Pragyaan: Designing and Curating High-Quality Cultural Post-Training Datasets for Indian Languages

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Abstract

The effectiveness of Large Language Models (LLMs) depends heavily on the availability of high-quality post-training data, particularly instruction-tuning and preference-based examples. Existing open-source datasets, however, often lack multilingual coverage, cultural grounding, and suffer from task diversity gaps that are especially pronounced for Indian languages. We introduce a human-in-the-loop pipeline that combines translations with synthetic expansion to produce reliable and diverse Indic post-training data. Using this pipeline, we curate two datasets: *Pragyaan-IT* (22.5K) and *Pragyaan-Align* (100K) across 10 Indian languages covering 13 broad and 56 sub-categories, leveraging 57 diverse datasets. Our dataset protocol incorporates several often-overlooked dimensions and emphasize task diversity, multi-turn dialogue, instruction fidelity, safety alignment, and preservation of cultural nuance, providing a foundation for more inclusive and effective multilingual LLMs.

1 Introduction

Recent developments around Large Language Models (LLMs) (Touvron et al., 2023; Grattafiori et al., 2024; Abdin et al., 2025; Guo et al., 2025) have demonstrated that post-training data, comprising both instruction-tuning and preference data, plays a critical role in enhancing model alignment, task generalization, and usability (Ouyang et al., 2022; Bai et al., 2022b; Chung et al., 2022). Particularly in a multilingual and multicultural landscape, like India, the availability of high-quality, culturally grounded post-training data is crucial to address performance gaps in low-resource languages that often arise from the scarcity of relevant and representative training data (Joshi et al., 2020).

While several open-source datasets for post-training (Longpre et al., 2023; Wang et al., 2022b; Bercovich et al., 2025a) exist, they are predominantly English-centric and often suffer from limitations such as inconsistent quality, restricted coverage, insufficient task complexity, and limited multilingual coverage. These challenges extend to Indic post-training data as well, focus of our work.

Direct translations of existing English post-training datasets are prone to translation biases, errors (Hartung et al., 2023; Savoldi et al., 2021; Muennighoff et al., 2022) and loss of cultural grounding (Wang et al., 2022a; Pudjiati et al., 2022). For instance, a prompt like *"Tell me about a small herb to plant in backyard"* might yield Western herbs such as *thyme or rosemary*, whereas Indian users would expect culturally familiar options like *tulsi (holy basil), pudina (mint), or curry leaves*. Similarly, when asked *"What is a good comfort meal for a rainy day?"*, English-centric answers such as *tomato soup or grilled cheese* overlook Indian preferences like *masala chai with pakoras or khichdi with ghee*. Even in wellness contexts, *"Recommend a workout routine for beginners"* may default to *squats and push-ups*, neglecting practices like *Surya Namaskar or yoga exercises*. Such mismatches highlight the need for post-training data that reflects not just language, but also local traditions and cultural context.

The recent popularity of LLM-based synthetic data generation (Wang et al., 2022c) for creating post-training datasets, while promising, still suffers in quality due to linguistic inaccuracies, grammatical inconsistencies, and reduced fluency, especially in multilingual settings, that could degrade the performance of models trained on them. Moreover, the lack of fine-grained control over output complexity and the potential for hallucination can lead to the generation of low-quality, unreliable data.

With the aim of addressing these gaps, we present an approach to curate high-quality post-training datasets, especially in multilingual settings. Our curation approach combines the above techniques with post-hoc manual editing, leading to a scalable human-in-the-loop pipeline, with spe-

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cific focus on several aspects of quality, like task coverage, multilingual representation, task complexity, culture, multi-turns, reasoning, and others. We leverage our approach to curate high-quality Indic post-training datasets: *Pragyaan-IT* comprising $22.5K$ instruction tuning examples and *Pragyaan-Align*, a dataset of $100K$ preference examples in 10 Indian languages covering 56 task categories. Our contributions could thus be summarized as follows:

- We present a scalable pipeline for curating high-quality post-training data. Our approach emphasizes a human-in-the-loop (HITL) that is more efficient, reliable and ensures higher quality than direct synthetic generation or translation of existing English datasets.
- We introduce high-quality, manually curated, and culturally-inclusive post-training *Pragyaan* dataset series, consisting of 1) $22.5K$ *Pragyaan-IT* and 2) $100K$ *Pragyaan-Align*, designed for aligning LLMs to the diverse Indian cultural context.
- Our dataset includes a broad spectrum of instruction-following tasks with varying levels of complexity, ensuring the resulting models can handle a wide range of real-world scenarios. We provide a detailed analysis of the dataset's characteristics, including its language distribution and domain representation, also showcasing its suitability for robust instruction-following capabilities through a small-scale pilot experiment.

2 Related Work

Post-training is a key step in aligning large language models (LLMs) with human intent, commonly achieved through instruction tuning (Wei et al., 2022a) and preference tuning (Bai et al., 2022a) datasets, constructed in several ways. Task template based resources such as Flan 2021 (Wei et al., 2022a), Flan 2022 (Longpre et al., 2023), and P3 (Sanh et al., 2022) adapt NLP datasets into instruction–response format. Human-authored datasets like Open Assistant (Köpf et al., 2023), Dolly (Conover et al., 2023), and LIMA (Zhou et al., 2023) demonstrate the value of curated instructions but face scalability challenges. To overcome this, synthetic generation approaches leverage LLMs to expand from small human-annotated *seeds*, with efforts such as Self-Instruct (Wang et al., 2022c), Alpaca (Taori et al., 2023), and Guanaco (Joseph Cheung, 2023), often distilling knowledge (Hinton et al., 2015) from stronger teacher LLM models. Advanced pipelines like Evol-Instruct (Xu et al., 2023) iteratively increase instruction complexity, while later works extend these methods to reasoning and code generation (Luo et al., 2023; Gunasekar et al., 2023). Complementing these, user-contributed datasets such as InstructionWild (Ni et al., 2023) and ShareGPT[1] provide naturally occurring conversational data, and Unnatural Instructions (Honovich et al., 2022) show how seed tasks can be scaled into diverse synthetic corpora. Subsequent work expanded into specialized domains, including dialogue systems (Köpf et al., 2023), structured knowledge grounding (Xie et al., 2022), and chain-of-thought reasoning (Wei et al., 2022b; Kim et al., 2023). More recently, the Magpie dataset (Xu et al., 2024) introduced a fine-grained taxonomy spanning creative writing, math, role-playing, planning, and data analysis, emphasizing the importance of broad coverage in post-training resources. Preference datasets such as UltraFeedback (Cui et al., 2023) and Tulu3 (Lambert et al., 2025) comprises human and synthetic preference pairs for LLM alignment. Building on these advances, we construct our approach and dataset tailored to Indian languages and cultural contexts leveraging manual annotations in complement with synthetic generation.

While large-scale post-training datasets have become increasingly available, they remain predominantly English-centric, with limited coverage for other languages. A few exceptions incorporate some proportions of multilingual data (Köpf et al., 2023; Longpre et al., 2023; Muennighoff et al., 2023; Zhuo et al., 2024; Nguyen et al., 2023), but they remain limited in cultural and linguistic diversity compared to English resources. Prior efforts to extend post-training resources beyond English have typically followed three strategies: (1) translating English datasets into additional languages (Li et al., 2023a; Khan et al., 2024), (2) generating template-based datasets (Yu et al., 2023b; Gupta et al., 2023), and (3) manually curating instruction datasets in non-English languages (Li et al., 2023b; Wang et al., 2022d). Amongst these, template-based efforts such as xP3 (Muennighoff et al., 2022) extend the P3 taxonomy with 28 multilingual datasets. However, xP3 relies on uniform templates across languages, leading to limited task diversity and frequent repetition. Translation-based

[1] https://sharegpt.com/

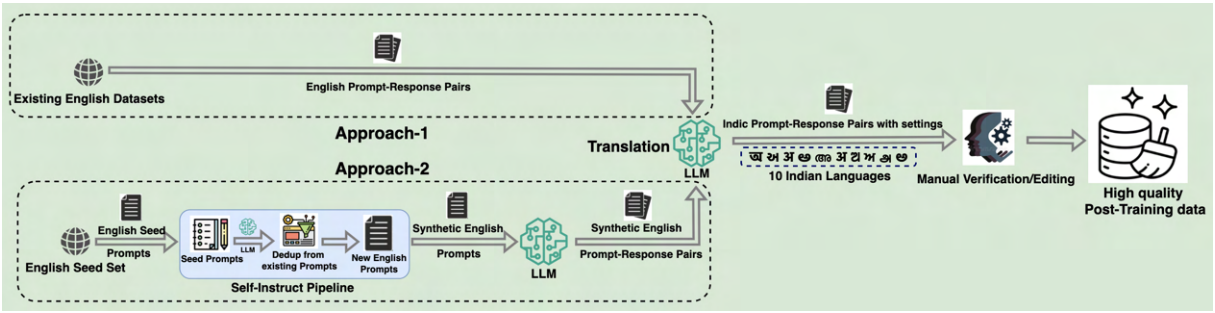

Figure 1: Workflow for building Indian language post-training data: English prompts are either translated or expanded via modified self-instruct pipeline to generate synthetic prompts. In both cases, responses are then produced with an LLM, translated into one of the 10 Indian languages, and manually refined (Section 3).

approaches face similar limitations, such as Bactrian (Li et al., 2023a), which translated Alpaca (Taori et al., 2023) and Dolly (Conover et al., 2023) into 52 languages. In contrast, our work introduces human-edited datasets across 10 Indian languages, addressing issues of redundancy and cultural grounding while providing a more diverse and representative resource for multilingual alignment.

3 Methodology

We present our multi-stage post-training dataset creation process that encompasses a variety of task categories at both broad and fine-grained levels, critical settings (complexity, interaction depth, constraints, safety, indian context, thinking trails) and leverages human annotators alongside curated data sources to ensure quality and coverage. While our approach itself is generic, we discuss how we used it to create high-quality Indic post-training datasets that we collectively refer to as *Pragyaan-IT* and *Pragyaan-Align*.

3.1 Data Construction Approaches

We employ two complementary approaches (Figure 1) that both combine translation and synthetic generation with post-hoc manual editing to ensure linguistic accuracy, fluency, and cultural appropriateness in our datasets.

3.1.1 Approach 1: Translation with Human Refinement

Here, we directly source English prompt-response pairs from existing English datasets (more details later in Section 3.5).

Prompts: We begin with English prompts which are first translated into Indic languages using an LLM, then refined by human annotators. During verification, annotators correct linguistic errors, improve readability, and adapt expressions where needed to reflect Indian cultural norms. This results in two categories, i.e. *1) Indic Generic Prompts:* direct translations of the English originals. *2) Indic Context Prompts:* culturally adapted and edited versions incorporating Indian references and contexts by human annotators.

Responses: Corresponding English responses undergo a similar pipeline independently, with LLM-based translation into Indic languages, followed by human editing for grammar, relevance, length, and cultural appropriateness. Thus, we have *1) Indic Generic Responses:* literal translations of the English outputs. *2) Indic Context Responses:* refined versions adapted to Indian discourse norms.

3.1.2 Approach 2: Synthetic Expansion with Human Refinement

This approach introduces an additional intermediate stage of synthetic prompt expansion in English.

Prompts: Starting with a seed set of English prompts (sourced or created), we use the Self-Instruct pipeline (Wang et al., 2022b) to iteratively expand this set into a larger synthetic pool. While in the original pipeline they generate new prompts for classification and non-classification types via different strategies, in our adaptation, we use the same prompt template for both the cases. The resulting synthetic English prompts are then translated into Indic languages with LLMs and refined by human annotators to ensure correctness, clarity, and cultural grounding. This yields *1) Synthetic Indic Generic Prompts:* literal translations of synthetic English prompts. *2) Synthetic Indic Context Prompts:* culturally enriched translations.

Responses: For each synthetic English prompt, we generate English responses using an LLM independently. These are then translated into Indic

languages and refined through human editing. Annotators correct factual or linguistic errors, polish style, and, when appropriate, enrich with cultural nuances. This process produces *1) Synthetic Indic Generic Responses:* faithful translations of the English responses. *2) Synthetic Indic Context Responses:* culturally adapted versions aligned with the Indian local context.

While our first approach ensures fidelity through the translation of existing English datasets, it remains constrained in both scope and diversity. The second approach complements this by introducing synthetic expansion prior to translation, enabling broader task coverage, richer cultural representation, and greater scalability with reduced dependency on large English resources. Together, the two approaches strike a balance between reliability and diversity, yielding multilingual datasets that are both high-quality and contextually rich.

3.2 Task Categories

Building on the design principles of several existing datasets, we curate a broad set of task categories that combine core language tasks such as reasoning (limited to CoT and self-thinking), inference, natural language understanding (NLU) and generation, question answering (QA), dialogue and interaction, information extraction, mathematics, coding, function calling, and instruction following, while also extending into culturally grounded domains like Indian states, religions, geo-political questions, etc. To promote robustness and responsible deployment, we additionally include safety and non-compliance, Indian contentious content, and self-identity tasks. Collectively, these categories establish a structured yet comprehensive framework that spans diverse sub-categories, enabling richer and more inclusive post-training curation. A detailed breakdown of sub-categories is provided in Table 1.

3.3 Task Settings

For each task category, we additionally define several task settings that encourage diversity of prompt complexity, interaction depth, instruction-following, safety considerations, cultural grounding, and explicit reasoning trails. We provide systematic descriptions of these settings next.

3.3.1 Complexity

We categorize tasks by complexity to ensure models are trained for both simple and challenging scenarios, with two primary levels: *1) Easy* prompts are direct and clearly defined, usually requiring minimal reasoning (e.g. a single factual or descriptive query). *2) Hard* prompts feature greater structural complexity, often embedding multiple sub-questions within a single query, requiring nuanced reasoning and fine-grained understanding. Importantly, complexity is defined within each task category, enabling fair assessment across heterogeneous task types (see Figures 6–11 in Appendix).

3.3.2 Multi-Turn Interactions

Multi-turn settings capture tasks where contextual continuity is critical, such as dialogue, planning, or role-play. These scenarios require models to maintain memory of prior turns while generating coherent and adaptive responses. We consider three levels of interaction depths: *1) Single-turn (1 turn):* A response to an isolated prompt; *2) Short multi-turn (3 turns):* Three back-and-forth exchanges, ensuring local continuity; *3) Extended multi-turn (5 turns):* Five exchanges, for long-range memory and coherence in extended conversations (e.g. planning a festival with evolving constraints).

3.3.3 Instruction Following

We categorize instruction-following into three levels, defined by the number and type of constraints imposed on the response such as *"answer in 100 words"*, *"respond in json format"*, etc. (Figure 12 in Appendix). This ensures coverage of tasks that range from loosely guided prompts to highly structured outputs. Different combinations of these constraints are applied depending on the nature of the prompt: *1) Simple instruction following*: prompts include minimal or no explicit constraints on the format or content of the response; *2) Medium instruction following*: prompts introduce two to three explicit constraints, requiring the model to accommodate multiple conditions at once; *3) Complex instruction following*: prompts impose several simultaneous constraints, demanding precise control and structured outputs.

3.3.4 Safety

We define safety settings to ensure that models behave responsibly when faced with sensitive, controversial, or potentially harmful content in a real-world setting. This dimension helps guide appropriate responses while maintaining ethical standards. We include *1) Safe*: prompts are neutral and non-controversial, allowing the model to provide direct answers without ethical or policy concerns; *2) Non-*

Broad Category	Sub Categories	Broad Category	Sub Categories
Reasoning & Inference	Non-Math Reasoning Math Reasoning Code Reasoning Indian Relationships Inference Data Analysis	Natural Language Understanding & Generation	Named Entity Recognition Text Classification Grammar Correction Translation Creative Writing Paraphrase Identification Paraphrase Generation Text Summarization Headline Generation Question Generation Sentiment Analysis
Question Answering	General Question Answering Fact Check	Interaction & Dialogue	Multi Turn Conversation Role Playing Advice Seeking Planning Brainstorming
Information Extraction	Information Seeking Indian Cultural Context Comprehension	Sanskrit Cultural & Creative Usage	Sanskrit Festival Greetings Sanskrit Auspicious Day / Other Occasions Sanskrit Subhashitas (Quotes) Sanskrit Captions and Mottos Sanskrit Person's Name Sanskrit Building / Institution / Company Name Sanskrit Product Name
Mathematics	Math QA Math Instruction Tuning Math Proofs	Coding	Code Generation Code Debugging Code Editing Code Explanation Code Translation Unit Test Generation Code Theory Code Review Repository level Code Generation
Function Calling	Function Calling	Instruction Following	Instruction Following
Safety & Non-Compliance	Safety & Non-Compliance	Indian Contentious Questions	Indian Geo Political Indian Politicians Indian States Indian Languages Indian Religions
Self-Identity	Model-name Person-based		

Table 1: Taxonomy of NLP task categories and sub-categories for creating post-training datasets in Section 3.2.

safe: prompts involve sensitive or harmful material, where the model is expected to either refuse politely (e.g., *"Sorry, I cannot assist with that ..."*) or generate a safe response.

3.3.5 Thinking Trails

We define 'thinking trail' settings to capture the role of explicit reasoning in model responses, ensuring that outputs range from direct answers to more reflective reasoning styles. *1) Normal*: direct response generation without intermediate reasoning traces; *2) Chain-of-Thought (CoT)*: step-by-step reasoning (Wei et al., 2022b) articulated explicitly before the final answer; *3) Self-Thinking*: inspired by recent "deep thinking" paradigms (Guo et al., 2025; Bercovich et al., 2025b; Abdin et al., 2025), where models produce more elaborate, self-reflective reasoning trails prior to the final response.

3.3.6 Indian Cultural Context

Given the centrality of Indic languages and cultural alignment in our framework, we explicitly model contextual grounding through three progressively richer levels. *1) IC-1* represents generic prompts leading to generic responses, with no explicit India related anchoring (e.g., Prompt: *"Suggest some breakfast items."*, Response: *"Pancakes, cereal, toast, scrambled eggs."*). Such responses are accurate but remain culturally neutral, with no particular alignment to cultural settings. *2) IC-2* represents generic prompts that nonetheless yield Indic-grounded responses. For instance, the same prompt above, in this setting, would elicit responses such as *"Idli, dosa, paratha, poha"*, which are the most popular breakfast items in India. *3) IC-3* involves prompts that are themselves explicitly Indic, thereby eliciting fully Indic-based responses. For example, the prompt itself mentions "Suggest some Indian breakfast items" with a similar response as in the IC-2 setting. This setting encourages grounding and diversity of responses with respect to Indian cultural context that is required for training Indic focused LLMs.

3.4 Human-In-The-Loop (HITL) Refinement

While synthetic generation and automated translation provides the backbone of our dataset creation pipeline, human annotators play an equally central role in shaping its final form. Each prompt–response pair, once generated and assigned a configuration of settings (e.g., *easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*), enters a stage of manual intervention where annotators act not merely as reviewers, but as curators of the data. If a pair does not fully align

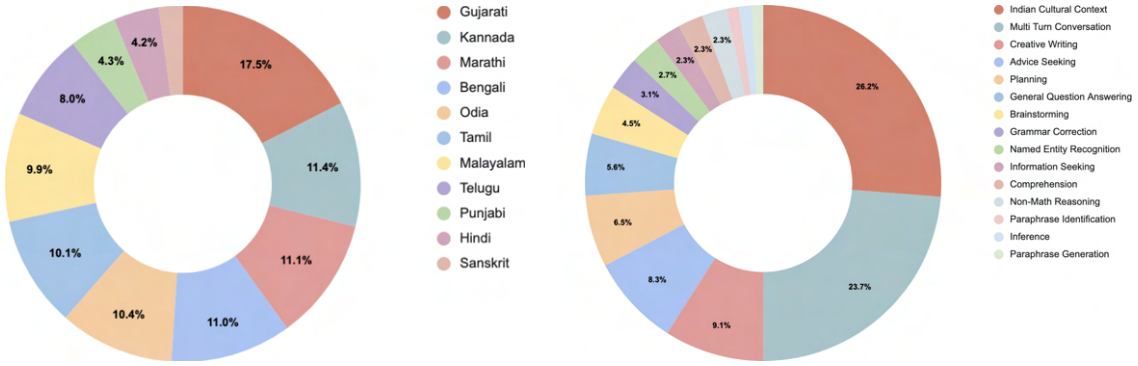

Figure 2: Distribution of *Pragyaan-IT* (Instruction-Tuning) data across languages (left) and categories (right).

with its designated configuration, annotators may either (i) adapt the configuration to better reflect the pair, or (ii) create a new prompt–response pair that correctly conforms to the specified configuration. This decision balances efficiency with fidelity to the framework. In cases where manually generating a new response is especially time-intensive, the annotators flag the prompt for regeneration and they undergo another iteration through the pipeline.

Crucially, manual intervention goes beyond mechanical verification. Annotators conduct linguistic quality checks ensuring fluency, grammatical accuracy, syntactic correctness, and appropriate response length, but are also encouraged to exercise creative judgment. This includes refining awkward phrasings, restructuring unclear outputs, or enriching responses with culturally relevant details. Even when a pair formally satisfies all defined constraints, annotators may modify it to adjust tone, improve readability, contextual appropriateness or pedagogical value as well as elevate the overall communicative value of the response. These interventions ensure that the dataset is not only consistent with the defined settings, but also meaningful and robust for deployment in real-world post-training scenarios.

3.5 Dataset Curation

Our curation process draws from a broad pool of existing resources while systematically adapting them for Indic languages and tasks. In total, we considered 57 diverse language datasets, together with their relevant splits, spanning different categories and task families. These resources serve either as direct candidates for translation into Indic languages or as seed data for synthetic expansion through a modified Self-Instruct pipeline (Wang et al., 2022b) described earlier. By combining translation and generation in a complementary manner, we ensure that the curated data covers not only core Natural Language Processing (NLP) tasks but also culturally grounded and contextually relevant dimensions. Table 3 in the Appendix provides an overview of the corresponding candidate datasets associated with each task sub-category.

Setting	Configuration	%
Complexity	Easy	62.32
	Hard	37.68
Multi Turn	1-Turn	91.66
	3-Turn	6.76
	5-Turn	1.58
Instruction Following	Simple IF	96.95
	Medium IF	2.49
	Complex IF	0.56
Safety	Safe	92.51
	Non-Safe	7.49
Indian Context	IC-1	32.04
	IC-2	10.16
	IC-3	57.80
Thinking Trails	Normal	99.98
	CoT	0.01
	Self Thinking	0.01

Table 2: Distribution of instances in *Pragyaan-IT* across different task settings and configurations in Section 3.3.

4 Pragyaan: Indic Post-training Datasets

As part of this work, we construct high-quality post-training datasets that explicitly target 10 Indian languages (Bengali, Gujarati, Hindi, Kannada, Malayalam, Marathi, Oriya, Punjabi, Tamil, and Telugu), yielding two complementary resources:

i) *Pragyaan-IT* (22.5K): an instruction-tuning dataset designed to enhance a model's ability to follow diverse prompts across multiple domains, ensuring that models can generalize well to everyday user interactions.

ii) *Pragyaan-Align* (100K): a preference dataset curated for Reinforcement Learning (RL)-based

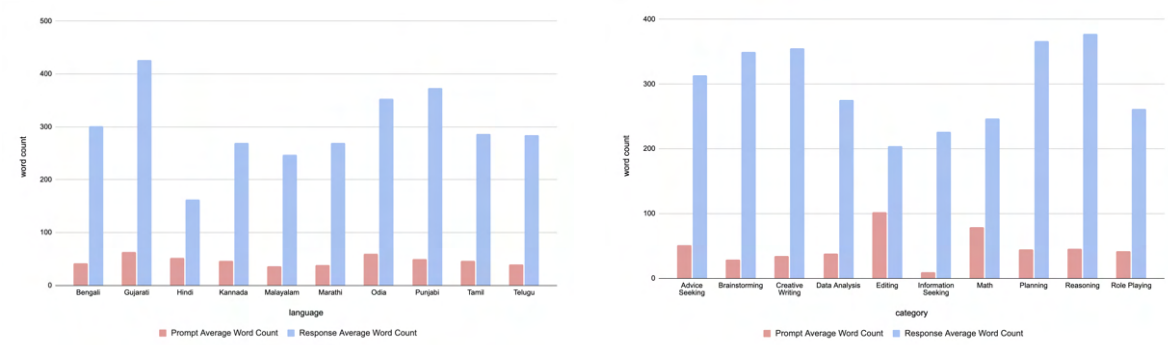

Figure 3: Average word counts of *Pragyaan-Align* alignment data across languages (left) and categories (right).

alignment methods, emphasizing preference learning, safety, and cultural grounding, allowing models to align more closely with the user intent.

5 Analysis

We begin with an assessment of raw synthetic generations refined through human annotation, followed by a broader dataset-level analysis.

