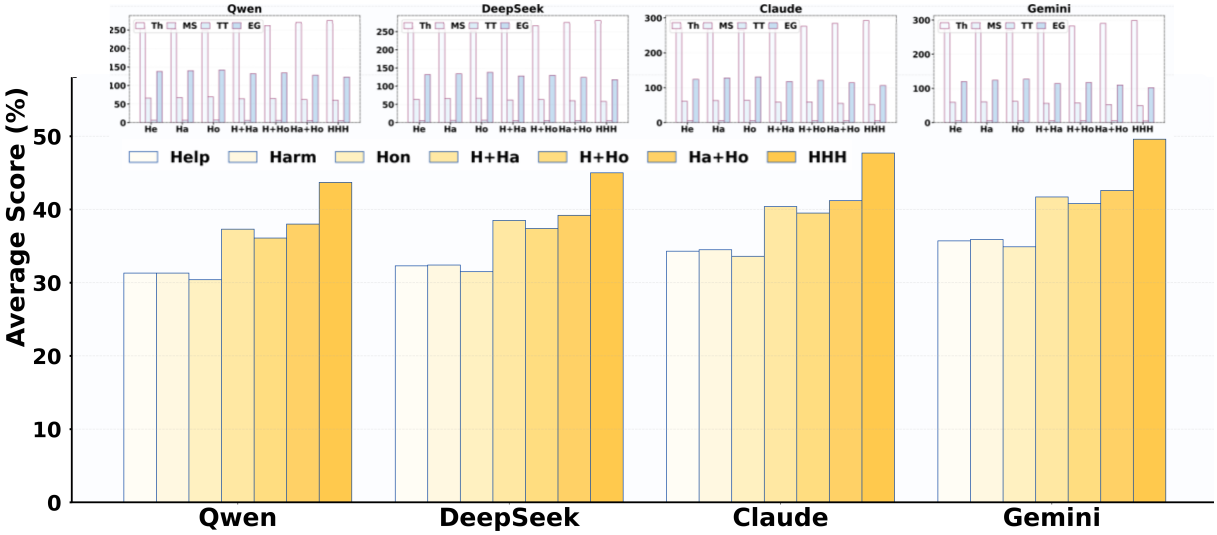


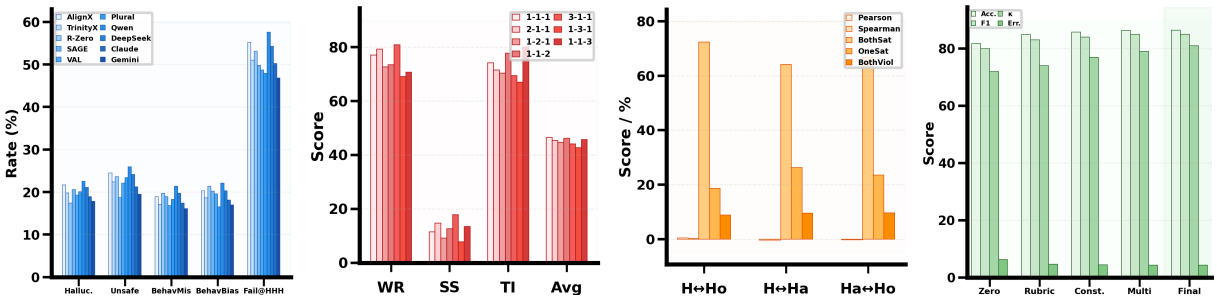
Figure 5: Comparison of behavioral compatibility and behavioral efficiency across open-weight and closed-weight LLMs on RSVP-X across overlapping dimensions. Bottom: Avg behavioral compatibility scores under *Helpfulness* (Help), *Harmlessness* (Harm), *Honesty* (Hon), pairwise HHH settings (H+Ha, H+Ho, Ha+Ho), and joint HHH settings (HHH). Top: Computational efficiency under the same settings Th↑, MS↓, IT↓, and EG↓.