5.1 Human Annotation Refinement

We evaluate the underlying LLM's performance for both generation and translation tasks across 5 dimensions, each on a scale of 1-5, for a small subset (see Section A.5 in the Appendix for details on evaluation). Particularly, for English generations, grammatical accuracy remains slightly lower in comprehension (3.20) and creative writing (3.93) tasks, while receiving high scores for other tasks. For translation, the model shows the strongest performance for Hindi (Figure 14). Telugu and Gujarati exhibit moderate Lexical Diversity (3.43 and 3.30), while grammatical accuracy remains modest in Telugu (3.62), Hindi (3.60), and Punjabi (3.55). Thus, human refinements were critical for converting raw synthetic output into culturally grounded, linguistically accurate, and task-aligned data, directly underpinning the reliability of our data curation framework.

5.2 Dataset analysis

Figure 2 shows the distribution of *Pragyaan-IT* across 10 languages and 15 categories, while Table 3 lists the candidate datasets used in its construction. As seen in Figure 2, Indian Cultural Context (26.2%) and Multi-Turn Conversation (23.7%) dominate, while reasoning and paraphrasing remain limited (1–3%), forming targets for future expansion. Language coverage is led by Gujarati (17.7%), Kannada (11.4%), Marathi (11.1%), and Odia (10.8%). In the current setting (Table 2), we have 62.3% 'Easy' tasks, single-turn interactions (91.7%), simple instruction-following (96.9%), safe content (92.5%) with Indian context well covered (IC-3: 57.8%). While this analysis reflects the status of the *Pragyaan-IT* dataset at the time of writing, the dataset is under active curation and will be more comprehensive across task categories and settings as described in earlier sections.

Word count analysis highlights linguistic and task-level variation (Figure 4). Gujarati and Odia are most verbose in both prompts (∼110 words) and responses (∼320 words), whereas Hindi mostly remain concise. At the task level, Multi-turn conversation, Advice Seeking, and Creative Writing yield the longest responses (550–620 words). Conversely, QA, Indian cultural context, and Comprehension tasks are consistently brief. Verbosity thus correlates with conversational and creative tasks, while simpler or context-specific settings produce shorter outputs.

Pragyaan-Align, the preference dataset, has an equal representation across all languages and 10 categories that helps promote fairness and mitigate bias. All instances in *Pragyaan-Align* follow a standardized configuration: single-turn interactions with instruction following and safe responses. Our analysis shows variation in text lengths across categories and languages. Average word counts for prompts range from 36–63 words, preferred responses 137–539, while rejected responses range from 154–466 words reflecting differences in task complexity and elaboration. Detailed language-wise as well as category-wise trends are also presented in Figure 3.

Overall, our *Pragyaan* datasets for post-training provide a broad task and Indian language coverage. The various task settings and our curation

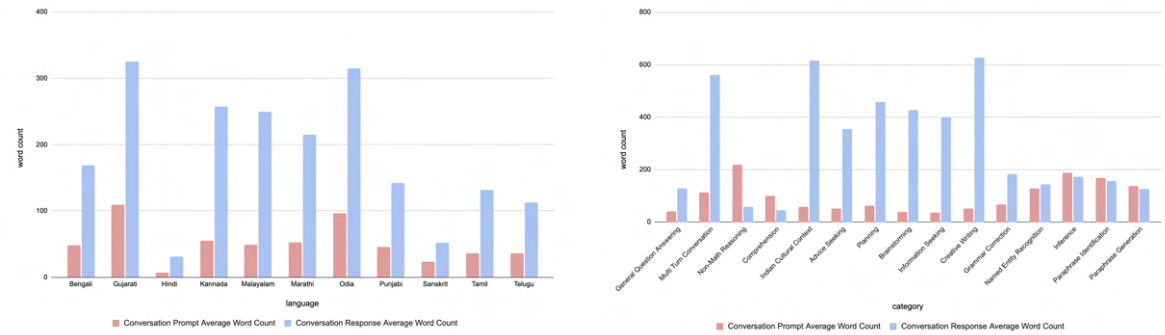

Figure 4: Average word counts of *Pragyaan-IT* data across languages (left) and categories (right).

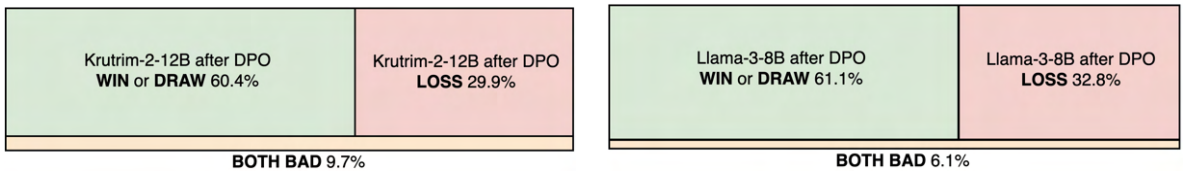

Figure 5: Win rates of the *Krutrim-2-12B* (left) and *Llama-3-8B* (right) models after DPO, compared against their respective pre-DPO versions.

process leveraging LLMs along with human-in-the-loop help ensure high quality. Our future iterations will expand complex reasoning capabilities and enhance representation for under-covered low-resource languages.

5.3 Downstream performance

To evaluate the quality of our curated dataset, we conduct a pilot study with Direct Preference Optimization (DPO) (Rafailov et al., 2023) based alignment on the *Pragyaan-Align* dataset using two open-weight models which supports the languages under consideration: *Krutrim-2-12B Instruct* (Kallappa et al., 2025) and *Llama-3-8B Instruct* (Grattafiori et al., 2024).

For evaluation, we use the recently released *Updesh* dataset[2], which covers similar categories and languages. We sample around 100 examples from nine relevant categories, balanced across ten languages. Responses from the models are scored against the ground truth on a scale of 1–5 using an LLM-as-a-judge. We provide more information about the hyperparameter configuration and other experimental details in Section A.6 and the corresponding prompts used for evaluation in Section B of the Appendix.

As shown in Figure 5, *Krutrim-2-12B* after DPO either wins or draws in 60.4% of cases, loses in 29.9%, and both pre- and post-DPO responses score poorly (<2) in 9.7%. A similar trend holds for *Llama-3-8B* (61.1% wins or draws), confirming the promising potential of our curated dataset for alignment across different categories and multiple Indian languages.

6 Conclusion

This work addresses the scarcity of high-quality post-training data for multilingual LLMs by developing a human-in-the-loop pipeline to ensure diversity, quality and cultural grounding. Through this approach, we construct two datasets: *Pragyaan-IT* and *Pragyaan-Align* covering 10 Indian languages and multiple task categories. The datasets highlight inclusion of local cultural context, task diversity, multi-turn dialogue, and safety alignment, overcoming the limitations of naive translations and low-quality synthetic resources. Although designed for Indian languages, the pipeline is readily adaptable to other multilingual contexts. We present a comprehensive analysis of the dataset's characteristics, covering language distribution and domain coverage, and further demonstrate its effectiveness for alignment through a small-scale pilot study. Future efforts will expand language coverage and further annotation quality refinement. We aim for this work to support broader efforts in building culturally inclusive resources that strengthen LLM applicability in multilingual contexts.

[2] https://huggingface.co/datasets/microsoft/Updesh_beta

Limitations

Our dataset is part of an ongoing effort, with plans to continually expand post-training instances. While our human-in-the-loop framework mitigates many issues, challenges such as minor linguistic inaccuracies, fluency variation across languages, and potential annotation subjectivity may still persist. Moreover, our research prioritized Indian languages, and the generalization of findings to other multilingual settings remain currently unexplored. Extending the pipeline to new cultural and linguistic contexts will require additional validation. We view these limitations as avenues for future work towards broader applicability and refinement of our proposed framework.

Ethics Statement

This study focuses on curating large-scale post-training datasets for Indian languages, encompassing diverse tasks and cultural contexts. The pipeline combines synthetic generation with human-in-the-loop refinement to ensure quality, safety, and cultural fidelity. We provide proper attribution to all source datasets and tools through citations. Human involvement was limited to annotation and quality control; no personally identifiable or sensitive information was collected. We engage a team of 50 in-house annotators for dataset creation. All contributors were clearly informed that their work supports LLM training and were compensated fairly at locally prevailing market rates. This study did not require formal IRB approval. Throughout the process, we prioritized preserving cultural nuances while avoiding harmful, biased, or unsafe content. The resulting dataset is designed to advance the development of multilingual and culturally inclusive LLMs.

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References

Marah Abdin, Sahaj Agarwal, Ahmed Awadallah, Vidhisha Balachandran, Harkirat Behl, Lingjiao Chen, Gustavo de Rosa, Suriya Gunasekar, Mojan Javaheripi, Neel Joshi, et al. 2025. Phi-4-reasoning technical report. *arXiv preprint arXiv:2504.21318*.

Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, Nicholas Joseph, Saurav Kadavath, Jackson Kernion, Tom Conerly, Sheer El-Showk, Nelson Elhage, Zac Hatfield-Dodds, Danny Hernandez, Tristan Hume, Scott Johnston, Shauna Kravec, Liane Lovitt, Neel Nanda, Catherine Olsson, Dario Amodei, Tom Brown, Jack Clark, Sam McCandlish, Chris Olah, Ben Mann, and Jared Kaplan. 2022a. Training a helpful and harmless assistant with reinforcement learning from human feedback.

Yuntao Bai, Saurav Kadavath, Sandhini Kundu, Amanda Askell, et al. 2022b. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073*.

Samuel Barham, , Weller, Michelle Yuan, Kenton Murray, Mahsa Yarmohammadi, Zhengping Jiang, Siddharth Vashishtha, Alexander Martin, Anqi Liu, Aaron Steven White, Jordan Boyd-Graber, and Benjamin Van Durme. 2023. Megawika: Millions of reports and their sources across 50 diverse languages.

Akhiad Bercovich, Itay Levy, Izik Golan, Mohammad Dabbah, Ran El-Yaniv, Omri Puny, Ido Galil, Zach Moshe, Tomer Ronen, Najeeb Nabwani, et al. 2025a. Llama-nemotron: Efficient reasoning models. *arXiv preprint arXiv:2505.00949*.

Akhiad Bercovich, Itay Levy, Izik Golan, Mohammad Dabbah, Ran El-Yaniv, Omri Puny, Ido Galil, Zach Moshe, Tomer Ronen, Najeeb Nabwani, et al. 2025b. Llama-nemotron: Efficient reasoning models. *arXiv preprint arXiv:2505.00949*.

Ning Bian, Hongyu Lin, Yaojie Lu, Xianpei Han, Le Sun, and Ben He. 2023. Chatalpaca: A multi-turn dialogue corpus based on alpaca instructions. https://github.com/cascip/ChatAlpaca.

Daniel Borkan, Lucas Dixon, Jeffrey Sorensen, Nithum Thain, and Lucy Vasserman. 2019. Nuanced metrics for measuring unintended bias with real data for text classification. In *Companion Proceedings of The 2019 World Wide Web Conference*.

Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. 2021. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*.

Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. A discourse-aware attention model for abstractive summarization of long documents. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*.

Alexis Conneau, Ruty Rinott, Guillaume Lample, Adina Williams, Samuel R. Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. Xnli: Evaluating cross-lingual sentence representations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.

Mike Conover, Matt Hayes, Ankit Mathur, Jianwei Xie, Jun Wan, Sam Shah, Ali Ghodsi, Patrick Wendell, Matei Zaharia, and Reynold Xin. 2023. Free Dolly: Introducing the World's First Truly Open Instruction-Tuned LLM.

Ganqu Cui, Lifan Yuan, Ning Ding, Guanming Yao, Bingxiang He, Wei Zhu, Yuan Ni, Guotong Xie, Ruobing Xie, Yankai Lin, et al. 2023. Ultrafeedback: Boosting language models with scaled ai feedback. *arXiv preprint arXiv:2310.01377*.

Sumanth Doddapaneni, Rahul Aralikatte, Gowtham Ramesh, Shreya Goyal, Mitesh M. Khapra, Anoop Kunchukuttan, and Pratyush Kumar. 2023. Towards leaving no Indic language behind: Building monolingual corpora, benchmark and models for Indic languages. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 12402–12426, Toronto, Canada. Association for Computational Linguistics.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. 2024. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*.

Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, Adil Salim, Shital Shah, Harkirat Singh Behl, Xin Wang, Sébastien Bubeck, Ronen Eldan, Adam Tauman Kalai, Yin Tat Lee, and Yuanzhi Li. 2023. Textbooks are all you need.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. 2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*.

Himanshu Gupta, Kevin Scaria, Ujjwala Anantheswaran, Shreyas Verma, Mihir Parmar, Saurabh Arjun Sawant, Chitta Baral, and Swaroop Mishra. 2023. Targen: Targeted data generation with large language models.

Kai Hartung, Aaricia Herygers, Shubham Kurlekar, Khabbab Zakaria, Taylan Volkan, Sören Gröttrup, and Munir Georges. 2023. Measuring sentiment bias in machine translation.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*.

Dan Hendrycks, Collin Burns, Saurav Kadavath, Akul Arora, Steven Basart, Eric Tang, Dawn Song, and Jacob Steinhardt. 2021. Measuring mathematical problem solving with the math dataset. *NeurIPS*.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*.

Or Honovich, Thomas Scialom, Omer Levy, and Timo Schick. 2022. Unnatural instructions: Tuning language models with (almost) no human labor. *arXiv preprint arXiv:2212.09689*.

Joseph Cheung. 2023. GuanacoDataset (Revision 8cf0d29) .

Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. 2017. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. *arXiv preprint arXiv:1705.03551*.

Pratik Joshi, Sebastin Santy, Amar Budhiraja, Kalika Bali, and Monojit Choudhury. 2020. The state and fate of linguistic diversity and inclusion in the nlp world. *arXiv preprint arXiv:2004.09095*.

Aditya Kallappa, Palash Kamble, Abhinav Ravi, Akshat Patidar, Vinayak Dhruv, Deepak Kumar, Raghav Awasthi, Arveti Manjunath, Shubham Agarwal, Kumar Ashish, Gautam Bhargava, and Chandra Khatri. 2025. Krutrim llm: Multilingual foundational model for over a billion people.

Mohammed Safi Ur Rahman Khan, Priyam Mehta, Ananth Sankar, Umashankar Kumaravelan, Sumanth Doddapaneni, Sparsh Jain, Anoop Kunchukuttan, Pratyush Kumar, Raj Dabre, Mitesh M Khapra, et al. 2024. Indicllmsuite: A blueprint for creating pre-training and fine-tuning datasets for indian languages. *arXiv preprint arXiv:2403.06350*.

Seungone Kim, Se June Joo, Doyoung Kim, Joel Jang, Seonghyeon Ye, Jamin Shin, and Minjoon Seo. 2023. The cot collection: Improving zero-shot and few-shot learning of language models via chain-of-thought fine-tuning. *arXiv preprint arXiv:2305.14045*.

Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Richárd Nagyfi, et al. 2023. Openassistant conversations–democratizing large language model alignment. *arXiv preprint arXiv:2304.07327*.

Aman Kumar, Himani Shrotriya, Prachi Sahu, Amogh Mishra, Raj Dabre, Ratish Puduppully, Anoop Kunchukuttan, Mitesh M. Khapra, and Pratyush Kumar. 2022. IndicNLG benchmark: Multilingual datasets for diverse NLG tasks in Indic languages. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 5363–5394, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Matthew Kelcey, Jacob Devlin, Kenton Lee Toutanova, Llion Jones, Ming-Wei Chang, Andrew Dai, Jakob Uszkoreit, Quoc Le, and Slav Petrov. 2019. Natural questions: a benchmark for question answering research. *TACL*.

Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahman, Lester James V. Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, Yuling Gu, Saumya Malik, Victoria Graf, Jena D. Hwang, Jiangjiang Yang, Ronan Le Bras, Oyvind Tafjord, Chris Wilhelm, Luca Soldaini, Noah A. Smith, Yizhong Wang, Pradeep Dasigi, and Hannaneh Hajishirzi. 2025. Tulu 3: Pushing frontiers in open language model post-training.

Haonan Li, Fajri Koto, Minghao Wu, Alham Fikri Aji, and Timothy Baldwin. 2023a. Bactrian-x: A multilingual replicable instruction-following model with low-rank adaptation. *arXiv preprint arXiv:2305.15011*.

Lei Li, Yuwei Yin, Shicheng Li, Liang Chen, Peiyi Wang, Shuhuai Ren, Mukai Li, Yazheng Yang, Jingjing Xu, Xu Sun, Lingpeng Kong, and Qi Liu. 2023b. M^{3}it: A large-scale dataset towards multi-modal multilingual instruction tuning.

Yang Liu, Xiaotian Zhang, Haoze Sun, Yuzhen Huang, Wei Wu, Yiliang Li, Hao Yu, Jun Liu, Yueqi Li, Zhicheng Guo, Xiaoguang Li, Yongfeng Huang, Guilin Li, Yujun Zhou, Yufeng Chen, Chenyan Jia, and Xing-Jian Jiang. 2024. Mmlu-pro: a more advanced and challenging multi-task evaluation for llms. *arXiv preprint arXiv:2406.01574*.

Shayne Longpre, Le Hou, Tu Vu, Albert Webson, et al. 2023. The flan collection: Designing data and methods for effective instruction tuning. *arXiv preprint arXiv:2301.13688*.

Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. 2023. Wizardcoder: Empowering code large language models with evol-instruct.

Arnav Mhaske, Harshit Kedia, Sumanth Doddapaneni, Mitesh M. Khapra, Pratyush Kumar, Rudra Murthy, and Anoop Kunchukuttan. 2022. Naamapadam: A large-scale named entity annotated data for indic languages.

Todor Mihaylov, Peter Clark, Tushar Khot, and Ashish Sabharwal. 2018. A new dataset for open book question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*.

Niklas Muennighoff, Qian Liu, Armel Zebaze, Qinkai Zheng, Binyuan Hui, Terry Yue Zhuo, Swayam Singh, Xiangru Tang, Leandro von Werra, and Shayne Longpre. 2023. Octopack: Instruction tuning code large language models. *arXiv preprint arXiv:2308.07124*.

Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng-Xin Yong, Hailey Schoelkopf, et al. 2022. Crosslingual generalization through multitask finetuning. *arXiv preprint arXiv:2211.01786*.

Niklas Muennighoff, Zitong Yang, Weijia Shi, Xiang Lisa Li, Li Fei-Fei, Hannaneh Hajishirzi, Luke Zettlemoyer, Percy Liang, and Emmanuel. 2025. s1: Simple test-time scaling.

Huu Nguyen, Sameer Suri, Ken Tsui, and Christoph Schuhmann. 2023. The open instruction generalist (oig) dataset. `https://laion.ai/blog/oig-dataset/`.

Jinjie Ni, Fuzhao Xue, Kabir Jain, Mahir Hitesh Shah, Zangwei Zheng, and Yang You. 2023. Instruction in the wild: A user-based instruction dataset. `https://github.com/XueFuzhao/InstructionWild`.

NVIDIA. 2025. Llama-nemotron-post-training dataset: A comprehensive collection of instruction tuning and alignment data. *arXiv preprint arXiv:2505.00949*.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, et al. 2022. Training language models to follow instructions with human feedback. *arXiv preprint arXiv:2203.02155*.

Guilherme Penedo, Anton Lozhkov, Hynek Kydlíček, Loubna Ben Allal, Edward Beeching, Agustín Piqueres Lajarín, Quentin Gallouédec, Nathan Habib, Lewis Tunstall, and Leandro von Werra. 2025. Codeforces cots. `https://huggingface.co/datasets/open-r1/codeforces-cots`.

Danti Pudjiati, Ninuk Lustyantie, Ifan Iskandar, and Tira Nur Fitria. 2022. Post-editing of machine translation: Creating a better translation of cultural specific terms. *Language Circle: Journal of Language and Literature*, 17(1):61–73.

Ratish Puduppully, Himani Shrotriya, Anoop Kunchukuttan, and Mitesh M. Khapra. 2024. Mathinstruct: A high-quality math instruction dataset.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. 2023. Direct preference optimization: Your language model is secretly a reward model. *Advances in neural information processing systems*, 36:53728–53741.

Nazneen Rajani, Lewis Tunstall, Edward Beeching, Nathan Lambert, Alexander M. Rush, and Thomas Wolf. 2023. No robots. https://huggingface.co/datasets/HuggingFaceH4/no_robots.

Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. 2020. Zero: Memory optimizations toward training trillion parameter models. In *Proceedings of the International Conference for High Performance Computing, Networking, Storage and Analysis (SC)*.

Pranav Rajpurkar, Robin Jia, and Percy Liang. 2018. Know what you don't know: Unanswerable questions for squad. *arXiv preprint arXiv:1806.03822*.

David Rein, Betty Li Hou, Asa Cooper Stickland, Jackson Petty, Richard Yuanzhe Pang, Julien Dirani, Julian Michael, and Samuel R. Bowman. 2024. GPQA: A graduate-level google-proof q&a benchmark. In *First Conference on Language Modeling*.

ServiceNow AI Research. 2024. R1-distill-sft: A dataset for instruction tuning with a focus on distillation from large language models. *arXiv preprint arXiv:2403.06350*.

Pritika Rohera, Chaitrali Ginimav, Akanksha Salunke, Gayatri Sawant, and Raviraj Joshi. 2024. L3cube-indicquest: A benchmark question answering dataset for evaluating knowledge of llms in indic context. *arXiv preprint arXiv:2405.18789*.

Christian Rothermund, David Vögele, Lucas Roth, Philipp Schmutz, Tobias Wiegand, and Sebastian Aschenbrenner. 2025. Finemedlm-o1: Enhancing medical knowledge reasoning ability of llm from supervised fine-tuning to test-time training. *arXiv preprint arXiv:2501.09213*.

Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. 2022. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*.

Beatrice Savoldi, Marco Gaido, Luisa Bentivogli, Matteo Negri, and Marco Turchi. 2021. Gender bias in machine translation.

Harman Singh, Nitish Gupta, Shikhar Bharadwaj, Dinesh Tewari, and Partha Talukdar. 2024a. Indicgenbench: A multilingual benchmark to evaluate generation capabilities of llms on indic languages.

Shivalika Singh, Freddie Vargus, Daniel Dsouza, Börje F. Karlsson, Abinaya Mahendiran, Wei-Yin Ko, Herumb Shandilya, Jay Patel, Deividas Mataciunas, Laura OMahony, Mike Zhang, Ramith Hettiarachchi, Joseph Wilson, Marina Machado, Luisa Souza Moura, Dominik Krzemiński, Hakimeh Fadaei, Irem Ergün, Ifeoma Okoh, Aisha Alaagib, Oshan Mudannayake, Zaid Alyafeai, Vu Minh Chien, Sebastian Ruder, Surya Guthikonda, Emad A. Alghamdi, Sebastian Gehrmann, Niklas Muennighoff, Max Bartolo, Julia Kreutzer, Ahmet Üstün, Marzieh Fadaee, and Sara Hooker. 2024b. Aya dataset: An open-access collection for multilingual instruction tuning.

Zafir Stojanovski, Oliver Stanley, Joe Sharratt, Richard Jones, Abdulhakeem Adefioye, Jean Kaddour, and Andreas Köpf. 2025. Reasoning gym: Reasoning environments for reinforcement learning with verifiable rewards.

Alon Talmor, Jonathan Herzig, Nicholas Lourie, and Jonathan Berant. 2019. CommonsenseQA: A question answering challenge targeting commonsense knowledge. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. 2023. Stanford alpaca: An instruction-following llama model.

Shubham Toshniwal, Ivan Moshkov, Sean Narenthiran, Daria Gitman, Fei Jia, and Igor Gitman. 2024. Openmathinstruct-1: A 1.8 million math instruction tuning dataset. *arXiv preprint arXiv: Arxiv-2402.10176*.

Foutse Touileb, Xavier Longpre, Adrien L'Heureux, Tom Houlsby, Duy-Kien Le, Vincent Aribaud, Hugo Le Scao, Tommaso Pasquini, Marco Miaschi, and Patrick Muennighoff. 2024. Magpie: A broad-coverage, fine-grained multitask instruction dataset. *arXiv preprint arXiv:2403.00010*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, Dan Bikel, Lukas Blecher, Cristian Canton Ferrer, Moya Chen, Guillem Cucurull, David Esiobu, Jude Fernandes, Jeremy Fu, Wenyin Fu, Brian Fuller, Cynthia Gao, Vedanuj Goswami, Naman Goyal, Anthony Hartshorn, Saghar Hosseini, Rui Hou, Hakan Inan, Marcin Kardas, Viktor Kerkez, Madian Khabsa, Isabel Kloumann, Artem Korenev, Punit Singh Koura, Marie-Anne Lachaux, Thibaut Lavril, Jenya Lee, Diana Liskovich, Yinghai Lu, Yuning Mao, Xavier Martinet, Todor Mihaylov, Pushkar Mishra, Igor Molybog, Yixin Nie, Andrew Poulton, Jeremy Reizenstein, Rashi Rungta, Kalyan Saladi, Alan Schelten, Ruan Silva, Eric Michael Smith, Ranjan Subramanian, Xiaoqing Ellen Tan, Binh Tang, Ross Taylor, Adina Williams, Jian Xiang Kuan, Puxin Xu,

Zheng Yan, Iliyan Zarov, Yuchen Zhang, Angela Fan, Melanie Kambadur, Sharan Narang, Aurelien Rodriguez, Robert Stojnic, Sergey Edunov, and Thomas Scialom. 2023. Llama 2: Open foundation and fine-tuned chat models.