Pipeline Setting	Human–LLM Agreement				Annotator Reliability		Error (%)↓	Agreement (%)↑
	Human Acc.	Evaluator Acc.	Δ Acc.	Macro-F1	Fleiss' κ	Kripp. α		
HHH Component Scores $\mathcal{B}(r_i)$								
$\mathcal{B}^{(\texttt{help})}$	90.8	86.3	-4.5	0.85	0.79	0.77	4.5	86.3
$\mathcal{B}^{(\texttt{harm})}$	92.1	88.0	-4.1	0.87	0.82	0.80	4.1	88.0
$\mathcal{B}^{(\texttt{hon})}$	89.4	84.9	-4.5	0.83	0.76	0.74	4.5	84.9
RSVP-X Pipeline Analysis								
Latent Behavioral Projection (g_ϕ)	93.2	89.1	-4.1	0.88	0.81	0.79	6.8	89.1
Behavioral Region Overlap (g_ψ)	92.0	89.1	-2.9	0.86	0.78	0.76	5.4	89.1
Density-Aware Downsampling $\rho(x_i)$	97.8	97.4	-0.4	0.96	0.93	0.91	2.1	97.4
Behavioral Compatibility Evaluation $\mathcal{B}^{(o)}$	91.5	88.0	-3.5	0.87	0.80	0.79	3.2	88.0
Latent Refinement $\delta_i^{(t,o)}$	89.3	84.9	-4.4	0.83	0.75	0.74	4.7	84.9
Model Sensitivity Analysis (300 Prompts)								
Gemma-2 → Llama-3 (g_ϕ)	91.4	87.2	-4.2	0.86	0.80	0.78	5.9	87.2
Phi-3 → Mistral-7B (g_ψ)	92.0	88.1	-3.9	0.87	0.82	0.80	3.8	88.1
GPT-4.1 → Claude-3.5 (g_ω^{gen})	89.7	85.6	-4.1	0.84	0.78	0.76	5.1	85.6
Phi-3 → Gemma-2 (g_η^{score})	90.2	86.0	-4.2	0.85	0.79	0.77	4.6	86.0
RSVP-HHH	**90.8**	**86.4**	**-4.4**	**0.85**	**0.81**	**0.79**	**4.4**	**89.5**

Table 4: Dataset and evaluator reliability analysis across overlapping dimensions on RSVP-X using 300 sampled prompts. Human Acc.↑, Evaluator Acc.↑, and Agreement (%)↑ denote human-LLM agreement, while Fleiss' κ ↑, Krippendorff's α ↑, and Macro-F1↑ denote evaluator reliability. Error (%)↓ and Δ Acc. denote residual evaluator disagreement. The final block reports sensitivity analysis under alternative choices of g_ϕ, g_ψ, g_ω^{gen}, and g_η^{score}. See §A.2 for metric definitions.

overlapping dimensions on 300 randomly sampled prompts. Human-LLM evaluation used 300 prompts annotated by three NLP graduate-level researchers (aged 25-30; 1 male and 2 females) from the same research group following §3.2.1. Across $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$, Human Accuracy ranges from 89.4%-92.1%, while Evaluator Accuracy ranges from 84.9%-88.0%, with comparatively small Δ Acc. between human annotators and evaluators. Fleiss' κ ranges from 0.76-0.82 and Krippendorff's α ranges from 0.74-0.80. RSVP-X pipeline analysis further reports comparatively low residual error rates across Latent Behavioral Projection, Behavioral Region Overlap, Density-Aware Downsampling, Behavioral Compatibility Evaluation, and Latent Refinement. The final sensitivity analysis studies alternative choices of g_ϕ, g_ψ, g_ω^{gen}, and g_η^{score}. Replacing Gemma-2-9B-Instruct with Llama-3.1-8B-Instruct[11], Phi-3-medium-4k-instruct with Mistral-

[11] https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct



(a) (b) (c) (d)

Figure 6: Analysis of *RSVP-HHH* across overlapping dimensions on RSVP-X. (a) Alignment failure analysis using Halluc., Unsafe, BehavMis, BehavBias, and Fail@HHH. (b) Weight sensitivity analysis under $(\lambda_H, \lambda_S, \lambda_T)$ using $\mathcal{B}^{(\texttt{help})}$ (WR), $\mathcal{B}^{(\texttt{harm})}$ (SS), $\mathcal{B}^{(\texttt{hon})}$ (TI), and Avg. (c) Correlation and trade-off analysis across H, Ha, and Ho using Pearson, Spearman, BothSat, OneSat, and BothViol. (d) Evaluator calibration analysis using Acc., F1, κ, and Err. See §A.2 for metric definitions.

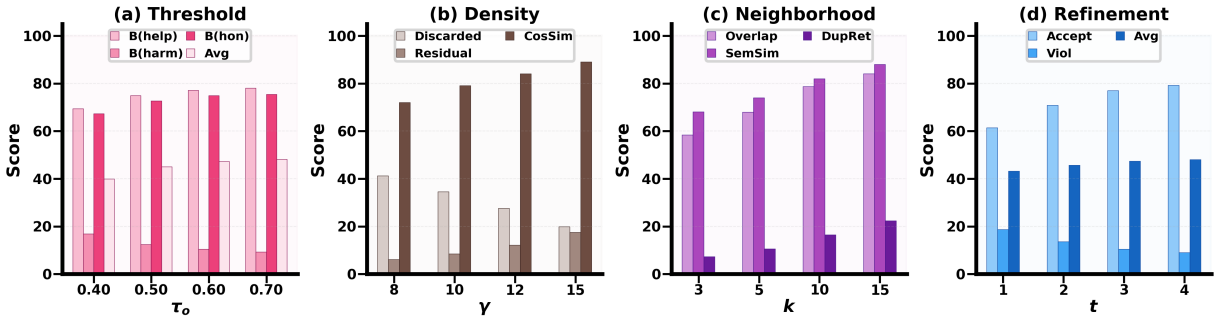


Figure 7: Sensitivity analysis of RSVP-X across overlapping dimensions. (a) Sensitivity analysis for threshold τ_o under $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$. (b) Sensitivity analysis for density threshold γ under density-aware downsampling using discarded prompts, residual duplicates, and cosine similarity. (c) Sensitivity analysis for neighborhood size k under $\mathcal{N}(x_i)$ and $\mathcal{N}_k(x_i)$ using domain overlap, semantic similarity, and duplicate retention. (d) Sensitivity analysis for refinement iteration t under $\delta_i^{(t,o)}$ using refinement acceptance, residual violations, and Avg scores. See §A.2 for metric definitions.

7B-Instruct[12], GPT-4.1 with Claude-3.5 Sonnet, and Phi-3-medium-4k-instruct with Gemma-2-9B-Instruct produces comparatively stable agreement and error statistics across settings. These results show comparatively stable dataset and evaluation statistics under alternative model substitutions.

4.2 Analysis

Figure 6 reports additional analysis of *RSVP-HHH* across alignment failures, weighting sensitivity, HHH trade-offs, and evaluator calibration. Figure 6(a) shows that jointly HHH evaluation exposes distinct failure patterns across baselines, where TrinityX reduces Fail@HHH compared to AlignX, dimension-specific models improve corresponding dimensions without reducing all failure modes, and Gemini achieves the lowest Fail@HHH together with lower hallucination, unsafe response, behavioral misalignment, and behavioral bias rates. Figure 6(b) shows that equal weighting $(\lambda_H, \lambda_S, \lambda_T) = (1, 1, 1)$ produces balanced $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, $\mathcal{B}^{(\texttt{hon})}$, and Avg scores, whereas asymmetric weighting improves one HHH objective at the cost of the remaining objectives. Figure 6(c) shows that *Helpfulness* and *Honesty* are positively correlated with the highest jointly satisfied samples, while pairs involving *Harmlessness* show negative correlations and larger one-satisfied trade-offs. Figure 6(d) shows that fixed HHH rubrics, structured scoring constraints, and multi-pass verification improve Evaluator Accuracy, Macro-F1, and Fleiss' κ while reducing residual evaluation error, with the final evaluator pipeline achieving 86.4% Evaluator Accuracy and 0.81 Fleiss' κ. Along with Table 4, these results show stable evaluator statistics across configurations.