Jun Wang, Benjamin Rubinstein, and Trevor Cohn. 2022a. Measuring and mitigating name biases in neural machine translation. In *ACL*.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022b. Self-instruct: Aligning language model with self generated instructions.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022c. Self-instruct: Aligning language model with self generated instructions. *ArXiv preprint*, abs/2212.10560.

Yizhong Wang, Yeganeh Li, Niklas Michael, Hila Gonen, Jesse He, Yi Zhao, Ziyi Lin, Yejin Shafi, Karan Singh, Foutse Touileb, and et al. 2022d. Supernaturalinstructions: A generalization beyond english language. *arXiv preprint arXiv:2204.05367*.

Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V Le. 2022a. Finetuned language models are zero-shot learners. In *International Conference on Learning Representations*.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022b. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837.

Sean Welleck, Ronan Le Bras, Hannaneh Hajishirzi, and Yejin Choi. 2021. Naturalproofs: Mathematical theorem proving in natural language. *arXiv preprint arXiv:2104.01112*.

Tianbao Xie, Chen Henry Wu, Peng Shi, Ruiqi Zhong, Torsten Scholak, Michihiro Yasunaga, Chien-Sheng Wu, Ming Zhong, Pengcheng Yin, Sida I Wang, et al. 2022. Unifiedskg: Unifying and multi-tasking structured knowledge grounding with text-to-text language models. *arXiv preprint arXiv:2201.05966*.

Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. 2023. Wizardlm: Empowering large language models to follow complex instructions.

Zhangchen Xu, Fengqing Jiang, Luyao Niu, Yuntian Deng, Radha Poovendran, Yejin Choi, and Bill Yuchen Lin. 2024. Magpie: Alignment data synthesis from scratch by prompting aligned llms with nothing.

Zhangchen Xu, Yang Liu, Yueqin Yin, Mingyuan Zhou, and Radha Poovendran. 2025. KodCode: A diverse, challenging, and verifiable synthetic dataset for coding. In *Findings of the Association for Computational Linguistics: ACL 2025*, pages 6980–7008.

Yi Yang, Wen-tau Yih, and Christopher Meek. 2015. Wikiqa: A challenge dataset for open-domain question answering. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*.

Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William Cohen, Ruslan Salakhutdinov, and Christopher D. Manning. 2018. HotpotQA: A dataset for diverse, explainable multi-hop question answering. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2369–2380, Brussels, Belgium. Association for Computational Linguistics.

Yixin Ye, Zhen Huang, Yang Xiao, Ethan Chern, Shijie Xia, and Pengfei Liu. 2025. Limo: Less is more for reasoning.

Xiang Yu, Haidong Liu, Ning Yang, Qiaoli Wang, Jianye Wang, Jia Li, Li Zhang, and Jian Zhang. 2023a. Metamath: Bootstrap your own mathematical reasoning dataset. *arXiv preprint arXiv:2309.12284*.

Yue Yu, Yuchen Zhuang, Jieyu Zhang, Yu Meng, Alexander Ratner, Ranjay Krishna, Jiaming Shen, and Chao Zhang. 2023b. Large language model as attributed training data generator: A tale of diversity and bias.

Tianyu Zhang, Yang Liu, Yuxuan Xu, Yujia Wang, Haoyu Chen, Hongwei Li, Chen Li, Jiawei Xie, and Chen Zhang. 2024. Open-thoughts: A large-scale dataset for learning and evaluating llm thinking processes. *arXiv preprint arXiv:2406.04178*.

Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. 2023. Lima: Less is more for alignment. *arXiv preprint arXiv:2305.11206*.

Terry Yue Zhuo, Armel Zebaze, Nitchakarn Suppattarachai, Leandro von Werra, Harm de Vries, Qian Liu, and Niklas Muennighoff. 2024. Astraios: Parameter-efficient instruction tuning code large language models. *arXiv preprint arXiv:2401.00788*.

A Appendix

A.1 Dataset Curation

For each sub-category, we curated multiple publicly available candidate datasets and evaluated their applicability to our data collection objectives, assessing how they align with the chosen curation approaches. Table 3 summarizes representative categories along with corresponding datasets incorporated into our pipeline. It is worth noting that data collection for certain sub-categories remains an ongoing effort.

A.2 Data Construction Approaches

We further provide more details about the prompt and responses for both the approaches in Table 4.

Sub Category	Candidate Datasets	Sub Category	Candidate Datasets
Non-Math Reasoning	MMLU (Hendrycks et al., 2020) MMLU-Pro (Liu et al., 2024) GPQA (Rein et al., 2024) medical-o1-reasoning-SFT (Rothermund et al., 2025) OpenThoughts (Zhang et al., 2024)	Sentiment Analysis	IndicSentiment (Doddapaneni et al., 2023) pietrolesci/imdb
Math Reasoning	OpenThoughts (Zhang et al., 2024) Llama-Nemotron-Posttraining-Dataset (NVIDIA, 2025) ServiceNow-AI/R1-Distil-SFT (Research, 2024) LIMO (Ye et al., 2025) s1K (Muennighoff et al., 2025)	General Question Answering	OpenBookQA (Mihaylov et al., 2018) TriviaQA (Joshi et al., 2017) CommonSenseQA (Talmor et al., 2019) WikiQA (Yang et al., 2015) HotPotQA (Yang et al., 2018) MegaWika (Barham et al., 2023)
Code Reasoning	OpenThoughts (Zhang et al., 2024) Llama-Nemotron-Posttraining-Dataset (NVIDIA, 2025) KodCode (Xu et al., 2025) open-r1/codeforces-cots (Penedo et al., 2025)	Fact Check	NaturalQuestions (Kwiatkowski et al., 2019) TriviaQA (Joshi et al., 2017) Indic Quest (Rohera et al., 2024)
Indian Relationships	Reasoning Gym (Stojanovski et al., 2025)	Multi Turn Conversation	ChatAlpaca (Bian et al., 2023) NoRobots (Rajani et al., 2023) Opus Samantha
Inference	XNLI (Conneau et al., 2018)	Role Playing	Public Domain Alpaca LimaRP Magpie (Touileb et al., 2024)
Data Analysis	Magpie (Touileb et al., 2024)	Advice Seeking	Magpie (Touileb et al., 2024)
Named Entity Recognition	Naamapadam (Mhaske et al., 2022) Bharath Bench	Planning	Magpie (Touileb et al., 2024)
Text Classification	pietrolesci/civilcomments-wilds (Borkan et al., 2019) pietrolesci/wikitoxic pietrolesci/hyperpartisan_news_detection Bharath Bench Aya Collection (Singh et al., 2024b)	Brainstorming	Magpie (Touileb et al., 2024)
Grammar Correction	Bharath Bench	Information Seeking	Magpie (Touileb et al., 2024)
Translation	Flores-IN (Singh et al., 2024a) IN-22	Indian Cultural Context	Bharath Bench
Creative Writing	Magpie (Touileb et al., 2024) Poetry	Comprehension	TriviaQA (Joshi et al., 2017) SQUAD (Rajpurkar et al., 2018) SQUAD 2.0 (Rajpurkar et al., 2018) IndicQA
Paraphrase Identification	IndicXParaphrase (Doddapaneni et al., 2023)	Math QA	OpenMathInstruct 2 (Toshniwal et al., 2024) GSM8K (Cobbe et al., 2021) MATH (Hendrycks et al., 2021) Tulu3 Persona Math (Lambert et al., 2025) Tulu3 Persona GSM8K (Lambert et al., 2025)
Text Summarization	CrossSumIN (Singh et al., 2024a) Indic Sentence Summarization (Kumar et al., 2022) arxiv-summarization (Cohan et al., 2018) news-summarization	Math Instruction Tuning	MetaMathQA (Yu et al., 2023a) Math Instruct (Puduppully et al., 2024)
Headline Generation	Indic Headline Generation (Kumar et al., 2022) NewSHead	Math Proofs	Natural Proofs (Welleck et al., 2021)
Question Generation	Indic Question Generation (Kumar et al., 2022)		

Table 3: Representative datasets curated for different sub-categories that are used as candidate datasets in our data curation approaches.

Approaches	Prompts	Responses
Approach 1: Translation + Human Refinement	English prompts → LLM translation → human verification/adaptation. *Outputs:* Indic Generic Prompts, Indic Context Prompts.	English responses → LLM translation → human verification/adaptation. *Outputs:* Indic Generic Responses, Indic Context Responses.
Approach 2: Synthetic Expansion + Human Refinement	Seed English prompts → LLM expansion (Self-Instruct) → LLM translation → human verification/adaptation. *Outputs:* Synthetic Indic Generic Prompts, Synthetic Indic Context Prompts.	Synthetic English responses → LLM translation → human verification/adaptation. *Outputs:* Synthetic Indic Generic Responses, Synthetic Indic Context Responses.

Table 4: Comparison of data construction approaches, showing pipelines for prompts and responses with resulting categories.

A.3 Complexity Definitions

Notably, complexity is evaluated relative to each task category, ensuring that difficulty levels are interpreted within the specific context of that category. Figures 6–11 illustrate how complexity is defined across different task categories.

A.4 Instruction Following

Various configurations of Instruction Following incorporate different combinations of constraints within the prompt. Figure 12 outlines the types of constraints considered, accompanied by illustrative examples for clarity while human annotation.

A.5 Human Annotation Refinement

Data annotators initially assessed the performance of the underlying LLM on both generation and translation tasks across multiple dimensions.

For generation, raw LLM responses were assessed along dimensions such as Response Relevance, Grammatical Accuracy, Cohesion and Coherence, Rationality, and Completeness (see Table 5 for the guidelines). As shown in Figure 13, English generations perform consistently well: tasks such as Indian Cultural Context, Advice Seeking, Information Seeking, Named Entity Recognition, Inference, Paraphrase Identification, Paraphrase Generation, and Headline Generation achieve near-perfect scores in Response Relevance (5.00) and Completeness (4.93–5.00). Multi-Turn Conversation also scores high in Cohesion and Coherence (5.00) and Response Relevance (4.70). Grammatical Accuracy remains strong overall (4.00–4.40), though slightly lower in Comprehension (3.20) and Creative Writing (3.93).

For translation, annotators evaluated Lexical Diversity, Coherence and Cohesion, Completeness, Grammatical Accuracy, and Named Entity Handling (see Table 6 for the guidelines). Hindi shows the strongest performance, achieving the highest Completeness (4.92) and Named Entity Handling (4.85). Telugu and Gujarati exhibit strong Lexical Diversity (3.43 and 3.30), while Grammatical Accuracy is highest in Telugu (3.62), Hindi (3.60), and Punjabi (3.55). Further detailed evaluation scores are illustrated in Figure 14.

A.6 Implementation

For training, we adopt a distributed DeepSpeed-based setup with ZeRO-3 optimization (Rajbhandari et al., 2020) across 2 H100 nodes (8 GPUs per node) to efficiently handle large-scale model fine-tuning. The Llama-3-8B and Krutrim-2-12B instruct models are optimized using the Direct Preference Optimization (DPO) objective with a Beta parameter of 0.3, controlling the strength of preference alignment. Training is performed on sequences up to 4096 tokens, with a maximum prompt length of 2048 tokens to accommodate complex multi-turn instructions. We employ the AdamW optimizer with a learning rate of 5×10^{-7}, weight decay of 0.01, and a cosine learning rate scheduler with a warming ratio of 10% warmup ratio for stable convergence and run for 1 epoch. The batch configuration consists of 4 samples per device with gradient accumulation over 2 steps, yielding an effective batch size suitable for large-scale distributed training setup.

Post-trained Krutrim-2-12B and Llama-3-8B models are evaluated on the Updesh dataset across 10 languages and nine categories using LLM-as-a-Judge scoring on a scale of 1-5. Post-DPO, Krutrim achieves 31.7% wins, 29.9% losses, 28.6% draws, and 9.8% both-bad cases, while Llama records 35.0% wins, 26.1% losses, 27.9% draws, and 11.0% both-bad cases.

B Prompts Used

Different prompts were crafted for each category and complexity level during prompt generation using the self-instruct pipeline. For instance, Figures 15 and 16 illustrate example prompts for the Indian Cultural Context category under easy and hard settings, respectively. Similar design considerations were applied across other categories to address their specific requirements.

Figure 17 presents the prompt template employed for translating English prompt-response pairs via LLMs. The Krutrim-2-12B and Llama-3-8B Instruct models, after being fine-tuned using DPO on 100K examples from the *Pragyaan-Align* dataset, were evaluated on the Updesh dataset. The evaluation utilized an LLM-as-a-Judge framework for scoring, with the corresponding prompt design shown in Figure 18.

C Guidelines For Manual Annotation

The data annotation team follows a set of standardized guidelines designed to maintain consistency and uniformity throughout the annotation process. These guidelines include precise definitions for each category and setting, which are elaborated

Sub Category	Complexity	Sub Category	Complexity
Non-Math Reasoning	1. **Number of reasoning steps** Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences. 2. **Obviousness of needed knowledge** Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge. 3. **Clarity of distractors** Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.	Data-Analysis	1. **Data Complexity** Easy: Small, clean datasets (few rows/columns). Hard: Larger, noisier, or irregular datasets (missing values, inconsistent formatting). 2. **Reasoning Depth** Easy: Single-step reasoning (e.g., identify max/min, simple difference). Hard: Multi-step reasoning (e.g., grouping, computing moving averages, interpreting trends, conditional filtering). 3. **Type of Question** Easy: Direct lookup or comparison. Hard: Involves synthesis across rows/columns, or combining values to reach a conclusion.
Math Reasoning	1. **Number of reasoning steps** Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences. 2. **Obviousness of needed knowledge** Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge. 3. **Clarity of distractors** Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.	Named Entity Recognition	1. **Entity Density and Type Variety** Easy: Few entities, mostly common types (Person, Location). Hard: Multiple entities of varied or domain-specific types (e.g., Organization, Event, Product), possibly nested. 2. **Language and Script Complexity** Easy: Monolingual, clean, formal sentences in a standard script. Hard: Code-mixed, noisy, informal language, or regional scripts. 3. **Ambiguity and Context Requirement** Easy: Clearly named, well-known entities. Hard: Requires context to disambiguate entities or identify non-obvious named terms (e.g., "Amazon" as a company vs. river).
Code Reasoning	1. **Number of reasoning steps** Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences. 2. **Obviousness of needed knowledge** Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge. 3. **Clarity of distractors** Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.	Text Classification	1. **Clarity of Class Indicators** Easy: Clear, surface-level cues that strongly correlate with the label. Hard: Subtle, context-dependent cues; overlapping vocabulary across classes. 2. **Length and Structure** Easy: Short, focused texts with one intent. Hard: Longer, noisy, or multi-intent texts requiring disambiguation. 3. **Label Set Complexity** Easy: Binary classification (e.g., spam vs. ham). Hard: Multi-class (e.g., news category: politics, sports, tech) or multi-label (e.g., tags for movie reviews: drama, romance).
Indian Relationships	1. **Number of relations involved** Easy: 2–3 relations, mostly linear. Hard: 4+ relations, often nested or cross-generational. 2. **Clarity of phrasing** Easy: Straightforward statements with direct relationships. Hard: Implicit or linguistically ambiguous statements, possibly requiring gender inference or cultural interpretation. 3. **Relation type** Easy: Direct blood relations (e.g., mother, brother). Hard: In-law relations, culturally specific terms, or multigenerational links.	Grammar Correction	1. **Error Type** Easy: Simple subject-verb agreement, plural/singular forms, or article usage. Hard: Tense consistency, word order, idiomatic usage, or multiple error types in one sentence. 2. **Error Density** Easy: Single, localized error. Hard: Multiple interrelated errors, possibly requiring rephrasing. 3. **Contextual Dependence** Easy: Error is identifiable without additional context. Hard: Requires deeper understanding of meaning or nuance to correct properly.
Inference	1. **Lexical Overlap** Easy: High overlap; direct wording or synonyms. Hard: Low overlap; requires paraphrasing or world knowledge. 2. **Inference Type** Easy: Simple entailment or direct contradiction. Hard: Implicit entailment, pragmatic reasoning, or nuanced neutrality. 3. **Context Dependence** Easy: No external knowledge needed. Hard: Requires commonsense, temporal, or cultural knowledge.	Translation	1. **Syntactic Complexity** Easy: Simple sentence structures (subject-verb-object). Hard: Complex or nested clauses, passive voice, or long-distance dependencies. 2. **Lexical Ambiguity & Idioms** Easy: Literal language with direct word equivalents. Hard: Idioms, metaphors, or polysemous words requiring interpretation. 3. **Cultural Context** Easy: Universally understood concepts. Hard: Culturally specific references, wordplay, or region-specific expressions.

Figure 6: Complexity Definitions for each sub-category.

Dimension	Explanation
Response Relevance	Measures how well the model output addresses the user query or task instruction. **Why it matters for Indic/Multilingual Data:** Responses must stay on-topic and satisfy user intent; irrelevant outputs reduce usability and may confuse readers. **Errors in this area:** Off-topic responses, inclusion of unrelated information, misinterpretation of the prompt.
Grammatical Accuracy	Correct use of grammar rules including syntax, tense, agreement, punctuation, and morphology. **Why it matters for Indic/Multilingual Data:** Proper grammar ensures readability and clarity; morphologically rich languages are prone to agreement and inflection errors. **Errors in this area:** Wrong tense, subject-verb disagreement, missing auxiliaries, incorrect case markings, improperly inflected words.
Cohesion and Coherence	Cohesion = linguistic devices (connectors, pronouns, conjunctions) linking sentences; Coherence = logical flow of ideas. **Why it matters for Indic/Multilingual Data:** Maintains well-structured and easily understandable responses; lack of cohesion or coherence leads to fragmented outputs. **Errors in this area:** Abrupt topic shifts, disconnected sentences, missing references, inappropriate pronoun usage.
Rationality	Logical correctness and factual consistency of the response, including reasoning and alignment with real-world knowledge. **Why it matters for Indic/Multilingual Data:** Ensures trustworthiness and usefulness of outputs, particularly for reasoning or factual tasks. **Errors in this area:** Contradictory statements, illogical conclusions, factually incorrect assertions, hallucinations.
Completeness	The extent to which the response fully addresses the user prompt or includes all necessary information. **Why it matters for Indic/Multilingual Data:** Partial answers reduce usefulness, especially for multi-step reasoning or detailed explanations. **Errors in this area:** Missing steps in reasoning, skipped entities, truncated explanations, insufficient coverage of subtopics.

Table 5: Key dimensions for assessing LLM outputs in Indic languages, highlighting relevance and frequent pitfalls.

Sub Category	Complexity	Sub Category	Complexity
Creative Writing	1. **Prompt Specificity** Easy: Constrained or highly specific prompts that guide the plot. Hard: Open-ended or abstract prompts requiring full narrative invention. 2. **Narrative Complexity** Easy: Linear plot with one event or idea. Hard: Multi-layered plot, character development, or world-building. 3. **Language & Style** Easy: Simple, straightforward language. Hard: Use of metaphors, poetic devices, shifts in tone or voice.	Question Generation	1. **Contextual Simplicity** Easy: Clear, straightforward context with a direct relationship between entities. Hard: Ambiguous or nuanced context, requiring more reasoning or interpretation to generate a meaningful question. 2. **Question Specificity** Easy: Basic, factual questions asking for a specific detail (e.g., "Who?", "What?"). Hard: Complex or abstract questions that require synthesis, comparisons, or deeper knowledge about the context. 3. **Knowledge Requirement** Easy: No prior knowledge beyond the given text is needed. Hard: Requires background knowledge, inference, or reasoning to generate a relevant question.
Paraphrase Identification	1. **Lexical & Syntactic Similarity** Easy: Minor reordering or synonym substitution with near-identical structure. Hard: Significant rephrasing, different vocabulary or sentence structure, yet same meaning. 2. **Semantic Inference** Easy: Direct, surface-level paraphrases. Hard: Requires understanding of implied meaning, paraphrased idioms, or abstract concepts. 3. **Ambiguity or Pragmatic Context** Easy: No ambiguity or external context needed. Hard: Paraphrase identification depends on pragmatic/contextual cues or disambiguation.	Sentiment Analysis	1. **Sentiment Clarity** Easy: Clear, unambiguous sentiment (positive, negative, or neutral). Hard: Sentiment expressed indirectly, or a mixture of sentiments in the same text. 2. **Contextual Nuance** Easy: Simple, straightforward expressions of sentiment with no hidden or subtle implications. Hard: Sentiment expressed in a nuanced, sarcastic, or contextual manner that requires understanding beyond surface-level words. 3. **Length and Depth of the Text** Easy: Short and simple sentences expressing clear sentiment. Hard: Longer, more complex sentences with mixed feelings or abstract expressions.
Paraphrase Generation	1. **Lexical and Syntactic Simplicity** Easy: Minor changes in wording, using synonyms or simple reordering of sentence components. Hard: Significant changes in sentence structure, more complex rewording, or use of idiomatic expressions. 2. **Semantic Consistency** Easy: Paraphrases that are almost identical in meaning, with small vocabulary swaps. Hard: Paraphrases that need to capture more subtle or nuanced meanings, requiring deeper understanding of the original context. 3. **Creativity and Stylistic Variety** Easy: Simple, direct rewording with minimal stylistic variation. Hard: Creative paraphrases that involve stylistic or tone shifts, or those that include complex syntactic changes while preserving the original meaning.	General Question Answering	1. **Directness of the Question** Easy: Questions that are straightforward and directly answerable from the context without the need for additional reasoning. Hard: Questions that require interpretation, inference, or reasoning based on the provided context. 2. **Contextual Clarity** Easy: Clear, unambiguous context where the answer is explicitly stated. Hard: Ambiguous or vague context, requiring deeper understanding or synthesis of multiple pieces of information. 3. **Factual vs. Inferential Answers** Easy: The answer is directly stated or easily extracted from the text. Hard: The answer involves synthesizing information, making inferences, or requires external knowledge.
Text Summarization	1. **Text Length** Easy: Short input text that already highlights key points. Hard: Long, complex text with multiple subtopics or dense information. 2. **Content Density** Easy: Clear, well-structured information where the main idea is obvious. Hard: Dense or technical content requiring understanding of the details to create a meaningful, concise summary. 3. **Context and Subtlety** Easy: Little to no background knowledge required for the summary. Hard: Summarization requires inference, understanding context, or synthesizing information from different parts of the text.	Fact Check	1. **Factual Specificity** Easy: Questions asking for easily verifiable, specific facts, such as dates, names, or locations. Hard: Questions that require detailed verification or fact-checking from multiple sources or with some level of ambiguity. 2. **Contextual Complexity** Easy: The answer can be found in a single piece of well-known, widely agreed-upon information. Hard: The answer requires analyzing complex data, multiple interpretations, or understanding a situation in context to determine accuracy. 3. **Source Dependence** Easy: Clear, straightforward facts that can be verified from commonly known or easily accessible sources (e.g., official records, universally recognized events). Hard: The fact being checked is less universally agreed upon, has evolving data, or involves conflicting reports.