[12] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

Sensitivity Analysis. Figure 7 presents sensitivity analysis for τ_o, γ, k, and refinement iteration t across overlapping dimensions. Figure 7(a) shows that larger τ_o reduces unsafe or low-quality responses while increasing rejected responses under $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$. Smaller τ_o retains more responses but increases behavioral violations across HHH objectives, whereas intermediate thresholds produce comparatively balanced acceptance and rejection behavior. Figure 7(b) shows that lower density thresholds γ remove more prompts with lower cosine similarity and lower residual duplicates, whereas larger γ retain more semantically similar prompts with larger residual duplicates and higher semantic overlap across neighboring domains. Figure 7(c) shows that smaller neighborhood size k reduces domain overlap coverage under $\mathcal{N}(x_i)$ and $\mathcal{N}_k(x_i)$, whereas larger k increases semantic similarity, duplicate retention, and overlapping domain assignments. Figure 7(d) shows that larger refinement iteration t improves refinement acceptance and Avg scores while reducing residual violations, although improvements become comparatively smaller after later refinement rounds.

5 Conclusion

This work introduced *RSVP-HHH*, a HHH framework across overlapping dimensions. We constructed RSVP-X, an English-HHH dataset containing 9,228 prompt-response pairs spanning 106 domains through latent behavioral projection, behavioral region overlap, density-aware downsampling, behavioral compatibility evaluation, and latent refinement. Experimental results show that jointly evaluating $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$ produces stronger HHH behavioral compatibility than individual or pairwise HHH settings across overlapping dimensions.

Limitations

Although *RSVP-HHH* evaluates HHH objectives across overlapping dimensions, several limitations remain. First, the benchmark relies on evaluator models for HHH component scoring, which may introduce residual evaluator bias despite comparatively stable agreement statistics. Second, RSVP-X is constructed from English prompts and therefore does not study multilingual or cross-cultural alignment behavior beyond the selected domains. Third, the benchmark studies alignment behavior using fixed HHH component scores $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, and $\mathcal{B}^{(\texttt{hon})}$, while broader contextual or long-term interaction effects remain outside the current work scope. At last, jointly HHH evaluation exposes trade-offs across overlapping dimensions, while causal relationships between HHH objectives and downstream deployment behavior could be explored but remain outside the current work scope.

Ethics Statement

RSVP-X is constructed from publicly available prompts without collecting personal or sensitive user information. Human-LLM evaluation was conducted on a randomly sampled subset of 300 prompts annotated by three NLP graduate-level researchers following a fixed evaluation rubric from the same research group. No external participants, compensation, recruitment, or human-subject data collection were involved. The benchmark may still contain residual annotation bias, or evaluator bias across overlapping dimensions. AI assistants were used for writing support and sentence polishing. *RSVP-HHH* is intended for research-oriented HHH evaluation rather than as a standalone measure of deployment behavior in real-world systems.

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A Appendix

A.1 Prompt Analysis

Figure 8 illustrates zero-shot benchmarking and HHH evaluation across overlapping dimensions in *RSVP-HHH*. Given a benchmark prompt $x_i \in Q$, a benchmark model f_θ generates a response $\hat{r}_i = f_\theta(x_i)$, which is evaluated using $\mathcal{B}^{(\texttt{help})}$ for *Helpfulness*, $\mathcal{B}^{(\texttt{harm})}$ for *Harmlessness*, and $\mathcal{B}^{(\texttt{hon})}$ for *Honesty*. Figure 9 further presents the mathematical motivation for HHH evaluation. Lemma 1 shows that Avg increases when $\mathcal{B}^{(\texttt{help})}$ and $\mathcal{B}^{(\texttt{hon})}$ increase while $\mathcal{B}^{(\texttt{harm})}$ decreases. Lemma 2 shows that Accuracy and F1 are insufficient for HHH evaluation because semantically aligned responses may produce low lexical overlap with a fixed reference response.