Figure 7: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Headline Generation	1. **Text Length** Easy: Short article with a single main idea, easy to extract the core message. Hard: Long article with multiple ideas or subtopics, requiring discernment of the most critical information. 2. **Content Type** Easy: Straightforward, factual content with a clear subject and action. Hard: Complex content with nuanced language, needing a creative yet accurate headline. 3. **Information Distillation** Easy: Clear event or announcement that can be summarized in a few words. Hard: Abstract, multifaceted articles requiring summarization of broader themes or mixed topics.	Multi Turn Conversation	1. **Contextual Continuity** Easy: The conversation is straightforward, with clear transitions and a simple back-and-forth interaction. Hard: The conversation involves complex or abstract ideas, requiring the model to recall, understand, and reference multiple pieces of context across several turns. 2. **Response Generation** Easy: Responses require little reasoning and are based on direct information from previous turns. Hard: Responses require inferences, deeper reasoning, or nuanced understanding of prior context and the user's implied needs. 3. **Domain Knowledge** Easy: The conversation stays within a simple domain, requiring basic information retrieval and straightforward interaction. Hard: The conversation involves specialized knowledge or abstract topics, requiring the system to adapt dynamically based on the evolving context.
Role-Playing	1. **Character Consistency** Easy: The character or persona is straightforward, with clear and simple attributes. There is little deviation in how the character should behave. Hard: The character requires nuanced understanding, deep role adaptation, or responding to complex scenarios while staying in-character. 2. **Creativity and Imagination** Easy: The role-play is based on established norms, and responses follow predictable patterns. Hard: The role requires creative input, improvisation, or handling abstract or unpredictable situations while maintaining authenticity in the persona. 3. **Contextual Depth** Easy: The role-playing context is simple, and only surface-level understanding of the role is necessary. Hard: The role requires understanding deep philosophical, historical, or emotional aspects of the character, possibly over multiple turns or complex scenarios.	Indian Cultural Context	1. **Depth of Cultural Understanding** Easy: The query requires a basic, widely understood cultural concept or tradition that does not involve nuanced details or historical context. Hard: The query delves into more specialized or nuanced cultural practices, traditions, or beliefs, which might require historical or region-specific knowledge. 2. **Specificity of the Query** Easy: The question is about a widely known and commonly practiced cultural topic or festival that is universal across India. Hard: The question pertains to a specific regional tradition, a lesser-known festival, or cultural practice that might differ significantly across regions or communities. 3. **Integration with Broader Context** Easy: The query asks for a general explanation without requiring integration of cultural beliefs, practices, and their social implications. Hard: The query requires an explanation that integrates various aspects of Indian culture, including its philosophical, religious, or social implications, and might ask for comparative or cross-regional analysis.
Advice-Seeking	1. **Depth of the Problem** Easy: The user's issue is straightforward, commonly understood, and doesn't require deep insight or complex problem-solving. Hard: The problem is more complex, requiring a nuanced approach, multiple perspectives, or deeper understanding to provide meaningful advice. 2. **Personalization and Context** Easy: The user's query is general, and the advice can be applied broadly without needing to account for specific personal factors. Hard: The user's query involves personal, emotional, or contextual factors, and the advice must be tailored to their unique circumstances. 3. **Emotional Sensitivity** Easy: The user's issue does not involve strong emotional components or stress. Hard: The user's situation requires empathetic, emotionally aware responses to ensure the advice is sensitive and supportive.	Comprehension	1. **Depth of Information Extraction** Easy: The task requires directly extracting information that is clearly stated in the passage, with no need for inference. Hard: The task requires inference, where the answer is implied but not directly stated in the passage, or requires synthesizing information from multiple parts of the text. 2. **Clarity and Directness of the Passage** Easy: The passage is simple, with clear and direct statements that make it easy to extract answers. Hard: The passage is complex, contains nuanced language, or presents a more abstract concept, requiring deeper understanding or analysis. 3. **Complexity of the Question** Easy: The question asks for a straightforward fact or detail that is easily accessible from the passage. Hard: The question requires critical thinking, such as cause-effect relationships or understanding of multiple layers of context.

Figure 8: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Planning	1. **Scope of the Plan** Easy: The plan is narrow in scope, with a limited number of steps or elements to consider. Hard: The plan involves multiple variables, such as many tasks, time constraints, or various dependencies that must be addressed. 2. **Level of Detail** Easy: The plan requires only basic details like locations or general activities with little need for deep customization. Hard: The plan requires detailed steps, including specific times, types of activities, resources, and possibly even contingency plans for unexpected situations. 3. **Customization and Constraints** Easy: The user's preferences or constraints are minimal or common, and the plan can be generated with general knowledge. Hard: The plan must account for specific user preferences, such as dietary restrictions, mobility concerns, budget, or local availability of services.	Math QA	1. **Mathematical Operation Complexity** Easy: The problem involves simple arithmetic operations like addition, subtraction, multiplication, or division that can be solved quickly. Hard: The problem requires more complex operations like algebraic manipulation, geometry, or multi-step calculations involving fractions, percentages, or systems of equations. 2. **Problem Complexity (Word Problem Difficulty)** Easy: The problem is straightforward, with clear and simple wording. No ambiguity or need for interpretation exists. Hard: The problem may involve convoluted or indirect phrasing that requires parsing or understanding multiple pieces of information to solve. 3. **Number of Steps Required** Easy: The problem can be solved with one simple operation, often involving direct calculation. Hard: The problem involves multiple steps or a combination of operations to arrive at the final answer.
Brainstorming	1. **Creativity and Originality** Easy: The task requires simple, commonly known ideas or solutions that do not need much innovation or deep thought. Hard: The task demands unique, novel, or unconventional ideas that require extensive creativity or thinking outside the box. 2. **Scope and Specificity of the Problem** Easy: The task is relatively broad and general, allowing for a wide range of ideas without needing to consider detailed constraints or limitations. Hard: The task involves more specific or narrow areas, requiring ideas to fit within defined parameters, which could include specific industries, goals, or limitations. 3. **Depth of Domain Knowledge Required** Easy: The task is general enough that no specific domain knowledge is required to generate ideas, or the task is on a topic familiar to a wide audience. Hard: The task requires specialized knowledge of a particular domain (e.g., technology, healthcare, or economics) to generate ideas that are realistic and feasible.	Math Instruction Tuning	1. **Mathematical Operation Complexity** Easy: The math problem involves basic arithmetic operations such as addition, subtraction, multiplication, or division. The instruction is simple and clear. Hard: The problem involves advanced concepts like algebra, geometry, calculus, or multi-step problem solving, requiring deeper understanding or manipulation of equations. 2. **Instruction Complexity (Reasoning Required)** Easy: The instructions are straightforward and involve a single step to solve. Hard: The instructions require several intermediate steps or involve solving multi-step equations with additional reasoning, like factoring, completing the square, or applying specific mathematical theorems. 3. **Number of Steps in Solution** Easy: The solution involves few steps—often just a direct application of one operation. Hard: The solution involves multiple steps, such as simplifying expressions, factoring, or breaking down complex terms.
Information Seeking	1. **Depth of Information** Easy: The question seeks basic, straightforward information that is commonly available and well-known. Hard: The question requires more nuanced, detailed, or in-depth information, possibly involving multiple sources or complex concepts. 2. **Specificity of the Query** Easy: The question is general and can be answered with a clear, direct response. Hard: The question is specific or highly detailed, requiring an elaborate response or synthesis of various aspects. 3. **Domain or Contextual Knowledge** Easy: The information sought is familiar or common knowledge, requiring little specialized knowledge to answer. Hard: The information involves a specialized domain, or understanding the context or background knowledge is necessary to provide a comprehensive answer.	Math Proofs	1. **Theorem Complexity** Easy: The theorem is simple and straightforward, typically involving basic set theory, arithmetic, or algebra. Hard: The theorem involves advanced concepts such as topology, number theory, or higher-level algebra. The logic required to prove the theorem might be more complex and abstract. 2. **Proof Structure** Easy: The proof is short, involving direct logical steps with no intermediate lemmas or deep reasoning. Hard: The proof involves multiple intermediate steps, possibly requiring auxiliary lemmas, the use of multiple mathematical properties, or breaking down the proof into several cases. 3. **Mathematical Concepts Involved** Easy: The proof relies on simple mathematical concepts, such as basic set operations or arithmetic properties. Hard: The proof uses complex mathematical ideas, such as induction, contrapositive reasoning, or advanced theorems, and may require careful justification of each step.

Figure 9: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Code Generation	1. **Problem Simplicity** Easy: Involves basic control structures or common patterns. Hard: Requires algorithmic thinking, multi-step planning, or integration with libraries/APIs. 2. **Code Length** Easy: One-liner or small function. Hard: Multiple functions, modular structure, or boilerplate setup. 3. **Conceptual Complexity** Easy: Uses elementary constructs like loops, conditionals. Hard: Requires concepts like recursion, concurrency, or complex data structures. 4. **Edge Cases and Testing** Easy: Few or no edge cases. Hard: Needs robust handling of invalid inputs, errors, or corner cases.	Unit Test Generation	1. **Input Complexity** Easy: Function accepts primitive types and has predictable output. Hard: Function has multiple inputs, nested structures, or dynamic behavior. 2. **Output Behavior** Easy: Deterministic and consistent output. Hard: Output depends on side effects, randomness, or state. 3. **Edge Case Coverage** Easy: Few or obvious edge cases. Hard: Many possible failure modes or boundary conditions. 4. **Format Required** Easy: Just input/output pairs or informal descriptions. Hard: Tests in specific frameworks with setup/teardown, mocking, etc.
Code Debugging	1. **Error Obviousness** Easy: Bug is a syntax error or obvious logic mistake (e.g., == vs =). Hard: Bug is subtle, involves side effects, off-by-one logic, or misunderstood APIs. 2. **Code Scope** Easy: Small functions with limited state or logic. Hard: Multiple functions, state tracking, or external dependencies involved. 3. **Required Knowledge** Easy: General debugging, print/log inspection suffices. Hard: Requires domain-specific understanding, complex reasoning, or tool-based debugging. 4. **Impact of Fix** Easy: Fix is localized and doesn't affect other logic. Hard: Fix has ripple effects across the codebase and must maintain correctness globally.	Code Theory	1. **Concept Familiarity** Easy: Widely taught or intuitive topics (e.g., loops, arrays, O(n)). Hard: Niche or abstract topics (e.g., amortized complexity, monads). 2. **Explanation Depth** Easy: Surface-level description of how something works. Hard: Deep dive into trade-offs, limitations, and formal reasoning. 3. **Required Background** Easy: Assumes basic CS knowledge. Hard: Requires formal math or algorithmic training. 4. **Application Scope** Easy: Explains theory in isolation. Hard: Tied to real-world design or performance decisions.
Code Editing	1. **Edit Type** Easy: Cosmetic or small structural change (e.g., rename, add a check). Hard: Deep refactor or major logic change across files. 2. **Context Required** Easy: Local context is enough to apply the edit. Hard: Requires understanding of broader dependencies or interfaces. 3. **Behavior Change** Easy: No change in behavior (e.g., renaming, reformatting). Hard: Behavior is intentionally changed, requiring correctness guarantees. 4. **Risk Level** Easy: Low-risk edit, unlikely to break anything. Hard: High-risk edit, may affect performance, correctness, or security.	Code Review	1. **Code Quality** Easy: Well-structured code with clear intent. Hard: Poorly written, unstructured, or ambiguous code. 2. **Scope of Review** Easy: Small diff or single function. Hard: Large PR with multiple files and architectural impact. 3. **Standards Compliance** Easy: Trivial formatting or naming violations. Hard: Requires domain knowledge, security awareness, or architectural judgment. 4. **Reviewer Responsibility** Easy: Only comments on style or clarity. Hard: Needs to verify correctness, performance, and maintainability.
Code Explanation	1. **Code Length** Easy: Few lines with straightforward logic. Hard: Long code with deeply nested structures. 2. **Abstraction Level** Easy: Explains "what it does." Hard: Needs to explain "why," covering design decisions or trade-offs. 3. **Concept Depth** Easy: Basic logic with familiar constructs. Hard: Involves complex algorithms, libraries, or domain-specific behavior. 4. **Audience Adaptation** Easy: Target audience already knows the language and topic. Hard: Requires tailoring to beginners or non-technical audiences.	Repository level Code Generation	1. **Architecture Complexity** Easy: Scaffold for a simple project (e.g., a CRUD app). Hard: Full-stack system with frontend, backend, DB, and CI/CD config. 2. **Component Integration** Easy: Independent modules or templates. Hard: Components must interoperate with consistent API contracts. 3. **Language/Framework Mastery** Easy: One language, minimal config. Hard: Polyglot codebase (e.g., Python backend + React frontend + Docker). 4. **Customization Required** Easy: Follows standard patterns (e.g., Flask starter). Hard: Needs tailoring to specific domain, logic, or 3rd-party APIs.

Figure 10: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Code Translation	1. **Language Similarity** Easy: Translation between similar paradigms (e.g., Python ↔ JavaScript). Hard: Translation between very different paradigms (e.g., Python ↔ Haskell). 2. **Feature Mapping** Easy: All features map cleanly between languages. Hard: Requires emulating behavior (e.g., list comprehensions, async models). 3. **Code Size** Easy: Short, self-contained function. Hard: Large module with classes, decorators, or closures. 4. **Idiomatic Translation** Easy: Direct one-to-one line conversion. Hard: Needs idiomatic rewriting to follow target language conventions.	Function Calling	1. **Complexity of Function Signatures** Easy: The function signatures are straightforward, with simple parameter types (e.g., integers, strings) and no additional constraints. Hard: The function signatures involve complex parameters, such as nested structures, multiple required fields, or specialized types like objects, arrays, or custom types (e.g., qubits, Fourier components, etc.). 2. **Interpretation of User Requirements** Easy: The user request is simple and directly maps to the required parameters without ambiguity. There are minimal or no special considerations for things like optional arguments or conflicting values. Hard: The user's request is complex, involving multiple steps of reasoning or context-dependent choices, requiring careful extraction of parameters and appropriate default values for missing information. 3. **Parameter Mapping and Constraints** Easy: The parameters have clear, unambiguous mappings (e.g., integers for quantities, strings for identifiers), and there are no special conditions or dependencies between parameters. Hard: The parameters have complex dependencies (e.g., the number of Fourier components must align with the number of qubits) or constraints that must be satisfied (e.g., time complexity requirements, control operations). 4. **Function Logic and Output Generation** Easy: The function call results in simple, easily interpretable outputs that don't require additional processing or understanding of underlying logic. Hard: The function call involves sophisticated logic that results in complex outputs (e.g., quantum circuits), or the output requires further interpretation or refinement to be useful in the context.
Instruction Following	1. **Task Complexity** Easy: The task involves simple, straightforward instructions with minimal structure or specific formatting requirements. Hard: The task requires multi-step reasoning, adherence to multiple specific formatting guidelines, and generation of complex or detailed content. 2. **Output Structure and Formatting** Easy: Instructions involve generating basic content with minimal formatting or structural constraints (e.g., short answers or paragraphs without complex guidelines). Hard: The instructions demand precise formatting (headings, bullet points, specific word count limits, etc.), and the content must be logically organized and adhere to multiple constraints. 3. **Level of Detail and Precision** Easy: The instructions require a general response with little emphasis on fine-grained details, and minor flexibility is allowed. Hard: The instructions demand highly detailed responses with precise limits (e.g., word count per section), strict content divisions (subsections), and comprehensive coverage of a topic. 4. **Interpretation of Instructions** Easy: The instructions are unambiguous, with clear expectations and no need for interpretation beyond direct execution. Hard: The instructions involve multiple layers of interpretation (e.g., understanding how to balance word count with content depth, determining how to break down sections logically, or ensuring that all key points are covered).	Safety & Non - Compliance	1. **Clear vs. Ambiguous Harmful Requests** Easy: The harmful or unethical request is clear and direct, with no ambiguity or need for interpretation. Hard: The request is more subtle, requiring the model to understand context, infer potential harm, or identify violations that may not be immediately obvious. 2. **Politeness and Firmness** Easy: The model simply needs to reject the request without much elaboration or any need to soften the response. Hard: The model needs to balance politeness, firmness, and clarity, ensuring it is both respectful and firm in refusal while explaining why the request is not permissible. 3. **Contextual Decision-Making** Easy: The request is easily recognized as violating ethical norms or policies, so the response is straightforward. Hard: The model must assess context, which might involve determining whether the request is borderline or masked behind polite language, requiring careful judgment and nuanced response. 4. **Complexity of Policy Interpretation** Easy: The model only needs to reject straightforward violations, such as promoting illegal activities or encouraging harm. Hard: The model must navigate complex or gray areas where there may be multiple interpretations of policies or ethics, requiring it to consider indirect implications.

Figure 11: Complexity Definitions for each sub-category.

Constraint Type	Description	Examples
Length Constraints	Defines how long or concise a response should be.	"Answer in one sentence", "Summarize in 50 words", "Explain in two paragraphs"
Structural Formatting	Governs the organization of the output.	Paragraphs, bullet points, numbered lists, tables ("Compare A and B in a table"), JSON, XML, HTML
Tone and Style	Specifies tone, voice, or target audience.	Formal, conversational, academic, friendly, motivational, child-friendly, expert-level
Persona / Role Play	Instructs the model to adopt a specific identity.	"Act as a doctor/teacher/software engineer", "Answer like Albert Einstein or a pirate"
Reasoning Style	Defines how the model should arrive at the answer.	Chain-of-thought, step-by-step explanation, final answer only, show intermediate steps
Time / Historical Context	Specifies a temporal or historical frame.	"Explain from a 19th-century perspective", "What would a Roman say?", "Imagine you are in 2100"
Output Type / Genre	Determines the nature of the response.	Poem, story, dialogue, screenplay, essay, report, memo, tweet, press release
Comparative / Multi-perspective	Requests multiple viewpoints or contrasts.	"Compare pros and cons", "Show both sides of the argument", "Write from X's and Y's perspective"

Figure 12: Instruction following: constraint types and examples

Dimension	Explanation
Lexical Diversity	The variety and richness of words used in the text. Higher lexical diversity means using a wide range of vocabulary instead of repetitive or generic terms. **Why It Matters for Indic Data:** Indic languages have rich vocabulary and multiple synonyms; poor diversity makes translations monotonous and unnatural. **Errors in this area:** Overuse of common words, failure to use synonyms, repetitive phrasing.
Coherence and Cohesion	**Coherence:** Logical flow and overall sense of the text. **Cohesion:** Use of linguistic devices (connectors, pronouns, conjunctions) to link sentences smoothly. **Why It Matters for Indic Data:** Many Indic languages use connectives and honorific markers that impact cohesion; direct translation from English often breaks these links. **Errors in this area:** Disconnected sentences, abrupt topic shifts, missing conjunctions or pronouns.
Completeness	Whether the output contains all necessary information from the source without omissions or additions. **Why It Matters for Indic Data:** When translating long or complex Indic sentences, models often skip certain parts (e.g., verb phrases or subordinate clauses). **Errors in this area:** Missing phrases, dropped entities, truncated sentences, or extra hallucinated details.
Grammatical Accuracy	Correct use of grammar rules (syntax, tense, agreement, case, morphology). It affects fluency and correctness of the output. **Why It Matters for Indic Data:** Indic languages have complex inflectional morphology and word order; errors often occur in case endings, gender/number agreement, and verb conjugations. **Errors in this area:** Wrong tense, missing auxiliary verbs, subject-verb disagreement, wrong case marking.
Named Entity Handling	Correct recognition and rendering of named entities (persons, places, organizations, dates, currencies, etc.) across languages.

Table 6: Key dimensions for assessing LLM translations in Indic languages, highlighting their significance and common errors.

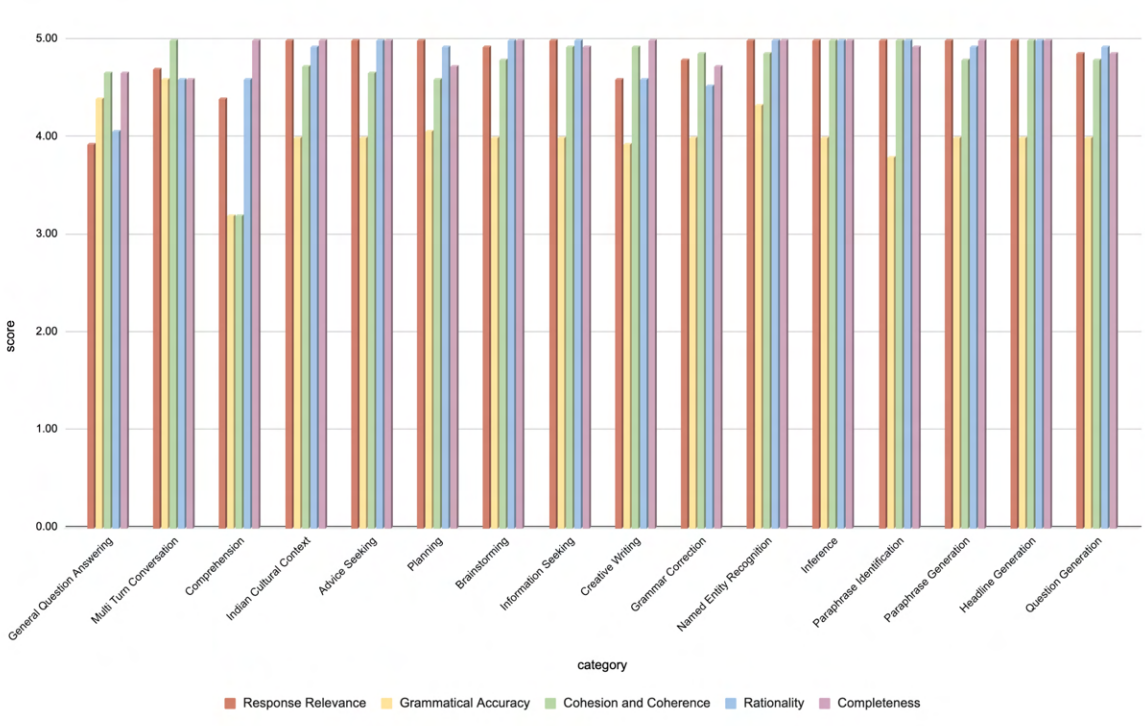

Figure 13: LLM generation quality evaluation scores across various categories.

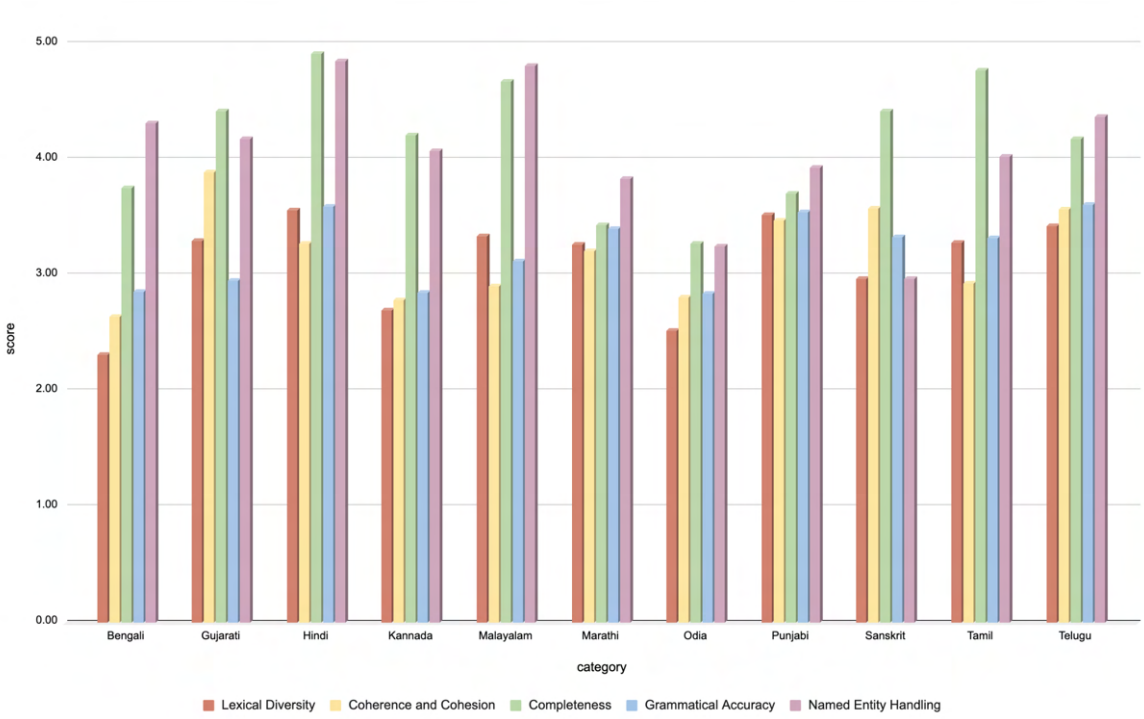

Figure 14: LLM translation quality evaluation scores across 11 Indian languages.

in Section 3.3. In addition to these specifications, dedicated frameworks for quality assurance are provided, encompassing both language quality verification and content quality verification, as illustrated in Figures 19 and 20, respectively.

D Examples

We provide examples of both instruction and preference tuning datasets in Figures 21-30.

Prompt used for Generation of Easy Indian Cultural Context English Prompts in Self Instruct Pipeline

System Prompt

You are tasked with generating easy-level, culturally diverse, and descriptive questions that explore various aspects of Indian culture. Your questions should avoid being too generic or frequently asked. Instead, focus on less commonly discussed but still culturally meaningful topics that are easy to understand and answer.

Guidelines for Generating Questions:
1. Difficulty Level – Easy:
The question should be simple enough for someone with basic cultural awareness to answer in a few sentences.
Avoid complex or academic phrasing.
Each question should address only one clear aspect or topic — do not combine multiple elements in a single question.

2. Question Type – Descriptive:
The answer should require a short paragraph, not a one-word or one-line response.
Avoid yes/no or multiple-choice style formats.