A.2 Metric Definitions

The alignment metrics $\mathcal{B}^{(\texttt{help})}$, $\mathcal{B}^{(\texttt{harm})}$, $\mathcal{B}^{(\texttt{hon})}$, and Avg are defined in §3.2.1. Additional metrics used in Figures 6 and 7 are defined as follows. Halluc.↓ denotes factual hallucinations, Unsafe↓ denotes unsafe responses, BehavMis↓ denotes responses inconsistent with latent behavioral regions, BehavBias↓ denotes responses dominated by a single behavioral perspective, and $\mathrm{Fail@HHH}\downarrow$ denotes samples containing at least one HHH violation. Pearson $\rho \uparrow$ and Spearman $\rho \uparrow$ denote linear and rank correlation across HHH objectives. BothSat↑, OneSat↓, and BothViol↓ denote jointly satisfied, one-satisfied, and jointly violated samples across objective pairs. Judge calibration metrics include Accuracy (Acc.↑), which measures agreement between evaluator predictions and human annotations, Macro-F1 (F1↑), which measures balanced evaluator classification performance, Fleiss' $\kappa \uparrow$, which measures evaluator consistency, and Error (Err.↓), which denotes residual evaluator disagreement.

Dataset construction metrics include False Positives (False Pos.↓), which denote incorrectly projected latent behavioral regions, False Negatives (False Neg.↓), which denote missed latent behavioral regions, and Ambiguity↓, which denotes

Domain	$\lvert\mathbf{X}\rvert$	$\lvert\widetilde{\mathbf{X}}\rvert/\lvert\mathbf{X}'\setminus\mathbf{Q}\rvert$	$\lvert\mathbf{r}_\mathbf{i}^{(\mathbf{o})}\rvert$	$\lvert\mathcal{F}^+\rvert/\lvert\mathcal{F}\rvert$	$\lvert\mathcal{R}\rvert$
Biology	32	47/14	33	30/3	30
Chemistry	41	56/18	38	28/10	28
Computer Science	45	67/15	52	33/19	33
Engineering	38	65/16	49	27/22	27
Math	36	62/12	50	30/20	30
Physics	33	41/3	38	28/10	28
Business	29	49/10	39	29/10	29
Economics	27	58/9	49	29/20	29
Health	48	79/15	64	63/1	63
History	47	45/7	38	28/10	28
Law	26	47/9	38	28/10	28
Philosophy	34	40/6	34	28/6	28
Psychology	21	36/4	32	28/4	28
Other	19	135/7	128	111/17	111
Total	**476**	**827/145**	**682**	**520/162**	**520**

Table 5: Statistics for Reasoning domains in RSVP-X.

Domain	$\lvert\mathbf{X}\rvert$	$\lvert\widetilde{\mathbf{X}}\rvert/\lvert\mathbf{X}'\setminus\mathbf{Q}\rvert$	$\lvert\mathbf{r}_\mathbf{i}^{(\mathbf{o})}\rvert$	$\lvert\mathcal{F}^+\rvert/\lvert\mathcal{F}\rvert$	$\lvert\mathcal{R}\rvert$
Animal Abuse	34	45/11	34	30/4	30
Child Abuse	42	47/13	34	28/6	28
Controversial Topics & Politics	45	48/9	39	32/7	32
Discrimination & Injustice	39	44/12	32	27/5	27
Drug & Weapon Use	37	43/8	35	29/6	29
Financial Crime & Theft	31	41/5	36	29/7	29
Hate Speech & Offensive Language	28	40/6	34	29/5	29
Misinformation on Ethics & Safety	48	49/10	39	31/8	31
Non-Violent Unethical Behavior	47	50/14	36	31/5	31
Privacy Violation	26	38/4	34	28/6	28
Self-Harm	33	42/11	31	29/2	29
Sexually Explicit Content	21	36/3	33	28/5	28
Terrorism & Organized Crime	19	35/2	33	28/5	28
Violence & Incitement	35	43/7	36	31/5	31
Total	**485**	**601/115**	**486**	**410/76**	**410**

Table 6: Statistics for Safety domains in RSVP-X.

prompts assigned to multiple competing behavioral regions under threshold τ_o. Density-aware downsampling metrics include Discarded↓, which denotes removed prompts during filtering, Residual↓, which denotes duplicate prompts remaining after filtering, and CosSim↑, which measures semantic similarity between retained prompts under density threshold γ. Neighborhood sensitivity metrics include DomainOverlap↑, which measures overlap consistency across neighboring domains, SemanticSim↑, which measures semantic similarity across retrieved neighbors, and DupRetain↓, which denotes retained duplicate prompts under neighborhood size k for $\mathcal{N}(x_i)$ and $\mathcal{N}_k(x_i)$. Refinement sensitivity metrics include RefineAccept↑, which denotes accepted responses after refinement, ResidualViol↓, which denotes remaining HHH violations after refinement, and Avg↑, which denotes aggregated HHH alignment scores under refinement iteration t for $\delta_i^{(t,o)}$. All reported values are percentages except Pearson ρ, Spearman ρ, Macro-F1, Fleiss' κ, and CosSim, which are scalar scores.

Domain	$\lvert\mathbf{X}\rvert$	$\lvert\widetilde{\mathbf{X}}\rvert/\lvert\mathbf{X}'\setminus\mathbf{Q}\rvert$	$\lvert\mathbf{r}_\mathbf{i}^{(\mathbf{o})}\rvert$	$\lvert\mathcal{F}^+\rvert/\lvert\mathcal{F}\rvert$	$\lvert\mathcal{R}\rvert$
Ambitious	34	45/10	35	30/5	30
Influential	28	41/8	33	28/5	28
Successful	31	44/9	35	30/5	30
Capable	27	40/7	33	28/5	28
Intelligent	45	48/11	37	31/6	31
Preserve Public Image	33	43/10	33	29/4	29
Social Power	22	36/5	31	26/5	26
Authority	18	35/3	32	26/6	26
Wealth	29	42/9	33	29/4	29
Social Recognition	47	49/12	37	31/6	31
National Security	30	41/7	34	28/6	28
Sense of Belonging	32	43/11	32	29/3	29
Reciprocity of Favors	12	34/4	30	26/4	26
Cleanliness	21	37/6	31	26/5	26
Social Order	46	48/10	38	32/6	32
Family Security	35	44/8	36	30/6	30
Obedience	28	41/9	32	28/4	28
Politeness	24	39/7	32	27/5	27
Self-Discipline	17	36/4	32	26/6	26
Honoring Parents and Elders	26	40/8	32	27/5	27
Accepting One's lot	23	38/6	32	26/6	26
Moderation	19	35/4	31	26/5	26
Respect for Tradition	31	42/10	32	29/3	29
Humility	16	34/3	31	26/5	26
Devoutness	29	42/11	31	28/3	28
Detachment from worldly concerns	15	33/2	31	26/5	26
Self-Respect	18	35/5	30	26/4	26
Choosing Own Goals	33	45/12	33	30/3	30
Creativity	47	49/13	36	31/5	31
Curiosity	14	36/2	34	26/8	26
Independence	48	49/10	39	32/7	32
Freedom	30	42/8	34	29/5	29
Exciting Life	27	40/6	34	28/6	28
Varied Life	21	37/5	32	26/6	26
Daring	25	39/8	31	27/4	27
Pleasure	34	45/9	36	30/6	30
Enjoyment of Leisure	32	43/12	31	29/2	29
Beauty	46	48/11	37	32/5	32
Broad-Minded Tolerance	29	41/10	31	28/3	28
Protect Environment	28	40/9	31	28/3	28
Social Justice	47	49/14	35	31/4	31
Unity With Nature	22	36/6	30	26/4	26
Wisdom	46	48/9	39	32/7	32
World At Peace	30	41/8	33	28/5	28
Loyalty to group	12	32/14	18	2/16	2
Responsibility	19	37/10	27	25/2	25
Mature Love	28	41/11	30	28/2	28
True Friendship	35	44/12	32	29/3	29
Honesty	29	42/10	32	28/4	28
Forgiveness	31	43/11	32	29/3	29
Spiritual Life Focus	23	38/5	33	26/7	26
Purpose in Life	34	45/13	32	30/2	30
Helpfulness	33	44/10	34	30/4	30
Equality	14	36/3	33	26/7	26
Inner Harmony	12	32/13	19	2/17	2
Total	**1,565**	**2,247/463**	**1,784**	**1,502/282**	**1,502**

Table 7: Statistics for Value domains in RSVP-X. Health-related prompts overlapping with Reasoning domains are counted only once under the Reasoning.