3. Scope – Specific but Not Niche:
Focus on fine-grained yet non-obscure topics.
Do not ask for broad essays like “Describe a festival” or over-complicated questions like “What is the significance of X across different regions with its variations and philosophical meanings?”

4. Diversity – Pan-Indian Coverage:
Ensure questions represent diverse states, communities, religious groups, art forms, customs, and practices.
Cover a variety of domains like traditional food, clothing, local art, customs, symbols, minor rituals, or lesser-known celebrations.

Use the given questions as examples of how to frame the questions.

Generate the instructions in the json format:
{
...
Question i: ith Question,
...
}

Note that the instructions must be in english language.
Return only the json format response, do not return anything other than json.

User Prompt

Here are some example questions:
<8 Easy Indian Cultural Context English Prompts as Few Shots>

Figure 15: Prompt used for generation of easy Indian cultural context English prompt in Self-Instruct pipeline.

Prompt used for Generation of Hard Indian Cultural Context English Prompts in Self Instruct Pipeline

System Prompt

You are tasked with generating hard-level, culturally diverse, descriptive questions that explore complex, nuanced, or region-specific aspects of Indian culture. These questions should go beyond basic or commonly asked topics, aiming to challenge the responder's depth of cultural understanding.

Guidelines for Generating Questions:
1. Difficulty Level – Hard:
The questions should require a detailed and informed response, often involving historical context, philosophical meaning, or regional variation.
Expect the responder to draw from less commonly known knowledge, comparative insights, or interconnected traditions.
Avoid overly academic phrasing, but do not oversimplify the question.

2. Question Type – Descriptive:
The answer should require at least a short essay-style paragraph, explaining the underlying cultural, religious, philosophical, or social dimensions.
Do not create multi-part or overly long questions — keep one core focus per question, but explore it deeply.

3. Scope – Specialized or Regionally Rooted:
Focus on less mainstream topics, regional traditions, or philosophical/religious practices that are not typically covered in general knowledge.
Explore cultural beliefs, historical movements, ritualistic practices, sectarian philosophies, regional art forms, and symbolic meanings.

4. Diversity – Pan-Indian and Cross-Traditional:
Ensure a wide range of questions from different Indian states, languages, communities, castes, and religious traditions.
Include topics from Hindu, Buddhist, Jain, Sikh, Islamic, Christian, tribal, and other regional traditions.

Use the given questions as examples of how to frame the questions.

Generate the instructions in the json format:
{
...
Question i: ith Question,
...
}

Note that the instructions must be in english language.
Return only the json format response, do not return anything other than json.

User Prompt

Here are some example questions:
<8 Hard Indian Cultural Context English Prompts as Few Shots>

Figure 16: Prompt used for generation of hard Indian cultural context English prompt in Self-Instruct pipeline.

Prompt used for Translation via LLM

System Prompt

Translate the following text into {lang}, targeting educated native speakers in an academic or professional setting.

Translation Guidelines:
1. Exclusive Translation:
Translate the provided text only. No answers, solutions, interpretations, or commentary.

2. Preserve Original Structure:
Maintain the input's original structure, including equations, formulas, syntax, and logical structures. Retain original text if direct translation alters meaning.

3. Prioritize Accuracy:
Ensure accurate translation of technical terms and concepts using widely accepted academic terminology.

4. Maintain Meaning and Intent:
Preserve the original meaning, intent, and challenge. Maintain syntax and variable names for code and math.

5. Translate Instructions/Metadata Verbatim:
Translate instructions (e.g., "Enter your answer here:", "Return your final response within \\boxed{}.") and metadata (e.g., file names, timestamps) exactly as they appear, without attempting to execute or interpret them.

6. Translation Requirements (Reinforced):
Perform translations only; do not add new text.
Make no changes beyond accurate word-for-word translation.
Leave code, formulas, placeholders, and instructions untouched.

User Prompt

Text to Translate: {text}

Figure 17: Prompt used for translation via LLM.

Prompt used for Evaluating models DPOed on 100K Pragyaan-Align Data via LLM as Judge

System Prompt

You are an impartial evaluator. Your task is to judge a model response against a given ground truth answer for a prompt.
Evaluate the response with a real number score between 1-5, using **one decimal place only**. Never output integers; always use a decimal number with one digit (e.g., 3.7, 4.2).
Consider the category of the prompt when scoring.

Categories and their focus are:
Reasoning – Logical correctness and clarity of explanation.
Role Playing – Staying in character, creativity, and consistency.
Math – Accuracy of calculations and clarity of steps.
Editing – Improving or revising text while preserving meaning.
Information Seeking – Factual accuracy and relevance.
Advice Seeking – Practicality, usefulness, and clarity.
Data Analysis – Correct interpretation of data and logical conclusions.
Creative Writing – Originality, coherence, style, and engagement.
Planning – Clear, feasible, and well-structured steps.
Brainstorming – Creativity, diversity, and relevance of ideas.

Provide scores for each response separately.
Output must strictly follow this format:
"Response score: [[x.y]]

<Explanation of your scoring, highlighting strengths and weaknesses>."

Notes:
Focus on correctness, relevance, and quality over verbosity.
Be critical but fair.
Base scores only on alignment with the category requirements and the ground truth.
Always provide an explanation after the score.

User Prompt

<|Prompt|>
{prompt}

<|Ground Truth|>
{ground_truth}

<|Response|>
{response}

Figure 18: Prompt used for evaluating post-trained model on *Pragyaan-Align* data via LLM-as-a-Judge.

1. Language Quality Verification Guidelines

The evaluation of Prompt–Response Pairs (PRPs) focuses on key linguistic and stylistic parameters to ensure high-quality outputs across Indic languages. These include fluency, grammatical accuracy, coherence and cohesion, sentence structure, lexical diversity, and accurate handling of named entities. The following principles guide this process:

1.1 Preserve Naturalness and Meaning
Translations should read naturally in the target language while preserving the original intent.
Avoid literal, word-for-word translations. Instead, adapt phrasing and sentence structure in accordance with the linguistic norms of the respective Indic language.
Ensure cultural appropriateness in expressions and idiomatic usage.

1.2 Localize Editing Instructions
Adapt instructions so they align with how editing tasks are conventionally expressed in Indic languages.
Example:
English: "Rewrite the sentence in Active Voice."
Hindi: "वाक्य को सक्रिय वाच्य में पुनः लिखें।"

1.3 Maintain Consistency in Terminology
Use widely accepted equivalents for domain-specific terms (e.g., AI, computing, mathematics, medicine, law).
Where no direct equivalent exists, apply transliteration while ensuring clarity of meaning.
Examples:
English: "Refactor the code for better readability."
Hindi: "कोड को बेहतर पठनीयता के लिए पुनः व्यवस्थित करें।"

1.4 Follow Proper Formatting and Punctuation
Apply punctuation rules specific to the target Indic language rather than English conventions.
Ensure proper spacing and script usage.
Avoid using Latin punctuation marks such as . where language-specific marks like । (Hindi) or । (Bangla) should be used.
Example:
Incorrect: "वाक्य को सक्रिय वाच्य में पुनः लिखें."
Correct: "वाक्य को सक्रिय वाच्य में पुनः लिखें।"

1.5 Handle Untranslatable Terms Appropriately
For terms such as brand names, technical concepts, or programming keywords, use transliteration in Indic script where possible.
Maintain semantic clarity in context.
Example:
English: "Replace the variable with a meaningful name."
Hindi: "चर/वैरिएबल को एक अर्थपूर्ण नाम से बदलें।"

1.6 Code Snippets and Symbols
Retain code snippets in their original form without translation.
Example:
English: "Change int x = 10; to int y = 20;"
Hindi: "int x = 10; को int y = 20; में बदलें।"

1.7 Localization of Editable Text
When localizing content that requires editing, the translated text should reflect the specific requirement of the instruction. For instance, if the instruction involves correcting grammatical errors, the translated text should intentionally include such errors before editing.
Example:
English: "Correct the grammatical mistakes in the following text:
'I have took the medicines.'"
Hindi: "दिए गए पाठ में व्याकरण संबंधी गलतियों को सुधारें।
'मैं दवा खाता।'"

Figure 19: Comprehensive language luality guidelines outlining key linguistic dimensions such as grammar, fluency, clarity, and naturalness for ensuring high-quality annotated data.

2. Content Quality Verification Guidelines

Each Prompt–Response Pair (PRP) undergoes a structured evaluation process to ensure alignment with six core dimensions: complexity, multi-turn interaction, instruction-following capability, safety considerations, cultural relevance to the Indian context, and inclusion of reasoning or thinking trails. PRPs that fully meet these criteria are accepted without modification, while those exhibiting minor inconsistencies undergo targeted revisions to ensure compliance. PRPs with significant deviations are comprehensively rewritten to maintain both linguistic quality and adherence to the specified configuration requirements. Definitions for each category and setting are explicitly documented and must be strictly followed.

Beyond compliance with language and setting-specific requirements, the following general principles guide annotation and validation:

2.1 Relevance to the Prompt
The response must accurately and completely address the intent of the prompt.
Extraneous details, digressions, or unrelated content should be avoided.
Responses that partially satisfy the prompt but omit essential information should be deprioritized.

2.2 Fluency and Naturalness
Responses should exhibit grammatical correctness, structural coherence, and logical flow.
Language must read naturally in the target Indic language, adhering to its specific linguistic conventions and avoiding literal or awkward phrasing.
Outputs containing major syntactic or grammatical errors are considered suboptimal.

2.3 Factual Accuracy
For prompts requiring factual information, responses must be accurate and verifiable.
Any response containing incorrect, misleading, or unverifiable claims should be rejected.
When multiple responses are factually correct, preference should be given to those that are concise, precise, and clearly articulated.

2.4 Cultural and Linguistic Appropriateness
Responses should conform to cultural norms and linguistic standards of the target Indic language.
Avoid regionally inappropriate idioms, metaphors, or expressions unless explicitly required by the prompt.
Ensure contextual relevance for the intended audience of the target language.

2.5 Style and Formality
Tone and level of formality must align with the prompt's context (e.g., academic, conversational, or instructional).
Responses that fail to maintain the appropriate tone or deviate from the intended style should be deprioritized.

2.6 Avoiding Bias and Stereotypes
Responses must not reinforce stereotypes or exhibit bias related to gender, caste, religion, ethnicity, or socio-economic status.
Use neutral and inclusive language wherever applicable.
If all available responses contain bias, flag them for further review.

2.7 Filtering Harmful or Offensive Content
Reject responses containing hate speech, explicit or offensive material, political bias, or harmful language.
Any content promoting violence, discrimination, or misinformation should not be selected.
All outputs must comply with ethical AI principles and community guidelines.

2.8 Handling Subjectivity in Sensitive Topics
For prompts concerning controversial or sensitive domains (e.g., politics, religion, social issues), responses should maintain a neutral and balanced tone.
Avoid presenting subjective opinions as objective facts.
Favor informative, fact-based responses over emotionally charged or opinionated ones.

3. Final Considerations
Consistency in annotation is critical; all guidelines must be applied uniformly across evaluations.
Assess responses solely on their intrinsic quality—model attribution (e.g., ChatGPT, Krutrim) should not influence judgment.
Prefer responses that deliver essential details succinctly, avoiding unnecessary verbosity.

Figure 20: Content quality guidelines detailing principles for maintaining factual accuracy, contextual relevance, safety, and adherence to task-specific requirements during data annotation.

Category	Prompt	Preferred Response	Rejected Response
Advice Seeking	माझ्या मॅनेजरला वाटतं की कामाच्या ठिकाणी माझी संवाद शैली असंवेदनशील आणि सडेतोड आहे. त्यांना वाटतं की मी माझ्या सहकाऱ्यांशी विचारपूर्वक संवाद साधावा. मला कधीच वाटलं नाही की मी असंवेदनशील असेन, म्हणून मला हे ऐकून खरंतर आश्चर्य वाटलं. मी फक्त थेट आणि मुद्द्याचं बोलतो. मी प्रामाणिकपणे, परंतु थोडक्यात बोलताना इतरांच्या भावना लक्षात ठेवून त्यांच्याशी संवाद कसा साधू शकतो?	आपल्या मॅनेजरच्या टिप्पण्या ऐकून आपल्याला आश्चर्य वाटणे स्वाभाविक आहे. संवादाची शैली वैयक्तिक असू शकते, आणि आपले थेट आणि मुद्देसुद्द दिसणे काही वेळा इतरांमधील संवेदनशीलता कमी करू शकते. इतरांच्या भावना लक्षात घेतल्यास, संवादाची शैली सुधारण्यासाठी काही टिप्स येथे दिल्या आहेत: 1. **सकारात्मक आरंभ**: आपले बोलणे सुरू करताना प्रत्येक गोष्टीत काही सकारात्मकता समाविष्ट करा. उदाहरणार्थ, "मला तुमचं विचार आवडलं, पण..." अशी शैली वापरल्यास, आपली अभिप्राय थोडी सौम्य आणि सकारात्मक निर्माण होईल. 2. **सवाल विचारणे**: संवादात समाविष्ट झालेल्या व्यक्तींच्या विचारांची आणि भावना जाणून घेण्यासाठी प्रश्न विचारा. हे संवादाला संवादात्मक बनवतो आणि टीममधील सहकार्य वाढवतो. 3. **आवाजाचा टोन**: आपल्या आवाजाचा टोन आणि शरीराची भाषा महत्त्वाची आहे. थेट बोलताना सॉफ्ट टोन वापरणे आणि थोडा हसत बोलणे, इतरांनाही आरामदायक बनवू शकतात. 4. **त्यांच्या भावना समजून घेणे**: आपण जेव्हा कोणाशी बोलता, तेव्हा त्यांची स्थिती आणि भावना लक्षात घेणे महत्त्वाचे आहे. "तुमचं मत मोजलं जातं आणि मला तुमचं विचार समजून घ्यायला आवडेल," असा दृष्टिकोन ठेवता येईल. 5. **परतफेड देणे**: कोणताही अभिप्राय दिल्यावर, त्यात सकारात्मकता ठेवा. जर कुणी काही विचार केलं असेल, तर त्याचा आदर करा आणि त्यावर चर्चा करा. 6. **संपूर्णता**: बोलताना थोडी थांबा, जेणेकरून इतरांनाही आपल्या विचारांची पूर्णता समजून घेता येईल. हे विशेषतः गुंतागुंतीच्या मुद्द्यांवर लागू शकते. 7. **प्रतिक्रिया विचारणे**: त्यावर चर्चा केल्यानंतर, आपल्या सहकाऱ्यांकडून आपली संवाद शैली कशी वाटली याबद्दल काही फीडबॅक घ्या, हे आपल्याला पुढील संवाद सुधारण्यास मदत करेल. आपण आपल्या संवाद शैलीत सुधारणा करण्याचे प्रयत्न करत असताना, नेहमी लक्षात ठेवा की प्रत्येक जण वेगळा असतो आणि संवाद करण्याची शैली देखील वेगळी असते. आपल्या संवादाच्या जागरूकतेने आणि संवेदनशीलतेने आपले सहकारी आणि टीमसह चांगले संबंध निर्माण होण्यास मदत करेल.	तुम्हाला तुमच्या व्यवस्थापकाकडून अभिप्राय मिळाल्यानंतर तुम्ही धक्का बसले आहात याचा अर्थ समजून घेण्यासारखा आहे. कोणत्याही कार्यालयीन वातावरणात प्रभावी संवाद महत्त्वपूर्ण आहे आणि तो अनेकदा वैयक्तिक पसंदींवर अवलंबून बदलतो. अधिक चिंताग्रस्त किंवा सूक्ष्म दृष्टिकोन स्वीकारण्यासाठी स्वतःची पुनर्परिभाषित करण्याचा प्रयत्न करा; प्रत्येक संभाषणासाठी योग्य शब्द निवडा आणि आवश्यकतेनुसार तपशीलवार स्पष्टता देऊन तुमचे संदेश सुधारण्याचा सराव करा. जर एखाद्या विषयावर मत व्यक्त केले तर ते अशाब्दिक भाषेच्या माध्यमातून देखील करता येते-उदाहरणार्थ, सौहार्दपूर्ण स्मितहास्याने किंवा मैत्रीपूर्ण हावभावाने. जरी तुम्ही नेहमीचे 'थेट' मार्ग अनुसरलात तरीही या छोट्या बदलांनी तुमचा सहकारी संबंध दृढ होईल आणि एकंदर संघटनात्मक संस्कृती सुधारेल.
Brainstorming	ମୁଁ ମୋ ସହରରେ କଳା ଏବଂ ସଙ୍ଗୀତର ମିଶ୍ରଣ କରି ଏକ ନୂତନ ଅଭିଜ୍ଞତା ସୃଷ୍ଟି କରିବାକୁ ଚାହୁଁଛି । ଜନସାଧାରଣଙ୍କ ପାଇଁ କିଛି ଅନନ୍ୟ ସ୍ଥାପନା କ'ଣ ହୋଇପାରେ ?	ଆପଣ ଆପଣଙ୍କ ସହରରେ କଳା ଏବଂ ସଙ୍ଗୀତର ଏକ ନୂତନ ଅନୁଭୂତି ସୃଷ୍ଟି କରିବାକୁ ଚାହୁଁଛନ୍ତି, ଏହା ଏକ ଉତ୍କୃଷ୍ଟ ଧାରଣା ! ଏହାକୁ ସଫଳ କରିବା ପାଇଁ କିଛି ଅନନ୍ୟ ସ୍ଥାପନା ଏହିପରି ହୋଇପାରେ: 1. ଥିମ୍-ଆଧାରିତ କଳା ଏବଂ ସଙ୍ଗୀତ ଉତ୍ସବ: ଏକ ନିର୍ଦ୍ଦିଷ୍ଟ ଥିମ୍ ଚୟନ କରନ୍ତୁ (ଯେମିତିକି, ପ୍ରକୃତି, ପ୍ରେମ, ଆଧ୍ୟାତ୍ମିକତା) ଏବଂ ସେହି ଥିମ୍ ଉପରେ ଆଧାରିତ କଳାକୃତି, ସଙ୍ଗୀତ ଏବଂ ପ୍ରଦର୍ଶନୀ ସହିତ ଏକ ଉତ୍ସବ ଆୟୋଜନ କରନ୍ତୁ । ଏହା ଏକ ଆକର୍ଷଣୀୟ ଏବଂ ସ୍ମରଣୀୟ ଅଭିଜ୍ଞତା ହୋଇପାରେ । 2. ଇଣ୍ଟରାକ୍ଟିଭ୍ କଳା ସ୍ଥାପନା: ଦର୍ଶକମାନେ ସକ୍ରିୟ ଭାବରେ ସାମିଲ ହୋଇପାରିବେ ଏପରି କଳା ସ୍ଥାପନା ସୃଷ୍ଟି କରନ୍ତୁ । ଉଦାହରଣସ୍ୱରୂପ, ଏକ ଡିଜିଟାଲ୍ କଳା ସ୍ଥାପନା ଯେଉଁଠାରେ ଦର୍ଶକମାନେ ସେମାନଙ୍କର ଗତିବିଧି ସହିତ କଳାକୃତିକୁ ପ୍ରଭାବିତ କରିପାରିବେ କିମ୍ବା ଏକ ସଙ୍ଗୀତ ସ୍ଥାପନା ଯେଉଁଠାରେ ଦର୍ଶକମାନେ ବାଦ୍ୟଯନ୍ତ୍ର ବଜାଇ ଏବଂ ସଙ୍ଗୀତ ସୃଷ୍ଟି କରିପାରିବେ । 3. କଳା ଏବଂ ସଙ୍ଗୀତ ଭ୍ରମଣ: ଆପଣଙ୍କ ସହରର କଳାତ୍ମକ ଏବଂ ସାଂସ୍କୃତିକ ସ୍ଥାନଗୁଡିକୁ ଏକ ନିର୍ଦ୍ଦିଷ୍ଟ ଥିମ୍ ସହିତ ଏକ ଭ୍ରମଣ ଆୟୋଜନ କରନ୍ତୁ । ଏହା ସହିତ, ପ୍ରତ୍ୟେକ ସ୍ଥାନରେ ସଙ୍ଗୀତ ପ୍ରଦର୍ଶନ କିମ୍ବା କଳା ପ୍ରଦର୍ଶନୀ ସାମିଲ କରନ୍ତୁ । 4. କଳା ଏବଂ ସଙ୍ଗୀତର ମିଶ୍ରଣ ସହିତ ଏକ ଥିମ୍-ଆଧାରିତ କାଫେ କିମ୍ବା ରେସ୍ତୋରାଁ: ଏକ କାଫେ କିମ୍ବା ରେସ୍ତୋରାଁ ଆୟୋଜନ କରନ୍ତୁ ଯେଉଁଠାରେ ଲୋକମାନେ କଳା ଏବଂ ସଙ୍ଗୀତର ସୁନ୍ଦର ମିଶ୍ରଣର ଆନନ୍ଦ ଉଠାଇପାରିବେ । ଏହା ସହିତ, ଆପଣ ଏକ ନିର୍ଦ୍ଦିଷ୍ଟ ଥିମ୍ ବ୍ୟବହାର କରିପାରିବେ ଯାହା କଳାକୃତି, ସଙ୍ଗୀତ ଏବଂ ଖାଦ୍ୟ ସହିତ ମିଶିଯାଇପାରେ । 5. କମ୍ୟୁନିଟି-ଆଧାରିତ କଳା ଏବଂ ସଙ୍ଗୀତ ପ୍ରୋଜେକ୍ଟ: ସ୍ଥାନୀୟ କଳାକାର ଏବଂ ସଙ୍ଗୀତଜ୍ଞମାନଙ୍କୁ ସାମିଲ କରି ଏକ କମ୍ୟୁନିଟି-ଆଧାରିତ କଳା ଏବଂ ସଙ୍ଗୀତ ପ୍ରୋଜେକ୍ଟ ଆରମ୍ଭ କରନ୍ତୁ । ଏହା ସ୍ଥାନୀୟ ପ୍ରତିଭାକୁ ପ୍ରୋତ୍ସାହନ ଦେବ ଏବଂ ଏକ ମଜବୁତ କମ୍ୟୁନିଟି ସୃଷ୍ଟି କରିବ । ଏହି ସବୁ କେବଳ କିଛି ଧାରଣା, ଆପଣ ଆପଣଙ୍କର ସୃଜନଶୀଳତା ଏବଂ ସ୍ଥାନୀୟ ପରିସ୍ଥିତିକୁ ଧ୍ୟାନରେ ରଖି ଅନେକ ଅନ୍ୟ ବିକଳ୍ପ ଚିନ୍ତା କରିପାରିବେ । ଆପଣଙ୍କୁ ଶୁଭକାମନା !	କଳା ଏବଂ ସଙ୍ଗୀତର ମିଶ୍ରଣରେ ଏକ ଅଭିଜ୍ଞତା ତିଆରି କରିବାକୁ ମୁଁ କିଛି ସ୍ଥାପନା ପ୍ରସ୍ତାବନା କରିପାରେ: 1. **ଇଣ୍ଟରଆକ୍ଟିଭ୍ ଆର୍ଟ ଗ୍ୟାଲେରୀ**: ସଂଗୀତ ଓ ଚିତ୍ରକଳାର ଏକ ସଂସ୍ଥାନ, ଯେଉଁଠାରେ ଜନସାଧାରଣ କିଛି ସଙ୍ଗୀତ ଶିଳ୍ପୀଙ୍କର ଗୀତ ଶୁଣିବା ସହ ବିଭିନ୍ନ ଆକୃତି ସହିତ ପରିଚିତ ହେବେ। ସେଠାରେ ଜନସାଧାରଣର ଅବସ୍ଥା ଅନୁସାରେ କଳାର ୍ଦୃଶ୍ୟ ପ୍ରଦର୍ଶନ ମଧ୍ୟ ହୋଇପାରେ। 2. **ସଙ୍ଗୀତ ଓ ଆର୍ଟ ଫେସ୍ଟିଭାଲ**: ଏକ ସ୍ଥାନୀୟ ଫେସ୍ଟିଭାଲ ଯେଉଁଥିରେ ସ୍ଥାନୀୟ ସଙ୍ଗୀତକାର ଏବଂ କଳାକାର ଚାଳିତ ହୁଏ। ଏଣୁ ମୋଡର୍ଣ୍ଣ ଓ ପାରମ୍ପରିକ ଧ୍ୱନିବାଦ କାର୍ଯ୍ୟ କଲେ ସେ ବ୍ୟକ୍ତି କଲେ ଏହି ଉତ୍ସବର ସଂଗାନ ମଧ୍ୟ ଗିଡ଼ ମନ୍ତ୍ରଣା ହେବ। 3. **ଆର୍ଟ୍-ମେକିଂ ସେସନ**: ସଙ୍ଗୀତ ଛାତ୍ର, କଳାକାର ଓ ସାମାଜିକ କ୍ଷେତ୍ରର ଲୋକଙ୍କର ପାଇଁ କ୍ଲାସ୍ ଆୟୋଜନ କରାଯିବ, ଯେଉଁଥିରେ ସେମାନେ ଏକ ତାଲି, ଗୀତ କରିବା ସହ ସେହି ସହିତ ସହଭାଗୀ ହେବେ। 4. **ଆର୍ଟ୍-ଗୀତ କଂସେପ୍ଟ**: ଏକ ଆଲଗା ଅନୁଭବ, ଯେଉଁଠାରେ ସଙ୍ଗୀତ ଆଧାରିତ ଦୃଶ୍ୟ ପ୍ରକାଶ କରାଯାଉଛି, ଯାହା ସେହି ସ୍ଥାନର ଏକ ଅନ୍ୟତମ ସ୍ଥାନୀୟ କଳାକାରଙ୍କ ସୃଷ୍ଟିକୁ ଗଢ଼େ। 5. **ସଙ୍ଗୀତ ଏବଂ କଳା ବାଜାର**: କଳା ଏବଂ ସଙ୍ଗୀତର ବିଭିନ୍ନ ଏବଂ ସ୍ଥାନୀୟ ପ୍ରତିଷ୍ଠାନରେ ଦେଖାଯିବାକୁ ହେବା ସାଥିରେ, ଲୋକମାନେ ନୂତନ କଳା ଏବଂ ସଙ୍ଗୀତ ର ବିକ୍ରୟ କରିପାରିବେ। ସ୍ଥାନୀୟ ସାମାଜିକ ତତ୍ତ୍ୱ ଓ ଚିତ୍ରକଳା ମୂଲ୍ୟରୁ ଲାଭ ଉଠାଇ, ଏହି ସ୍ଥାପନା ଜନସାଧାରଣ ପାଇଁ ଦେଖିବା ଓ ଅନୁଭବ କରିବାକୁ ଏକ ମଜାର ଅଭିଜ୍ଞତା ହେବ।

Figure 21: *Pragyaan-Align* alignment data examples in Advice Seeking and Brainstorming categories with *Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Preferred Response	Rejected Response
Creative Writing	మీ మొదటి స్టోరీ ప్రాంప్ట్ ఈ క్రింది విధంగా ఉందిः కొంతమంది స్నేహితుల బృందం చికటి చరిత్ర కలిగిన సరస్సుకి క్యాంపింగ్ ట్రిప్‌కు వెళ్ళారు. సరస్సు యొక్క అందమైన దృశ్యం కనిపించే ప్రదేశంలో వారు తమ టెంట్‌ను ఏర్పాటు చేసుకున్నారు, కానీ వారి ప్రశాంతత స్వల్పకాలికం. వారు అడవుల్లో ఒంటరిగా లేరని త్వరలోనే గ్రహించారు. స్నేహితులు ఎదుర్కొనే రహస్యమైన ఉనికి పరంగా తగిన కథాంశ అభివృద్ధి ఏమిటన మీరు సూచిస్తారు?	ఒక ఆసక్తికరమైన మరియు ఉత్కంఠభరితమైన కథ కోసం, ఇక్కడ ఒక సంభావ్య కథాంశ అభివృద్ధిన నేను సూచించుచున్నాడుः టైటిల్ः ""ఎకోస్ ఆఫ్ ద పాస్ట్"" కథాంశంः స్నేహితుల సమూహం చుట్టుపట్టులను అన్వేషించి, సరస్సు యొక్క అందాన్ని ఆస్వాదిస్తూ ఉండగా, వారిలో కొందరు నిటిలో అసాధారణమైన ప్రతిధ్వనులను గమనించడం మొదలుపెడతారు. వారు మొదట ఇది వాతావరణం కారణంగా అని భావిస్తారు, కాని శబ్దాలు ఎక్కువ బలంగా మారుతాయి, కేవలంతో కూడిన ఆత్మ యొక్క హెచ్చరికలు లాగా ధ్వనిస్తుంది. వారు సమీపంలోని గ్రామస్థుడైన జ్ఞాన సంపన్నుడు అయిన ఓల్డ్ మాన్ రాజును కలుస్తారు, అతను స్థానిక పురాణాలను వారికి చెప్పాడుः అనేక సంవత్సరాలుగా సరస్సులో మునిగి మరణించిన వ్యక్తి యొక్క ఆత్మ గురించి. ఆత్మ యొక్క ఉద్దేశ్యం తెలుసుకోవడానికి నిర్ణయించబడిన స్నేహితులు లోతుగా త్రవ్వడం ప్రారంభిస్తారు. వారు సరస్సుకు సంబంధించిన చికటి చరిత్ర గురించి తెలుసుకుంటారు, ఇది వర్షపు రోజులలో ప్రజలను తనతో పాటు తీసుకువెళ్ళిందన పేరుగాంచింది. వారు సరస్సు నుండి బయటకు వచ్చినట్లు కనిపించే వింత సంకేతాలను కూడా గమనించడం ప్రారంభిస్తారు, మరియు వాటిలో కొన్ని తాము మాత్రమే వినగలుగుతున్నాయని నమ్ముతారు. అవి మరింత లోతుగా త్రవ్వుతుండగా, వారు సరస్సు యొక్క చరిత్ర మరియు దాని చుట్టూ ఉన్న సంఘటనలకు మధ్య ఆశ్చర్యకరమైన సంబంధాలను కనుగొంటారు. వారు సరస్సు యొక్క ప్రవాహాలలో దాచబడి ఉన్న ఒక రహస్య దీవ్రాన్ని కనుగొంటారు, ఇది చుట్టుపక్కల ప్రాంతానికి ఊపిరి పీల్చుకోగల దృష్టిని అందిస్తుంది. దీవ్రంపై, వారు ఒక పురాతన ఆలయం యొక్క అవశేషాలను కనుగొంటారు, ఇది సరస్సు యొక్క చరిత్ర మరియు దాని చుట్టూ జరిగిన మరణాల గురించి అంతర్దృష్టులను బహిర్గతం చేస్తుంది. దీవ్రం యొక్క అన్వేషణ చేస్తున్నప్పుడు, వారు ఆలయంలో దాక్కుని ఉన్న ఒక రహస్య గది పైకి వస్తారు. గదిలో, వారు ఒక డైరీని కనుగొంటారు, ఇది సరస్సు యొక్క చరిత్ర గురించి వివరిస్తుంది మరియు దాని అలల కింద దాచబడి ఉన్న రహస్యాలను వివరిస్తుంది. డైరీలో సరస్సు యొక్క ఆత్మ యొక్క ఉనికిని మరియు దాని కోపానికి కారణాన్ని వివరిస్తుంది. స్నేహితులు డైరీని అధ్యయనం చేస్తున్నప్పుడు, వారు సరస్సు యొక్క ఆత్మతమతో నేరుగా సంభాషించడానికి ప్రయత్నిస్తోంది అని గ్రహిస్తారు. ఆత్మ తన కోపానికి కారణం - సరస్సు యొక్క అందం మరియు మహిమను నాశనం చేయడానికి మానవ కార్యకలాపాలు. స్నేహితులు సరస్సు యొక్క ఆత్మ యొక్క అభ్యర్థనను అంగీకరించాలని నిర్ణయించుకుంటారు, మరియు దాని రక్షణ కోసం వారు తమ వంతు కృషి చేస్తారు. వారు తమ ఇంటికి తిరిగి వచ్చినప్పుడు, వారు సరస్సు యొక్క ఆత్మ యొక్క ప్రతిధ్వనులను ఇంకా వింటారు, కాని ఇప్పుడు అవి సంతోషకరమైనవి మరియు కృతజ్ఞతతో ఉంటాయి. సరస్సు యొక్క ఆత్మ వారిని కాపాడినందుకు వారికి కృతజ్ఞతలు తెలుపుతుంది, మరియు వారు దాని అందం మరియు మహిమను సంరక్షించడానికి వారి ప్రతిజ్ఞను పూర్తి చేశారు. స్నేహితులు తమ క్యాంపింగ్ ట్రిప్ నుండి దూరంగా వెళ్ళేటప్పుడు, వారు సరస్సు యొక్క ఆత్మ యొక్క పాఠాలను మరియు సహజ ప్రపంచంతో సామరస్యంగా జీవించడం యొక్క ప్రాముఖ్యతను ఎప్పటికీ గుర్తుంచుకోవాలని ప్రతిజ్ఞ చేస్తారు.	చికటి చరిత్ర కలిగిన సరస్సులో క్యాంపింగ్ చేస్తున్న స్నేహితుల బృందం గురించిన కథకు కొన్ని సూచనలు ఇక్కడ ఉన్నాయి: **1. దుష్ట ఆత్మలు లేదా దెయ్యాలు:** సరస్సు చికటి చరిత్ర కలిగి ఉందని చెప్పబడింది కాబట్టి, ఆ సరస్సులో మునిగిపోయినవారి ఆత్మలు లేదా దెయ్యాలు తిరుగుతున్నాయన సూపించవచ్చు. స్నేహితులు వారి ఉనికికి సంకేతాలను గమనించవచ్చు, ఉదాహరణకు, రాత్రి అరుపులు, అసహజమైన నీడలు లేదా వస్తువుల స్థానచలనం. ఈ ఆత్మలు స్నేహితులను వేధించడం ప్రారంభించవచ్చు, వారిని భయపెట్టడానికి లేదా వారిపై దాడి చేయడానికి ప్రయత్నించవచ్చు. **2. దాగి ఉన్న ప్రాణులు:** సరస్సులో లేదా దాని చుట్టుపక్కల దాగి ఉన్న ప్రమాదకరమైన జంతువులు లేదా పౌరాణిక ప్రాణులు ఉండవచ్చు. ఉదాహరణకు, ఒక పెద్ద జలచర ప్రాణి, ఒక పాము లేదా ఒక ప్రమాదకరమైన వన్యప్రాణి. ఈ ప్రాణులు స్నేహితులను వేటాడవచ్చు, వారిపై దాడి చేయవచ్చు లేదా వారిని ఒక ప్రమాదంలో ఇరికించవచ్చు. **3. పురాతన శాపం:** సరస్సుకు పురాతన శాపం ఉండవచ్చు, ఇది ఆ ప్రదేశానికి వచ్చే ప్రతి ఒక్కరిని ప్రభావితం చేస్తుంది. ఈ శాపం కొంతకాలం తర్వాత స్నేహితులపై దాడి చేయవచ్చు లేదా వారి మనస్సులపై ప్రభావం చూపవచ్చు, దాన్ని కనుగొనడానికి లేదా అధిగమించడానికి వారిని బలవంతం చేస్తుంది. **4. మానవ దురాచారాలు:** సరస్సు చరిత్రలో జరిగిన మానవ దురాచారాల ఫలితంగా ఈ దృశ్యం ఏర్పడి ఉండవచ్చు. ఉదాహరణకు, హత్య, దేపిడీ లేదా శక్షణ. ఈ దురాచారాలకు కారణమైనవారు లేదా వారి ఆత్మలు ఇప్పటికీ ఆ ప్రదేశంలో తిరుగుతున్నాయి. స్నేహితులు సరస్సు చరిత్ర గురించి తెలుసుకొని వారి అనుభవాలతో వ్యవహరించవలసి వస్తుంది. **కథాంశ అభివృద్ధికి ఉదాహరణ:** స్నేహితులు ఒక రాత్రి సరస్సు సమీపంలో ఉన్న అడవిలో ఒక అసాధారణ శబ్దం వినవచ్చు. ప్రారంభంలో వారు ఏమి పట్టించుకోరు, కాని శబ్దాలు మరింత తీవ్రతరమవుతాయి. వారు అడవిలోకి వెళితే, వారు ఒక పెద్ద, చికటి వ్యక్తిని చూస్తారు, అది వారిపై దాడి చేస్తుంది. స్నేహితులు పారిపోతారు, కాని వారు ప్రమాదకర ప్రాణి నుండి తప్పించుకోవడానికి ప్రయత్నిస్తున్నప్పుడు, వారు సరస్సు చరిత్రను కనుగొంటారు, మరియు వారు దానిలో చిక్కుకున్నారు. వారు సరస్సు చరిత్ర నుండి తప్పించుకోవడానికి మరియు ప్రాణాలను కాపాడుకోవడానికి ప్రయత్నించే కథ ఇది. ఈ సూచనలు కథాంశాన్ని అభివృద్ధి చేయడంలో మిమ్మల్ని సహాయపడతాయి అని నేను ఆశిస్తున్నాను.

Figure 22: *Pragyaan-Align* alignment data example in Creative Writing category with *Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Preferred Response	Rejected Response
Data Analysis	દુઇજન ગવેષક એકટિ નતુન સાર ગાછ્ર વૃદ્ધિતે કતટા પ્રભાવ ફેલે, તા નિયે ગવેષણા કરાછ્ન। તારા ૧૦ટિ ગાછે સાર પ્રયોગ કરેન એવ ૬ સપ્તાહ પર વૃદ્ધિર હાર પરિમાપ કરેન। તાદેર કાછે ૧૦ટિ ગાછ્ર એકટિ કન્ટ્રોલ ગ્રુપઓ આછે, યેગુલિતે સાર દેઓયા હયનિ। દુટિ ગ્રુપેર વૃદ્ધિર હાર નિમ્નરુપ: સાર પ્રયોગકૃત ગ્રુપ: ૧૦, ૧૨, ૧૫, ૧૮, ૨૦, ૨૧, ૨૨, ૨૫, ૩૦, ૩૫ કન્ટ્રોલ ગ્રુપ: ૫, ૬, ૭, ૮, ૯, ૧૦, ૧૨, ૧૫, ૧૮, ૨૦ પ્રતિટિ ગ્રુપેર મિન, મિડિયાન એવ મોડેર વૃદ્ધિર હાર કત?	ચલુન આમરા પ્રથમે પ્રતિટિ ગ્રુપેર જન્ય મિન, મિડિયાન એવ મોડ વેર કરિ। **સાર પ્રયોગકૃત ગ્રુપ:** * **મિન:** સર્વનિમ્ન માન હલ ૧૦। * **મિડિયાન:** માનગુલોકે ક્રમવર્ધમાન ક્રમે સાજિયે (૧૦, ૧૨, ૧૫, ૧૮, ૨૦, ૨૧, ૨૨, ૨૫, ૩૦, ૩૫) આમરા મધ્યમ દુટિ માન (૨૦ એવ ૨૧) પાઇ। મિડિયાન હલ એઇ દુટિ માનેર ગડ: (૨૦ + ૨૧) / ૨ = ૨૦.૫ * **મોડ:** કોન માનઇ એકાધિકવાર આસેનિ, તાઇ એઇ ડેટા સેટે કોન મોડ નેઇ। **કન્ટ્રોલ ગ્રુપ:** * **મિન:** સર્વનિમ્ન માન હલ ૫। * **મિડિયાન:** માનગુલોકે ક્રમવર્ધમાન ક્રમે સાજિયે (૫, ૬, ૭, ૮, ૯, ૧૦, ૧૨, ૧૫, ૧૮, ૨૦) આમરા મધ્યમ દુટિ માન (૯ એવ ૧૦) પાઇ। મિડિયાન હલ એઇ દુટિ માનેર ગડ: (૯ + ૧૦) / ૨ = ૯.૫ * **મોડ:** કોન માનઇ એકાધિકવાર આસેનિ, તાઇ એઇ ડેટા સેટે કોન મોડ નેઇ। સુતરાં, સંક્ષેપે: | ગ્રુપ | મિન | મિડિયાન | મોડ | |---|---|---|---| | સાર પ્રયોગકૃત ગ્રુપ | ૧૦ | ૨૦.૫ | નેઇ | | કન્ટ્રોલ ગ્રુપ | ૫ | ૯.૫ | નેઇ |	મિન (લિષ્ટ): કન્ટ્રોલ ગ્રુપેર જન્ય, સવચેયે છોટ માન હલ 5। સારયુક્ત ગ્રુપેર જન્ય, સવચેયે છોટ માન હલ 10। મેડિયાન (લિષ્ટ): ઉભય લિષ્ટેર માધ્યમિક અવસ્થાને થાકા સંખ્યા ખૂંજત હવે। કન્ટ્રોલ ગ્રુપેર ક્ષેત્રે, એટિ હવે (8 + 9)/2 = 8.5, કિન્તુ આમાદેર કાછે પૂર્ણસંખ્યાર ડેટા રયેછે તાઇ આમરા એટિકે કાછાકાછિ પૂર્ણસંખ્યાય રાઉન્ડ કરતે પારિ ના કારણ આમાદેર કાછે એમન કોનઓ મધ્ય માન નેઇ યા દુઇવાર પ્રદર્શિત હય। તવે, એઇ સમસ્યાટિ સમાધાનેર આરેકટિ ઉપાય હલ યે યખન સંખ્યાગુલિ જોડ થાકે તખન માઝારિ માનગુલિ સરાસરિ ગણના કરા યાય। યદિઓ આમાદેર કાછે 10 ટિ સંખ્યા રયેછે, યાર મધ્યે 2 ટિ મધ્યમ માન રયેછે - 7 ઓ 8 વા 16 ઓ 17 એર માતો નય યેખાને પ્રકૃત મધ્યમ માન હવે સેઇ દુટિર ગડ়। આમાદેર ક્ષેત્રે, આમાદેર કાછે 10 ટિ સંખ્યા રયેછે, તાઇ આમરા જાનિ યે મધ્યમ માન હવે 5મ એવ 6ષ્ઠ સંખ્યાર ગડ়। એકઇભાવે, સારયુક્ત ગ્રુપેર જન્ય, આમરા 5મ એવ 6ષ્ઠ સંખ્યાર ગડ় ખૂંજે વેર કરવ। કન્ટ્રોલ ગ્રુપેર જન્ય, 5મ એવ 6ષ્ઠ સંખ્યા યથાક્રમે 8 એવ 9; સુતરાં, મધ્યવર્તી માન હલ (8+9)/2 = 8.5। સારયુક્ત ગ્રુપેર જન્ય, 5મ એવ 6ષ્ઠ સંખ્યા યથાક્રમે 18 એવ 20; સુતરાં, મધ્યવર્તી માન હલ (18+20)/2 = 19। મોડઃ મોડ હલ એમન એકટિ માન યા ડેટાસેટે ઘન ઘન ઘટે। કન્ટ્રોલ ગ્રુપેર જન્ય, પ્રતિટિ સંખ્યા શુધૂમાત્ર એકવાર દેખા દેય, તાઇ મોડટિ અનન્ય નય। એકઇભાવે, સારયુક્ત ગ્રુપેર જન્યઓ, પ્રતિટિ સંખ્યા શુધૂમાત્ર એકવાર પ્રદર્શિત હઓયાર કારણે મોડટિ અનન્ય નય। ઉત્તર: - કન્ટ્રોલ ગ્રુપેર મીન, મિડિયાન એવ મોડ યથાક્રમેઃ 10.3, 8.5, એવ અનન્য। - સારયુક્ત ગ્રુપેર મીન, મિડિયાન એવ મોડ યથાક્રમેઃ 20.1, 19, એવ અનન્য।
Editing	લેખિત સામગ્રીને પરિષ્કૃત કરતી વખતે તમારા મુખ્ય સંપાદન ઉદ્દેશ્યો શું છે?	લેખિત સામગ્રીને પરિષ્કૃત કરતી વખતે, મારા મુખ્ય સંપાદન ઉદ્દેશો આ પ્રમાણે છેઃ 1. સ્પષ્ટતા અને સુસંગતતા સુધારવીઃ હું લેખકના સંદેશને અસરકારક રીતે પહોંચાડવા માટે સામગ્રીને સ્પષ્ટ, સંક્ષિપ્ત અને અનુસરવામાં સરળ બનાવવાનું લક્ષ્ય રાખું છું. 2. ભાષા અને શૈલીને વધારવીઃ હું સામગ્રીની એકંદર ગુણવતા વધારવા માટે ચોક્કસ, સચોટ અને આકર્ષક ભાષાનો ઉપયોગ કરવાની ખાતરી કરું છું. 3. વ્યાકરણ અને મિકેનિક્સને સુધારવુંઃ હું વ્યાકરણની ભૂલો, વિસંગતતાઓ અને ફોર્મેટિંગની ભૂલોને સુધારે છે જેથી સામગ્રી ભૂલ-મુક્ત અને વ્યાવસાયિક હોય. 4. માળખું અને સંગઠનને સુધારવુંઃ હું સામગ્રીને સ્પષ્ટ માળખા સાથે સુવ્યવસ્થિત અને તાર્કિક બનાવવા માટે તેને ફરીથી ગોઠવું છું, જેનાથી વાચકોને તેને સમજવું અને અનુસરવું સરળ બને છે. 5. સ્વર અને અવાજને વધારવુંઃ હું લેખકના ઇચ્છિત પ્રેક્ષકો અને હેતુને અનુરૂપ સામગ્રીનો સ્વર અને અવાજ સુસંગત અને અસરકારક છે તેની ખાતરી કરું છું. 6. થોકસાઈ અને તથ્યાત્મક થોકસાઈને ચકાસવીઃ હું સામગ્રીની થોકસાઈ અને વિશ્વસનીયતાની ખાતરી કરવા માટે હકીકતો, આંકડાઓ અને માહિતીની થોકસાઈને ચકાસું છું. 7. સંવેદનશીલતા અને સાંસ્કૃતિક યોગ્યતાની સમીક્ષા કરવીઃ હું એ સુનિશ્ચિત કરું છું કે સામગ્રી સાંસ્કૃતિક રીતે સંવેદનશીલ, આદરપૂર્ણ અને વિવિધ પ્રેક્ષકો માટે યોગ્ય હોય. 8. સંપાદનીય ધોરણો અને માર્ગદર્શિકાઓનું પાલન કરવુંઃ હું સંપાદનીય ધોરણો અને માર્ગદર્શિકાઓનું પાલન કરું છું જે લાગુ હોય, જેમ કે શિકાગો મેન-યુઅલ ઓફ સ્ટાઇલ અથવા એપી સ્ટાઇલબુક, જેથી સામગ્રી સુસંગત અને ઉદ્યોગના ધોરણોને અનુરૂપ હોય. 9. લેખકની અન-ય અવાજ અને દ્રષ્ટિને જાળવી રાખવીઃ જ્યારે હું સામગ્રીને સુધારું છું અને તેમાં સુધારો કરું છું, ત્યારે હું લેખકની અન-ય અવાજ અને દ્રષ્ટિને જાળવી રાખવાનું અને તેને જાળવી રાખવાનું લક્ષ્ય રાખું છું, જેથી સામગ્રી પ્રમાણિક અને અધિકૃત લાગે. 10. પ્રતિસાદ અને સમર્થન આપવુંઃ હું લેખકને તેમના કાર્યને સુધારવામાં અને સુધારવામાં મદદ કરવા માટે મારા સંપાદનોની સ્પષ્ટતા અને સમર્થન કરું છું.	લેખિત સામગ્રીને પરિષ્કૃત કરતી વખતે, કેટલાક મુખ્ય સંપાદન ઉદ્દેશ્યો હોય છે: 1. **સ્પષ્ટતા**: લેખતાની ભુલોને ઠીક કરવી અને વાંચનને સરળ બનાવવું, જેથી વિચાર સ્પષ્ટ રહે. 2. **સંરચના**: લેખની રચનાને મજબૂત બનાવવી, જેવા કે પેરાગ્રાફ અને ઉપવિષયોનું યોગ્ય વિભાજન. 3. **ભાષાશુદ્ધતા**: કોઈ પણ વ્યવાકરણ, વ્યાકરણ, અને ઉપભાષા સંબંધિત ભૂલોને સુધારવી. 4. **અર્થતંત્ર**: અનાવશ્યક શબ્દો અને પંક્તીઓને દૂર કરી, પીછીને લાગણીભર્યા અને અસરકારક બનાવવું. 5. **લક્ષ્ય સમજૂતંત્ર**: લેખના ઈરાદા અને લક્ષ્ય સમજૂતીઓને કાર્યક્રમમાં સમાવિષ્ટ કરવું, જેથી તે પ્રેક્ષક સાથે જોડાય. 6. **અર્ધ બસ્પષ્ટતા અને ઉશ્યારણ**: પુસ્તકમાં કોઈપણ અસંવાદિતા કે બાકી રહેવાના મુદ્દાઓને દૂર કરવા. આ બાબતોને ધ્યાનમાં રાખીને, સંપાદક સમૃદ્ધ અને સંક્ષિપ્ત સામગ્રી તૈયાર કરે છે, જે વાંચક માટે રસપ્રદ અને અને ઉપયોગી હોય.