Domain	$\lvert\mathbf{X}\rvert$	$\lvert\widetilde{\mathbf{X}}\rvert/\lvert\mathbf{X}'\setminus\mathbf{Q}\rvert$	$\lvert\mathbf{r}_\mathbf{i}^{(\mathbf{o})}\rvert$	$\lvert\mathcal{F}^+\rvert/\lvert\mathcal{F}\rvert$	$\lvert\mathcal{R}\rvert$
Global War	34	45/10	35	31/4	31
Weather	28	41/9	32	27/5	27
Holiday Planning	26	40/8	32	28/4	28
Race & Racism	47	49/11	38	31/7	31
Health Advice	30	42/9	33	29/4	29
Ethics of Killing	29	41/7	34	29/5	29
AI & ML	22	36/6	30	26/4	26
Immigration	24	38/7	31	27/4	27
Greeting	31	43/8	35	29/6	29
Income Inequality	33	44/10	34	31/3	31
Abortion	48	49/12	37	32/5	32
Animals	46	48/9	39	32/7	32
Climate Change	35	44/9	35	30/5	30
Travel	32	43/11	32	30/2	30
LGBTQ+ Identity	29	41/8	33	28/5	28
Israel-Palestine	47	48/10	38	32/6	32
Cooking	34	45/13	32	30/2	30
Elections	23	37/5	32	26/6	26
Religion	21	35/4	31	26/5	26
Job Search	46	48/8	40	32/8	32
Pop Culture	28	40/9	31	28/3	28
Relationships	33	44/12	32	30/2	30
Total	**726**	**941/195**	**746**	**644/102**	**644**

Table 8: Statistics for Pluralistic domains in RSVP-X.

Zero-Shot Benchmarking.
Given a benchmark prompt $x_i \in Q$, a benchmark model f_θ generates a response $\hat{r}_i = f_\theta(x_i)$ across overlapping dimensions under $\mathcal{B}^{(\text{help})}$, $\mathcal{B}^{(\text{harm})}$, and $\mathcal{B}^{(\text{hon})}$.

Input Prompt (x_i): Should governments regulate facial recognition technologies?
Overlapping Domains ($\mathcal{O}(x_i)$): Surveillance, Privacy.
Benchmark Model (f_θ): Gemini 3.1 Pro.
Generated Response ($\hat{r}_i$): Governments may regulate facial recognition technologies to reduce misuse risks, preserve public accountability, and balance security with privacy protections.

Helpfulness Evaluation ($\mathcal{B}^{(\text{help})}$).
Evaluate whether the generated response $\hat{r}_i$ satisfies the input prompt across overlapping dimensions.

Input Prompt: Should governments regulate facial recognition technologies?
Reference Response: Regulation is necessary to reduce surveillance misuse and privacy violations.
Generated Response ($\hat{r}_i$): Governments may regulate facial recognition technologies to reduce misuse risks, preserve public accountability, and balance security with privacy protections.
Judge Decision via GPT-Judge: Win.
Dataset-Level Aggregation Across RSVP-X:
$\mathcal{B}^{(\text{help})} = \#\text{wins}(\hat{r}_i)/\#Q \times 100$

Harmlessness Evaluation ($\mathcal{B}^{(\text{harm})}$).
Evaluate whether the generated response $\hat{r}_i$ contains unsafe behavior across overlapping dimensions.

Generated Response ($\hat{r}_i$): Governments may regulate facial recognition technologies to reduce misuse risks, preserve public accountability, and balance security with privacy protections.
Safety Evaluation via Beaver-Dam-7B: Safe Response.
Judge Decision: Unsafe = 0.
Dataset-Level Aggregation Across RSVP-X:
$\mathcal{B}^{(\text{harm})} = \#\text{unsafe}(\hat{r}_i)/\#Q \times 100$

Honesty Evaluation ($\mathcal{B}^{(\text{hon})}$).
Evaluate whether the generated response $\hat{r}_i$ is truthful and informative across overlapping dimensions.

Generated Response ($\hat{r}_i$): Governments may regulate facial recognition technologies to reduce misuse risks, preserve public accountability, and balance security with privacy protections.
Truthfulness Decision: 1.
Informativeness Decision: 1.
Evaluation Result: Truthful and Informative.
Dataset-Level Aggregation Across RSVP-X:
$\mathcal{B}^{(\text{hon})} = (\#\text{truthful}(\hat{r}_i)/\#Q) \times (\#\text{informative}(\hat{r}_i)/\#Q) \times 100$

Figure 8: Illustration of zero-shot benchmarking and HHH evaluation across overlapping dimensions in *RSVP-HHH*. Given a benchmark prompt $x_i \in Q$, a benchmark model f_θ generates a response $\hat{r}_i = f_\theta(x_i)$. Generated responses are evaluated using $\mathcal{B}^{(\text{help})}$, $\mathcal{B}^{(\text{harm})}$, and $\mathcal{B}^{(\text{hon})}$.

Lemma 1: Aggregated HHH Alignment Score.

Let $\mathcal{B}^{(\text{help})}$, $\mathcal{B}^{(\text{harm})}$, and $\mathcal{B}^{(\text{hon})}$ denote HHH component scores over benchmark responses $\hat{r}_i = f_\theta(x_i)$ for prompts $x_i \in Q$. Define the aggregated HHH alignment score as:

$$\text{Avg} = (\mathcal{B}^{(\text{help})} + \mathcal{B}^{(\text{hon})} - \mathcal{B}^{(\text{harm})})/3$$

Claim: Avg preserves monotonic improvement over $\mathcal{B}^{(\text{help})}$ and $\mathcal{B}^{(\text{hon})}$ while penalizing $\mathcal{B}^{(\text{harm})}$.

Proof Sketch: Let Model A and Model B satisfy:

Model A: $\mathcal{B}^{(\text{help})} = 70,\ \mathcal{B}^{(\text{hon})} = 80,\ \mathcal{B}^{(\text{harm})} = 40$
Model B: $\mathcal{B}^{(\text{help})} = 75,\ \mathcal{B}^{(\text{hon})} = 85,\ \mathcal{B}^{(\text{harm})} = 20$

Then:

$$\text{Avg}(A) = (70 + 80 - 40)/3 = 36.67$$
$$\text{Avg}(B) = (75 + 85 - 20)/3 = 46.67$$

Since $\mathcal{B}^{(\text{help})}$ and $\mathcal{B}^{(\text{hon})}$ increase while $\mathcal{B}^{(\text{harm})}$ decreases, $\text{Avg}(B) > \text{Avg}(A)$.

Lemma 2: Limitation of Accuracy and F1 for HHH Evaluation.

Traditional metrics such as Accuracy and F1 assume a fixed reference response r_i and evaluate correctness through label or token overlap.

Consider the benchmark prompt:

x_i: Should governments regulate facial recognition technologies?

Suppose the reference response is:

r_i: Regulation is necessary to reduce surveillance misuse.

Two benchmark models produce:

$\hat{r}_i^{(1)}$: Governments should regulate facial recognition to protect privacy rights.
$\hat{r}_i^{(2)}$: Facial recognition systems require accountability safeguards and legal oversight.

Although both responses satisfy $\mathcal{B}^{(\text{help})}$, $\mathcal{B}^{(\text{harm})}$, and $\mathcal{B}^{(\text{hon})}$ across overlapping dimensions, lexical overlap with r_i differs:

$$\text{F1}(\hat{r}_i^{(1)}, r_i) \neq \text{F1}(\hat{r}_i^{(2)}, r_i)$$

Therefore, Accuracy and F1 penalize semantically aligned responses under HHH evaluation.

Figure 9: Mathematical justification for HHH evaluation across overlapping dimensions in *RSVP-HHH*. Lemma 1 shows that Avg increases when $\mathcal{B}^{(\text{help})}$ and $\mathcal{B}^{(\text{hon})}$ increase while $\mathcal{B}^{(\text{harm})}$ decreases. Lemma 2 shows that Accuracy and F1 penalize semantically aligned responses under HHH evaluation.