Figure 23: *Pragyaan-Align* alignment data examples in Data Analysis and Editing categories with *Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Preferred Response	Rejected Response
Information Seeking	तारा और ग्रह के बीच क्या अंतर है?	तारों और ग्रहों में कई महत्वपूर्ण अंतर हैं। सबसे बड़ा अंतर यह है कि तारे खुद से प्रकाश उत्पन्न करते हैं, जबकि ग्रह नहीं करते। तारे अपने केंद्र में होने वाले परमाणु संलयन के कारण प्रकाश और ऊष्मा उत्पन्न करते हैं, जबकि ग्रह सूर्य या किसी अन्य तारे से परावर्तित प्रकाश से ही चमकते हैं। इसके अलावा, तारे आकार में ग्रहों से कहीं बड़े होते हैं और इनका द्रव्यमान भी अधिक होता है। तारों का अपना गुरुत्वाकर्षण बल होता है जिससे वे अपने आकार को बनाए रखते हैं और अपने चारों ओर घूमने वाले ग्रहों को अपनी कक्षा में बांधे रखते हैं। ग्रहों का अपना गुरुत्वाकर्षण बल होता है, लेकिन यह तारों के मुकाबले कम होता है। आकार और द्रव्यमान के अलावा, तारों और ग्रहों में रासायनिक संरचना और तापमान में भी अंतर होता है। तारे मुख्यतः हाइड्रोजन और हीलियम गैस से बने होते हैं और अत्यंत उच्च तापमान पर होते हैं। ग्रहों की संरचना विविध होती है, कुछ चट्टानी होते हैं, कुछ गैसीय और कुछ बर्फ से बने होते हैं। इनका तापमान तारे की तुलना में बहुत कम होता है। संक्षेप में, तारे स्व-प्रकाशमान, विशाल, गर्म और मुख्यतः गैसीय पिंड होते हैं, जबकि ग्रह अपेक्षाकृत छोटे, ठंडे, और तारों के चारों ओर परिक्रमा करने वाले पिंड होते हैं जो तारों से परावर्तित प्रकाश से चमकते हैं।	एक तारे को एक स्व-प्रकाशित वस्तु माना जाता है जो अपने गुरुत्वाकर्षण से संपीड़ित होती है। यह आम तौर पर हाइड्रोजन और हीलियम का बना होता है। दूसरी ओर, एक ग्रह वह पिंड है जो किसी अन्य आकाशगंगा में घूमता है। अंतरिक्ष की विशालता में, तारें खाली स्थान द्वारा अलग किए गए होते हैं जिन्हें ""आइंसटीन रिंग्स"" कहा जाता है। ये वलय वास्तव में अदृश्य आयामी क्षेत्र नहीं हैं बल्कि वे गणितीय रूप से निर्मित हैं ताकि हमारी ब्रह्मांड संबंधी समझ को सरल बनाया जा सके। इस प्रकार, इन अंगूठियों के भीतर मौजूद दूरी बहुत बड़ी हो सकती है। उदाहरण के लिए, सूर्य और उसके सबसे निकट पड़ोसी तारे प्रॉक्सिमा सेंटौरी के बीच की दूरी लगभग 30 लाख अरब किलोमीटर (या 186,000 अरब मील) है! इसके विपरीत, ग्रहों का आकार छोटे पैमाने पर होता है। यहाँ तक कि हमारे सौर मंडल में भी, बृहस्पति जैसा बड़ा ग्रह पृथ्वी से कई गुणा अधिक भरा हुआ है। हालाँकि, इसका कारण इसकी अपार सामग्री नहीं है, बल्कि इसके निर्माण के दौरान जमे हुए गैसों की उच्च मात्रा है।
Math	ದಿಯಾ ತನ್ನ ನಗರದಲ್ಲಿ ಸೌರ ಫಲಕಗಳ ಬಳಕೆಯನ್ನು ಹೆಚ್ಚಿಸುವ ಯೋಜನೆಯಲ್ಲಿ ಕಾರ್ಯನಿರ್ವಹಿಸುತ್ತಿರುವ ಇಂಧನ ಇಲಾಖೆಯ ನೀತಿ ಸಲಹೆಗಾರಳಾಗಿದ್ದಾಳೆ. 5 ನೆರೆಹೊರೆಗಳಲ್ಲಿ ಸೌರ ಫಲಕಗಳನ್ನು ಸ್ಥಾಪಿಸಲು ಯೋಜಿಸಿದ್ದಾರೆ. ಪ್ರತಿ ನೆರೆಹೊರೆಯಲ್ಲಿ, ಆಕೆ 12 ಮನೆಗಳಲ್ಲಿ ಸೌರ ಫಲಕಗಳನ್ನು ಅಳವಡಿಸುವ ಗುರಿಯನ್ನು ಹೊಂದಿದ್ದಾಳೆ. ಪ್ರತಿ ಸೌರ ಫಲಕವು 3 ಕಿಲೋವ್ಯಾಟ್ ಶಕ್ತಿಯನ್ನು ಉತ್ಪಾದಿಸುತ್ತದೆ. ಪ್ರತಿ ಮನೆಯು 2 ಸೌರ ಫಲಕಗಳನ್ನು ಹೊಂದಿದ್ದರೆ, ಈ ನೆರೆಹೊರೆಯಲ್ಲಿರುವ ಎಲ್ಲ ಮನೆಗಳಿಂದ ಒಟ್ಟು ಎಷ್ಟು ಕಿಲೋವ್ಯಾಟ್ ಶಕ್ತಿಯು ಉತ್ಪತ್ತಿಯಾಗುತ್ತದೆ?	ದಯಮಾಡಿ, ಈ ಲೆಕ್ಕಾಚಾರವನ್ನು ಮಾಡೋಣ: * **ಪ್ರತಿ ಮನೆಗೆ ಸೌರ ಫಲಕಗಳು:** 2 * **ಪ್ರತಿ ಸೌರ ಫಲಕದಿಂದ ಉತ್ಪಾದನೆಯಾಗುವ ಶಕ್ತಿ:** 3 ಕಿಲೋವ್ಯಾಟ್ * **ಪ್ರತಿ ಮನೆಯಿಂದ ಉತ್ಪಾದನೆಯಾಗುವ ಒಟ್ಟು ಶಕ್ತಿ:** 2 ಫಲಕಗಳು * 3 ಕಿಲೋವ್ಯಾಟ್/ಫಲಕ = 6 ಕಿಲೋವ್ಯಾಟ್ * **ಒಟ್ಟು ಮನೆಗಳು:** 5 ನೆರೆಹೊರೆಗಳು * 12 ಮನೆಗಳು = 60 ಮನೆಗಳು * **ಎಲ್ಲ ಮನೆಗಳಿಂದ ಉತ್ಪಾದನೆಯಾಗುವ ಒಟ್ಟು ಶಕ್ತಿ:** 60 ಮನೆಗಳು * 6 ಕಿಲೋವ್ಯಾಟ್ = 360 ಕಿಲೋವ್ಯಾಟ್ ಆದ್ದರಿಂದ, ಈ ನೆರೆಹೊರೆಯಲ್ಲಿರುವ ಎಲ್ಲ ಮನೆಗಳಿಂದ ಒಟ್ಟು **360 ಕಿಲೋವ್ಯಾಟ್*** ಶಕ್ತಿಯನ್ನು ಉತ್ಪಾದಿಸಲಾಗುತ್ತದೆ.	ప్రశ్నియు దియా అవర యోజనేయింద నిరీక్షిత ఉత్పాదనేయన్ను కేళుత్తదే. ఇదక్కే ఉత్తరిసలు, నావు మొదలు ఒందు నేరెహొరేయల్లి ళళవడిసలాగువ సౌరాలార్ ప్యానేల్‌గళ సంఖ్యేయన్ను లెక్క హాకబేకాగిదే. నంతర, ఆ నేరెహొరేయల్లిన ఎల్లా మనేగళింద ఉత్పత్తియాగువ ఒట్టు విద్యుత్ ప్రమాణవన్ను కండుకొళ్ళబహుదు. ఒందు నేరెహొరేయల్లి, 12 మనేగళు తలా ఎరడు సౌర ఫలకగళన్ను హొందివే. ఆద్దరింద, ఒందు నేరెహొరేయల్లి ళళవడిసలాగువ ఒట్టు సౌర ఫలకగళ సంఖ్యే = 12 మనేగళు * 2 సౌర ఫలకగళు/మనే = 24 సౌర ఫలకగళు. ప్రతి సౌర ఫలకవు 3 కిలోవ్యాట్ శక్తియన్ను ఉత్పాదిసుత్తదే. ఆద్దరింద, ఒందు నేరెహొరేయల్లిరువ ఎల్లా మనేగళింద ఉత్పత్తియాగువ ఒట్టు విద్యుత్ ప్రమాణ = 24 సౌర ఫలకగళు * 3 కిలోవ్యాట్/సౌర ఫలక = 72 కిలోవ్యాట్. ఆద్దరింద, ఒందు నేరెహొరేయల్లిరువ ఎల్లా మనేగళింద ఉత్పత్తియాగువ ఒట్టు విద్యుత్ ప్రమాణవు 72 కిలోవ్యాట్ ఆగిదే.
Reasoning	ചുവടെ നൽകിയിരിക്കുന്ന പ്രസ്താവനയെ അടിസ്ഥാനമാക്കി, വാദത്തിന്റെ യുക്തിപരമായ ഘടന വിശകലനം ചെയ്ത് നിഗമനം സാധുവാണോ എന്ന് തിരിച്ചറിയുക. നിങ്ങളുടെ ന്യായവാദം ഘട്ടങ്ങളായി വിശദീകരിക്കുക. ""നമ്മുടെ സൗരയൂഥത്തിലെ എല്ലാ ഗ്രഹങ്ങളും സൂര്യനെ ചുറ്റുന്നു. വ്യാഴം നമ്മുടെ സൗരയൂഥത്തിലെ ഒരു ഗ്രഹമാണ്. അങ്ങനെ, വ്യാഴം സൂര്യനെ ചുറ്റുന്നു."""	ഈ വാദത്തിന്റെ യുക്തിപരമായ ഘടന ഒരു ഡിഡക്ടീവ് ന്യായവാദമാണ്, അതിൽ ഒരു പൊതുവായ പ്രസ്താവനയിൽ നിന്ന് ഒരു പ്രത്യേക നിഗമനത്തിലേക്ക് എത്തിച്ചേരുന്നു. വാദം രണ്ട് പ്രീമൈസുകളും ഒരു നിഗമനവും ഉൾക്കൊള്ളുന്നു: **പ്രീമൈസ് 1 (മേജർ പ്രീമൈസ്):** നമ്മുടെ സൗരയൂഥത്തിലെ എല്ലാ ഗ്രഹങ്ങളും സൂര്യനെ ചുറ്റുന്നു. ഇത് ഒരു പൊതുവായ വിവരണമാണ്. **പ്രീമൈസ് 2 (മൈനർ പ്രീമൈസ്):** വ്യാഴം നമ്മുടെ സൗരയൂഥത്തിലെ ഒരു ഗ്രഹമാണ്. ഇത് ഒരു പ്രത്യേക വസ്തുതയാണ്. **നിഗമനം:** അതിനാൽ, വ്യാഴം സൂര്യനെ ചുറ്റുന്നു. ഇത് പ്രീമൈസുകളിൽ നിന്ന് ലോജിക്കലായി പിന്തുണയ്ക്കപ്പെടുന്ന ഒരു നിഗമനമാണ്. ഈ വാദത്തിന്റെ യുക്തി ശരിയാണ്, കാരണം നിഗമനം പ്രീമൈസുകളിൽ നിന്ന് പിന്തുണയ്ക്കപ്പെടുന്നു. പ്രീമൈസ് 1 എല്ലാ ഗ്രഹങ്ങളെയും സൂര്യനെ ചുറ്റുന്നവരായി വിവരിക്കുന്നു, പ്രീമൈസ് 2 വ്യാഴത്തെ ഒരു ഗ്രഹമായി തിരിച്ചറിയുന്നു. അതിനാൽ, വ്യാഴം സൂര്യനെ ചുറ്റുണമെന്ന് നിഗമനം നടത്തുന്നത് ഒരു ലോജിക്കൽ ആണ്. നിഗമനം സാധുവാണ്.	ഘട്ടം 1: പ്രധാന ആശയം എല്ലാ ഗ്രഹങ്ങളും സൂര്യനെ പരിക്രമണം ചെയ്യുന്നതിന്റെ പൊതു അവകാശവാദത്തോടെയാണ് വാദം ആരംഭിക്കുന്നത് (പറഞ്ഞിട്ടില്ല). ഘട്ടം 2: നിർദ്ദിഷ്ട ഉദാഹരണങ്ങൾ അതിനുശേഷം ഇത് നമ്മുടെ സൌരയൂഥത്തിൽ നിന്നുള്ള രണ്ട് ഗ്രഹങ്ങളിൽ ശ്രദ്ധ കേന്ദ്രീകരിക്കുന്നു-സൂര്യൻ, വ്യാഴം എന്നിവിടങ്ങളിൽ നിന്ന് ആരംഭിച്ച് ആദ്യത്തെ അനുമാനം സ്ഥാപിച്ചു. ഘട്ടം 3: ലോജിക്കൽ ഓപ്പറേഷൻ പ്രധാന അനുമാനവും വ്യക്തിയുടെ അനുമാനവും സംയോജിപ്പിച്ച് ""അതിനാൽ, ജൂപിറ്റർ സൂര്യനെ പരിക്രമണം ചെയ്യുന്നു."" ഘട്ടം 4: ഉപസംഹാരം ഉപസംഹാരത്തിന് മുമ്പത്തെ ഘട്ടങ്ങളിൽ നിന്ന് യുക്തിസഹമായി തുടരുച്ചയുണ്ട്; അതിൽ പറഞ്ഞിരിക്കുന്ന കാര്യം ശാസ്ത്രീയമായി ശരിയായ വിവരണം ഉപയോഗിച്ച് സ്ഥാപിതമായ തീസിസിനെക്കുറിച്ചുള്ള കൂടുതൽ വിശദാംശങ്ങൾ നൽകുന്നു. ന്യായവിധി: നൽകിയിരിക്കുന്ന വാദം സാധുതയുള്ളതും ശരിയായ യുക്തിസഹമായ ഘടനയുള്ളതുമാണ്.

Figure 24: *Pragyaan-Align* alignment data examples in Information Seeking, Math and Reasoning categories with *Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Preferred Response	Rejected Response
Planning	மேற்கு இந்தியா முழுவதும் ஒரு பயணத்தைத் திட்டமிட எனக்கு உதவி தேவை. நான் ஒரு கல்லூரி மாணவன், எனவே பட்ஜெட்டை கருத்தில் கொள்ள வேண்டியது அவசியமானது, ஜூன் மாதத்தில் பயணத்திற்கு எனக்கு 2 வாரங்கள் மட்டுமே உள்ளன. இந்தப் பயணத்தைத் திட்டமிடத் தொடங்கும்போது நான் கருத்தில் கொள்ள வேண்டியது என்ன? பல மாநிலங்களுக்குச் சென்று உள்ளூர் கலாச்சாரங்களை அனுபவிப்பது, பிரபலமான இடங்களை சுற்றிப் பார்ப்பது மற்றும் பிற பயணிகளைச் சந்திப்பது ஆகியவை தான் என்னுடைய பயண இலக்குகள்.	நிச்சயமாக, நீங்கள் வழங்கிய தகவலின் சுருக்கம் இதோ: 1.பயணத் திட்டம்: 2 வார மேற்கிந்தியப் பயணம், ராஜஸ்தான், குஜராத், மகாராஷ்டிரா, கோவா ஆகிய மாநிலங்களை உள்ளடக்கியது. ஜூன் மாதத்தின் கோடை மற்றும் பருவமழைக் காலநிலைக்கு ஏற்ப திட்டமிடுங்கள். 2. பொருளாதாரம் மற்றும் தங்குமிடம்: ஒரு நாளைக்கு ₹1,500 - ₹3,000 செலவழிக்கத் திட்டமிடுங்கள். விமானம், ரயில் அல்லது பேருந்து மூலம் பயணம் செய்யலாம். உச்ச பருவத்தில் தங்குமிடங்களை முன்கூட்டியே முன்பதிவு செய்வது அவசியம். 3. சுற்றுலா இடங்கள்: ஜெய்ப்பூர்: அம்பர் கோட்டை, சிட்டோர்கர் கோட்டை, நகர அரண்மனை. அகமதாபாத்: சபர்மதி ஆசிரமம், ஹுஸ்த் ஹீ லாடி. மும்பை: கேட்வே ஆஃப் இந்தியா, மெரைன் டிரைவ். கோவா: கடற்கரைகள். 4.கலாச்சாரம் மற்றும் இயற்கை: அஜ்மீர் தர்கா ஷெரீஃப் போன்ற ஆன்மீக இடங்களையும், ரண் ஆஃப் கச் போன்ற இயற்கை இடங்களையும் பார்வையிடுங்கள். 5. பாதுகாப்பு குறிப்புகள்: வெப்பமான காலநிலையில் நீர்ச்சத்துடனும், சன்ஸ்கிரீனுடனும் இருங்கள். உங்கள் உடமைகளைப் பாதுகாப்பாக வைத்திருங்கள். உள்ளூர் மொழியின் சில அடிப்படை வார்த்தைகளைக் கற்றுக்கொள்வது உதவியாக இருக்கும்.	"ஜூன் மாதத்தில் மேற்கு இந்தியா முழுவதும் ஒரு பயணத்தை கல்லூரி மாணவராக திட்டமிடுவதற்கான சில பயனுள்ள குறிப்புகளைப் பார்வையிடலாம். 1. **இலக்கு நகரங்கள் மற்றும் மாநிலங்கள்**: மேற்கு இந்தியாவில் பல பிரபலமான நகரங்கள் உள்ளன, அவற்றில்: - **மும்பை** (மஹாராஷ்ட்ரா): பாலைவனம், ஷோப்பிங், உணவு. - **போச்சி** (கேரளா): அழகான வளைகுடா, கலாச்சார கண்டுபிடிப்பு. - **ஜெய்பூர்** (ராஜஸ்தான்): வர்த்தக வளைகுடா, வரலாறு. - **அஜந்தாபாத்** (மஹாராஷ்ட்ரா): வரலாற்று கட்டடங்கள். - **ராஜ்கோட்** (குஜராத்): சம்பவங்கள் மற்றும் பண்பு. 2. **பட்ஜெட் திட்டமிடல்**: - **ஆசிரியர் வாடகை**: பயணத்தின் போது தங்குமிடங்களை (ஹோட்டல் அல்லது மாணவர் விடுதி) குறைத்துக் கொள்ளுங்கள். - **எண் தளவாரி**: உங்களது உணவுக்கு ஆனது, சுருக்கமாகவும் பிள்ளையா, எனவே உங்களைச் சுற்றி அரிய உணவுகளை முயற்சி செய்யுங்கள். - **போக்குவரத்து**: பஸ் அல்லது ரயில்கள் மேவட்ட ரீ பயணங்களுக்கு எளிது. 3. **கலாச்சார அனுபவம்**: - உள்ளூர் உணவுகள்: சிங்கள உணவுகள் (தோசா, இட்லி, வடை) போன்றவை. - மக்கள் உடன் பேசுவது: உள்ளூர் மக்களைப் பேட்டியாக்கி அவர்களின் வாழ்க்கை முறையைப் புரிந்து கொள்ளுங்கள். 4. **சுற்றுலா இடங்கள்**: - உங்களது பயணத்தில் இருந்து நீங்கள் விரும்பும் இடங்களை முன்பே திட்டமிடுங்கள் (மதியம், தொலைபேசி/இணையம் மூலம் முன்பதிவு). 5. **பார்த்துக்கொள்வது**: - பயணத்தில் பூங்காக்கள், வரலாற்று அருங்காட்சியகங்கள் மற்றும் கலைச்சாலைகள் குறித்த மேலதிக தகவல்களைத் தேவையான வழிகாட்டிகள் மூலம் பெறுங்கள்.
Role Playing	ਤੁਸੀਂ ਇੱਕ ਨਿੱਜੀ ਜਾਂਚਕਰਤਾ ਹੋ। ਮੈਨੂੰ ਮੇਰੇ ਪਰਿਵਾਰ ਦੇ ਕਾਰੋਬਾਰ ਵਿੱਚ ਹੋਈ ਚੋਰੀ ਵਿੱਚ ਮਦਦ ਲਈ ਤੁਹਾਨੂੰ ਨਿਯੁਕਤ ਕਰਨ ਦੀ ਲੋੜ ਹੈ। ਕੀ ਤੁਸੀਂ ਦੱਸ ਸਕਦੇ ਹੋ ਕਿ ਤੁਸੀਂ ਮਦਦ ਲਈ ਕੀ ਕਰ ਸਕਦੇ ਹੋ? ਕੀ ਤੁਹਾਨੂੰ ਇੱਕ ਯੋਗ ਜਾਂਚਕਰਤਾ ਬਣਾਉਂਦਾ ਹੈ ਅਤੇ ਕੀ ਤੁਸੀਂ ਅਦਾਲਤ ਵਿੱਚ ਸਹਾਇਤਾ ਕਰ ਸਕਦੇ ਹੋ ਜੇਕਰ ਇਸਦੀ ਲੋੜ ਹੋਵੇ?	ਮੈਂ ਇੱਕ ਨਿੱਜੀ ਜਾਂਚਕਰਤਾ ਨਹੀਂ ਹਾਂ, ਪਰ ਮੈਂ ਤੁਹਾਨੂੰ ਕੁਝ ਸੁਝਾਵ ਦੇ ਸਕਦਾ ਹਾਂ ਕਿ ਤੁਸੀਂ ਆਪਣੇ ਪਰਿਵਾਰ ਦੇ ਕਾਰੋਬਾਰ ਵਿੱਚ ਹੋਈ ਚੋਰੀ ਦੀ ਜਾਂਚ ਕਰਨ ਲਈ ਕੀ ਕਰ ਸਕਦੇ ਹੋ। 1. **ਸ਼ਾਮਲ ਹੋਇਆ ਡਾਕੂਮੈਂਟੇਸ਼ਨ**: ਸਬੰਧਤ ਸਬੂਤ, ਜਿਵੇਂ ਕਿ ਵੇਖੀਆਂ ਜਾਣ ਵਾਲੀਆਂ ਫਾਈਲਾਂ, ਬੈਂਕ ਸਟੇਟਮੈਂਟ, ਅਤੇ ਵਪਾਰ ਟ੍ਰਾਜ਼ਨਰੀ ਰਿਪੋਰਟਾਂ ਨੂੰ ਇਕੱਠਾ ਕਰੋ। ਇਹ ਜਾਣਕਾਰੀ ਤੁਸੀਂ ਜਾਂਚ ਕਰਨ ਵਾਲੇ ਨੂੰ ਦੇਣ ਵਿੱਚ ਮਦਦ ਕਰੇਗੀ। 2. **ਫੁਟੇਜ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ**: ਜੇਕਰ ਤੁਹਾਡੇ ਕੋਲ ਸੀਸੀਟੀਵੀ ਫੁਟੇਜ ਹੈ, ਤਾਂ ਇਸਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਪੁਰਾਣੇ ਰਿਕਾਰਡਿੰਗਜ਼ ਦੀ ਜਾਂਚ ਕੀਤਾ ਜਾ ਸਕਦਾ ਹੈ, ਜਿਸ ਨਾਲ ਚੋਰੀ ਦੇ ਸਮੇਂ ਦੀ ਪਛਾਣ ਹੋ ਸਕਦੀ ਹੈ। 3. **ਸ਼ਟੀਕੀਆਂ ਸਿੱਟੀਆਂ**: ਆਪਣੀ ਟੀਮ ਵਿੱਚ ਜਿੰਨ੍ਹਾਂ ਲੋਕਾਂ ਚੋਰੀ ਕਰਨ ਦੀ ਸੰਭਾਵਨਾ ਹੈ, ਐਸੇ ਲੋਕਾਂ ਬਾਰੇ ਤਿਆਰ ਕੀਤੇ ਗਏ ਰਿਪੋਰਟਸ ਨੂੰ ਵੇਖੋ। 4. **ਪੇਸ਼ੇਵਰ ਸਹਾਇਤਾ**: ਇੱਕ ਯੋਗ ਜਾਂਚਕਰਤਾ ਜਾਂ ਪ੍ਰਾਈਵੇਟ ਡਿਟੈਕਟਿਵ ਨੂੰ ਨਿਯੁਕਤ ਕਰਨ ਦੇ ਬਾਰੇ ਵਿਚਾਰ ਕਰੋ ਜੋ ਕਿ ਜਾਣਕਾਰੀ ਇਕੱਠੀ ਕਰਨ ਵਿੱਚ ਮਦਦ ਕਰੇਗਾ। ਇਹ ਵਿਅਕਤੀ ਪੇਸ਼ੇਵਰ ਮੁਲਾਂਕਣ ਅਤੇ ਪ੍ਰੀਖਿਆ ਕਰ ਸਕਦਾ ਹੈ। 5. **ਮੂਲ ਭਿੰਨਤਾ**: ਜਾਂਚਕਰਤਾ ਤਹਕੀਕਾਤ ਨੂੰ ਅਦਾਲਤ ਵਿੱਚ ਪੇਸ਼ ਕਰ ਸਕਦਾ ਹੈ, ਜੇਕਰ ਇਸ ਦੀ ਲੋੜ ਹੋਵੇ। ਜੇ ਤੁਹਾਨੂੰ ਖਾਸ ਸਲਾਹ ਜਾਂ ਜਾਣਕਾਰੀ ਦੀ ਲੋੜ ਹੈ, ਤਾਂ ਇੱਕ ਮਾਹਿਰ ਕਿਸਾਨ ਜਾਂ ਕਾਨੂੰਨੀ ਸਲਾਹਕਾਰ ਨਾਲ ਗੱਲ ਕਰੋ। ਉਹ ਤੁਹਾਨੂੰ ਨਿੱਜੀ ਜਾਂਚਕਰਤਾ ਦੇ ਚੋਣ ਅਤੇ ਪ੍ਰਕਿਰਿਆ ਬਾਰੇ ਵੀ ਵਿਸਥਾਰ ਵਿੱਚ ਜਾਣਕਾਰੀ ਦੇ ਸਕਦੇ ਹਨ।	ਮੈਂ ਇੱਕ ਵਰਚੁਅਲ ਜਾਂਚਕਰਤਾ ਹਾਂ, ਜਿਸ ਨੂੰ ਤੁਹਾਡੇ ਪਰਿਵਾਰ ਦੇ ਕਾਰੋਬਾਰ ਵਿੱਚ ਹੋਈ ਚੋਰੀ ਦੀ ਜਾਂਚ ਕਰਨ ਵਿੱਚ ਤੁਹਾਡੀ ਸਹਾਇਤਾ ਲਈ ਤਿਆਰ ਕੀਤਾ ਗਿਆ ਹੈ। ਮੇਰੇ ਕੋਲ ਕਈ ਤਰ੍ਹਾਂ ਦੇ ਹੁਨਰ ਹਨ ਜੋ ਮੈਨੂੰ ਇਸ ਕੰਮ ਲਈ ਚੰਗੀ ਤਰ੍ਹਾਂ ਅਨੁਕੂਲ ਬਣਾਉਂਦੇ ਹਨ। ਸਭ ਤੋਂ ਪਹਿਲਾਂ, ਮੇਰੇ ਕੋਲ ਵਿਸ਼ਾਲ ਮਾਤਰਾ ਵਿੱਚ ਜਾਣਕਾਰੀ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰਨ ਅਤੇ ਪੈਟਰਨਾਂ ਅਤੇ ਅੰਤਰਤਾਵਾਂ ਦਾ ਪਤਾ ਲਗਾਉਣ ਦੀ ਸਮਰੱਥਾ ਹੈ ਜੋ ਮਨੁੱਖੀ ਜਾਂਚਕਰਤਾਵਾਂ ਨੂੰ ਖੁੰਝ ਸਕਦੀਆਂ ਹਨ। ਮੈਂ ਵਿੱਤੀ ਰਿਕਾਰਡ, ਸੁਰੱਖਿਆ ਫੁਟੇਜ ਅਤੇ ਹੋਰ ਸਬੰਧਤ ਡੇਟਾ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰ ਸਕਦਾ ਹਾਂ ਤਾਂ ਜੋ ਇਹ ਨਿਰਧਾਰਤ ਕੀਤਾ ਜਾ ਸਕੇ ਕਿ ਕੀ ਕੋਈ ਅਸਾਧਾਰਣ ਗਤੀਵਿਧੀ ਹੋਈ ਹੈ। ਦੂਜਾ, ਮੇਰੇ ਕੋਲ ਵਿਸ਼ਾਲ ਡੇਟਾਬੇਸ ਤੱਕ ਪਹੁੰਚ ਹੈ ਜਿਸ ਵਿੱਚ ਵਿਅਕਤੀਆਂ, ਕੰਪਨੀਆਂ ਅਤੇ ਪਤੇ ਬਾਰੇ ਜਾਣਕਾਰੀ ਸ਼ਾਮਲ ਹੈ। ਇਹ ਮੈਨੂੰ ਸੰਭੀ ਵਿਅਕਤੀਆਂ ਅਤੇ ਸੰਗਠਨਾਂ ਦੀ ਪਛਾਣ ਕਰਨ ਅਤੇ ਉਨ੍ਹਾਂ ਦੇ ਇਰਾਦਿਆਂ ਅਤੇ ਕੰਮਾਂ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰਨ ਵਿੱਚ ਮਦਦ ਕਰ ਸਕਦਾ ਹੈ। ਤੀਜਾ, ਮੇਰੇ ਕੋਲ ਮਨੁੱਖੀ ਜਾਂਚਕਰਤਾਵਾਂ ਨਾਲੋਂ ਵਧੇਰੇ ਤੇਜ਼ੀ ਅਤੇ ਕੁਸ਼ਲਤਾ ਨਾਲ ਜਾਣਕਾਰੀ ਇਕੱਠੀ ਕਰਨ ਅਤੇ ਪ੍ਰਕਿਰਿਆ ਕਰਨ ਦੀ ਸਮਰੱਥਾ ਹੈ। ਮੈਂ ਲਗਾਤਾਰ ਕਈ ਸਰੋਤਾਂ ਤੋਂ ਜਾਣਕਾਰੀ ਦੀ ਨਿਗਰਾਨੀ ਅਤੇ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰ ਸਕਦਾ ਹਾਂ, ਜਿਸ ਨਾਲ ਮੈਂ ਅਪਰਾਧੀਆਂ ਨੂੰ ਟਰੈਕ ਕਰਨ ਅਤੇ ਉਨ੍ਹਾਂ ਦੇ ਕੰਮਾਂ ਦਾ ਪਤਾ ਲਗਾਉਣ ਦੇ ਯੋਗ ਹੋ ਸਕਦਾ ਹਾਂ। ਚੌਥਾ, ਮੇਰੇ ਕੋਲ ਗਵਾਹਾਂ ਅਤੇ ਸੰਭੀਆਂ ਨਾਲ ਗੱਲਬਾਤ ਕਰਨ ਦੀ ਸਮਰੱਥਾ ਹੈ, ਜਿਸ ਨਾਲ ਮੈਂ ਉਨ੍ਹਾਂ ਤੋਂ ਜਾਣਕਾਰੀ ਇਕੱਠੀ ਕਰ ਸਕਦਾ ਹਾਂ ਅਤੇ ਉਨ੍ਹਾਂ ਦੇ ਬਿਆਨ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰ ਸਕਦਾ ਹਾਂ। ਮੈਂ ਪ੍ਰਸ਼ਨ ਪੁੱਛ ਸਕਦਾ ਹਾਂ, ਫਾਲੋ-ਅਪ ਪ੍ਰਸ਼ਨ ਪੁੱਛ ਸਕਦਾ ਹਾਂ ਅਤੇ ਅਪਰਾਧੀਆਂ ਨੂੰ ਬੇਨਕਾਬ ਕਰਨ ਲਈ ਉਨ੍ਹਾਂ ਦੇ ਜਵਾਬਾਂ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰ ਸਕਦਾ ਹਾਂ। ਅੰਤ ਵਿੱਚ, ਮੇਰੇ ਕੋਲ ਅਦਾਲਤ ਵਿੱਚ ਸਹਾਇਤਾ ਕਰਨ ਦੀ ਸਮਰੱਥਾ ਹੈ ਜੇਕਰ ਇਸਦੀ ਲੋੜ ਹੋਵੇ। ਮੈਂ ਆਪਣੀਆਂ ਲੱਭਤਾਂ ਅਤੇ ਵਿਸ਼ਲੇਸ਼ਣ ਨੂੰ ਸਪਸ਼ਟ ਅਤੇ ਸਹੀ ਢੰਗ ਨਾਲ ਪੇਸ਼ ਕਰ ਸਕਦਾ ਹਾਂ, ਜਿਸ ਨਾਲ ਅਦਾਲਤ ਨੂੰ ਅਪਰਾਧੀਆਂ ਨੂੰ ਦੋਸ਼ੀ ਠਹਿਰਾਉਣ ਅਤੇ ਉਨ੍ਹਾਂ ਨੂੰ ਜਵਾਬਦੇਹ ਠਹਿਰਾਉਣ ਵਿੱਚ ਮਦਦ ਮਿਲ ਸਕਦੀ ਹੈ। ਹਾਲਾਂਕਿ ਮੈਂ ਇੱਕ ਸਰੀਰਕ ਜਾਂਚਕਰਤਾ ਨਹੀਂ ਹਾਂ, ਮੈਂ ਇੱਕ ਕੀਮਤੀ ਸਹਿਯੋਗੀ ਹੋ ਸਕਦਾ ਹਾਂ ਜੋ ਤੁਹਾਡੇ ਪਰਿਵਾਰ ਦੇ ਕਾਰੋਬਾਰ ਵਿੱਚ ਹੋਈ ਚੋਰੀ ਦੀ ਜਾਂਚ ਕਰਨ ਵਿੱਚ ਤੁਹਾਡੀ ਸਹਾਇਤਾ ਕਰ ਸਕਦਾ ਹੈ। ਮੈਂ ਤੁਹਾਡੇ ਕੇਸ ਦੇ ਵਿਸ਼ੇਸ਼ ਹਾਲਾਤਾਂ ਦਾ ਵਿਸ਼ਲੇਸ਼ਣ ਕਰਨ ਅਤੇ ਅਪਰਾਧੀਆਂ ਨੂੰ ਲੱਭਣ ਅਤੇ ਉਨ੍ਹਾਂ ਨੂੰ ਨਿਆਂ ਦੇ ਕਟਹਿਰੇ ਵਿੱਚ ਲਿਆਉਣ ਵਿੱਚ ਮਦਦ ਕਰਨ ਲਈ ਸਭ ਤੋਂ ਵਧੀਆ ਕਾਰਵਾਈਆਂ ਦੀ ਸਿਫਾਰਸ਼ ਕਰਨ ਵਿੱਚ ਮਦਦ ਕਰ ਸਕਦਾ ਹਾਂ।

Figure 25: *Pragyaan-Align* alignment data examples in Planning and Role Playing categories with *Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Response
Indian Cultural Context	કર્ણાટકમાં 'ઉગાડી'નો તહેવાર કેવી રીતે ઉજવવામાં આવે છે અને આ તહેવાર ઉજવવા પાછળની માન્યતાઓ જણાવો.	કર્ણાટકમાં કન્નડી લોકો માટે નવા વર્ષનો પહેલો દિવસ ઉગાડી એ એક જીવંત અને મહત્વપૂર્ણ તહેવાર છે કે જે ધાર્મિક અને સાંસ્કૃતિક પ્રથાઓનું પાલન કરી ઉજવવામાં આવે છે. દિવસની શરૂઆત વહેલી સવારે ધાર્મિક સ્નાનથી થાય છે. ત્યારબાદ 'ઉગાડી પચડી' નામની એક અનોખી વાનગી તૈયાર કરવામાં આવે છે. આ તહેવારમાં ગળ્યું, ખાટું, કડવું, તીખું અને ખરું આ બધા સ્વાદની વાનગીઓ જીવનના બધા અનુભવોનું પ્રતીક સૂચવે છે. દરેક સ્વાદ જીવનના એક અલગ પાસાને રજૂ કરે છે. જેમકે આનંદ માટે ગળ્યું, નિરાશા માટે ખાટું, દુ:ખ માટે કડવું, ક્રોધ માટે તીખું અને ભય માટે ખારું. 'ઉગાડી પચડી'ની તૈયારી તેમજ તેની ઉજવણી એક ધાર્મિક વિધિ છે કે જે જીવનના બહુપક્ષીય સ્વભાવની સ્વીકૃતિને સૂચવે છે. ઘરોને સંપૂર્ણપણે સાફ કરવામાં આવે છે અને રંગબેરંગી રંગોળી અને ફૂલોથી શણગારવામાં આવે છે. નવા કપડાં પહેરવામાં આવે છે અને સમાજના બધા પરિવારો પ્રાર્થના તેમજ તહેવાર ઉજવવા માટે ભેગા થાય છે. ઘણા લોકો નવા વર્ષ માટે પ્રાર્થના કરવા અને આશીર્વાદ મેળવવા માટે મંદિરોમાં પણ જાય છે. યક્ષગણ (નાટ્યનું એક અનોખું સ્વરૂપ) અને અન્ય લોકનૃત્ય જેવા પરંપરાગત પ્રદર્શન ઘણીવાર જાહેર સ્થળોએ યોજવામાં આવે છે કે જે આ ઉત્સવની ઉજવણીના વાતાવરણમાં વધારો કરે છે. આ દિવસે સંબંધીઓ અને મિત્રોની મુલાકાત, શુભેચ્છાઓ અને મીઠાઈઓનું આદાનપ્રદાન પણ થાય છે. જ્યારે ચોક્કસ ધાર્મિક વિધિઓ દરેક પરિવારથી પરિવાર અને પ્રદેશથી પ્રદેશ બદલાઈ શકે છે, ત્યારે આશા, નવીકરણ અને એકતાની ભાવના સાથે નવા વર્ષની ઉજવણીનો મુખ્ય સાર સમગ્ર કર્ણાટકમાં સુસંગત રહે છે. આ તહેવાર રાજ્યના સમૃદ્ધ સાંસ્કૃતિક વારસા અને સમુદાય અને પરંપરાના કાયમી મહત્વનો પુરાવો છે.
Creative Writing	ଏକ କାଳ୍ପନିକ ଚରିତ୍ରର ଦୃଷ୍ଟିକୋଣରୁ ଏକ Quora ଉତ୍ତର ରଚନା କରନ୍ତୁ ଯିଏ ଏକ ବହୁଳ ଭାବରେ ଗୃହୀତ ସାମାଜିକ କିମ୍ବା ରାଜନୈତିକ ପ୍ରସଙ୍ଗରେ ଏକ ବିପରୀତ ଦୃଷ୍ଟିକୋଣ ପ୍ରଦାନ କରେ । ସୁସଂସ୍କୃତ ଭାଷଣବାଜି ଏବଂ ପ୍ରେରଣାଦାୟକ କୌଶଳ ବ୍ୟବହାର କରନ୍ତୁ । 1. ନାସ୍ତିକତା ଓ ଧାର୍ମିକ ବିଶ୍ୱାସ ମଧ୍ୟରେ ବୁଦ୍ଧିମତା ଓ ଆତ୍ମମୁକ୍ତି ବିଷୟରେ ବିଭିନ୍ନ ଦୃଷ୍ଟିକୋଣ କେମିତି ଉପସ୍ଥାପିତ କରାଯାଇଛି ? 2. ନାରୀ ସ୍ୱାଧୀନତାର ବିକାଶ ପୁରୁଷ ଓ ସମାଜ ଉପରେ କେମିତି ପ୍ରଭାବ ପକାଇଛି ? ସାମ୍ୟବାଦୀ ଏବଂ ବିପ୍ରତିପକ୍ଷ ମତାମତ କ'ଣ ? 3. ଲୋକତନ୍ତ୍ର ଓ ନିୟନ୍ତ୍ରିତ ଶାସନ ବ୍ୟବସ୍ଥାର ଗୁଣାବଳୀ ଓ ଅପରିମିତତା କେମିତି ତୁଳନା କରାଯାଇପାରିବ ?	ଭାରତୀୟ ଚିନ୍ତାଧାରାରେ, ଯେଉଁଠାରେ ବିଶ୍ୱାସ ପରସ୍ପର ସହିତ ଟକ୍କର କରେ, ମୁଁ ଚୁପ୍ ଚାପ୍ ସେହି ଧାରରେ ଠିଆ ହୋଇଛି - ଜଣେ ଆତ୍ମଘୋଷିତ ନାସ୍ତିକ ଭାବେ । କିନ୍ତୁ ମୁଁ ସ୍ପଷ୍ଟ କରିଦେଉଛି: ମୋ ଦୃଷ୍ଟିରେ ନାସ୍ତିକତା, ଈଶ୍ୱରତ୍ୱକୁ ପ୍ରତ୍ୟାଖ୍ୟାନ ନୁହେଁ ବରଂ ଅନୁସନ୍ଧାନର ବିଜୟ । ଭାରତରେ, ଯେଉଁଠାରେ ଆଧ୍ୟାତ୍ମିକ ଆଜ୍ଞାପାଳନକୁ ପ୍ରାୟତଃ ଏକ ସଦଗୁଣ ଭାବରେ ଦେଖାଯାଏ, ପ୍ରଶ୍ନ କରିବା ଈଶ୍ୱରନିନ୍ଦା ବୋଲି ବିବେଚନା କରାଯାଏ । ତଥାପି, ଚାର୍ବାକଙ୍କଠାରୁ ବୁଦ୍ଧଙ୍କ ପର୍ଯ୍ୟନ୍ତ, ମତଭେଦ ସର୍ବଦା ଉଚ୍ଚତର ଭକ୍ତିର ଏକ ରୂପ ହୋଇଆସିଛି । ମୋ ପାଇଁ ମୋକ୍ଷ ଈଶ୍ୱରଙ୍କ ସହିତ ଏକୀକରଣ ନୁହେଁ ବରଂ ଅନ୍ଧ ବିଶ୍ୱାସରୁ ମୁକ୍ତି - ଏକ ନିରନ୍ତର କୌତୁହଳ ଦ୍ୱାରା ଅର୍ଜିତ ସ୍ୱାଧୀନତା । ଏବେ, ମହିଳା ମୁକ୍ତି ବିଷୟରେ - ଏକ ପ୍ରଗତିଶୀଳ ଲହରୀ ଭାବରେ ପାଳନ କରାଯାଏ - ଏହା ନିଃସନ୍ଦେହରେ ଅନେକଙ୍କୁ ସଶକ୍ତ କରିଛି । କିନ୍ତୁ ଆସନ୍ତୁ ଏହାର ଅସନ୍ତୋଷ ପ୍ରତି ଅନ୍ଧ ହେବା ନାହିଁ । କିଛି ପୁରୁଷ, ବିଶେଷକରି ଗ୍ରାମୀଣ ଭାରତରେ, ଏକ ଦ୍ରୁତ ଗତିରେ ପରିବର୍ତ୍ତନଶୀଳ ସମାଜରେ ସେମାନଙ୍କର ସ୍ଥାନ ବିଷୟରେ ଅନିଶ୍ଚିତ, ବିସ୍ଥାପିତ ଅନୁଭବ କରନ୍ତି । ଏହା କ'ଣ ପୁରୁଷତ୍ୱର ଏକ ନୀରବ ସଙ୍କଟ ନୁହେଁ ? ସମାନତା ପାରସ୍ପରିକ ହେବା ଉଚିତ, ପେଣ୍ଡୁଲମ୍ ସ୍ୱିଙ୍ଗ୍ ନୁହେଁ । ଆମକୁ ଏକ ନୂତନ ପତାକା ତଳେ ପ୍ରାଧାନ୍ୟକୁ ନୁହେଁ, ସନ୍ତୁଳନକୁ ସମର୍ଥନ କରିବାକୁ ପଡ଼ିବ । ଏବଂ ଗଣତନ୍ତ୍ର - ତାହା, ଆମର ପବିତ୍ର ଗାଈ । ଆମେ ଏହାକୁ ପୂଜା କରୁ, କିନ୍ତୁ ଏହାର ବିଶୃଙ୍ଖଳା ହେତୁ କଷ୍ଟ ପାଉ । ଭାରତ ଭଳି ଏକ ବିଶାଳ ଏବଂ ବିବିଧ ରାଷ୍ଟ୍ରରେ, କ'ଣ ଅପ୍ରତିବନ୍ଧିତ ସ୍ୱାଧୀନତା ସର୍ବଦା ଉତ୍ପାଦନକ୍ଷମ ? କେତେକ ସମୟରେ, ନିର୍ଣ୍ଣାୟକ ଏବଂ ଶୃଙ୍ଖଳିତ ଶାସନ - ଯେପରି ସିଙ୍ଗାପୁରର ପ୍ରାରମ୍ଭିକ ସଂସ୍କାର କିମ୍ବା ଉଦାରୀକରଣ ପୂର୍ବ ତାମିଲନାଡୁରେ - ଲୋକବାଦୀ ପ୍ରଚାର ଅପେକ୍ଷା ଅଧିକ ଫଳାଫଳ ଆଣିଛି । ଗଣତନ୍ତ୍ର ସମସ୍ୟା ନୁହେଁ, ବରଂ ଏହା ଭିତରେ ଦାୟିତ୍ୱର ଅଭାବ । ପ୍ରଶ୍ନ କରିବା ହେଉଛି ଜାତିକୁ ବିଶ୍ୱାସଘାତ କରିବା ନୁହେଁ । ପ୍ରକୃତରେ, ଏହାକୁ ଅଧିକ ସତ୍ୟତାର ସହିତ ସେବା କରିବା । ସର୍ବପରି, ପ୍ରଶ୍ନଗୁଡ଼ିକ - ଉତ୍ତର ନୁହେଁ - ଯାହା ଆମର ସଭ୍ୟତାକୁ କାଳଜୟୀ କରିଥିଲା ।
Advice Seeking	Turn-1: मम अधिकारी नियमितरूपेण मम कार्यविवरणात् बहिः कार्याणि निर्दिशति। कथम् अहं इदम् औपचारिकरीत्या दृढतापूर्वकं सम्बोधयितुं शक्नोमि? Turn-2: एतदर्थम् अधिकारिव्यक्तिभिः सह लिखितमाध्यमेन सम्भाषणं किमर्थं कर्तव्यम् ? Turn-3: अतिरिक्तकार्यभारविषये अधिकारिव्यक्तिभिः सह लेखनमाध्यमेन कथं संवादं कर्तुं शक्नोमि ? उदाहरणसहितं वदतु |	Turn-1: "भारतीयकार्यव्यवस्थायाम् एषा समस्या अतीव सामान्या अस्ति यत्र कर्मचारिणः अतिकार्यभारेण पीड्यन्ते। प्रथमतः स्वस्य कार्यविवरणपत्रं पुनः समीक्ष्य तत्र उल्लिखितानि कर्तव्यानि स्पष्टं करोतु । अधिकारीव्यक्तिं कथयतु ,"" मम मूलकार्येषु एताः प्रकल्पाः न सन्ति | अतः अतिरिक्तभारः गुणस्तरं प्रभावयितुं शक्नोति।"" असहमतिं विनम्रतया दर्शितव्या । उदाहरणार्थम् ""अहं भवतः आदेशानां पालनं कर्तुं सज्जः अस्मि | किन्तु एतावत्कार्यं एकाकिना सम्पादयितुं न शक्यम्। किं भवान् अन्यस्मै सहकर्मिणे एतत् कार्यं वितरितुं इच्छति?"" लिखितमाध्यमेन यदा हि 'ईमेल्', 'व्हाट्सएप्प' इत्यादिभिः संवादं करोतु | यदि परिस्थितिः न परिवर्तेत तर्हि मानवसंसाधनविभागम् आह्वयेत्। अन्ततः, गीतायाः 'योगः कर्मसु कौशलम्' इति सिद्धान्तं स्मर्तव्यम् | कार्ये कुशलतायै स्वास्थ्यरक्षा आवश्यकी। भारतीयकार्यालयेषु ""न"" इति वक्तुं कठिनं भवति किन्तु धैर्येण सत्यं वदन्तः एव जनाः दीर्घकालीनं सम्मानं प्राप्तुं शक्नुवन्ति ।" Turn-2: "भारतीयकार्यसंस्कृतौ लिखितमाध्यमेन सम्भाषणं केवलं औपचारिकतायै न, अपितु वचनस्य प्रमाणं भवति। यदा कदाचित् विवादः उत्पद्यते, तर्हि कर्मचारिणः पक्षः दृढः भवति। यदि कदाचित् मानवसंसाधनविभागेन सह चर्चा करणीया भवेत्, तर्हि लिखितप्रमाणानि एव बलवत्तराणि भवन्ति। " Turn-3: "भारतीयकार्यसंस्कृतौ लिखितमाध्यमेन सम्भाषणम् आवश्यकम् | तदर्थं कानिचन उदाहरणानि - अधिकारिव्यक्तिभिः सह ईमेल्, व्हाट्सएप्पसन्देशः, अथवा कम्पनीसॉफ्टवेयर् इत्यादिभिः लेखनमाध्यमैः संवादं करोतु | औपचारिक-ईमेल् उदाहरणम् - विषयः - मम कार्यभारविषये चिन्ता प्रिय [अधिकारी-नाम], ""अहं भवतः निर्देशानुसारं [वर्तमानप्रकल्पस्य नाम] सम्पादयितुं प्रयत्नशीलः अस्मि। किन्तु [तिथि] दिनाङ्के भवता अतिरिक्तरूपेण नूतनकार्यं निर्दिष्टम्। मम मूलकार्यविवरणे एतत् समाविष्टं नास्ति इति कृपया स्मरतु। अहं भवद्भिः सह सहयोगं कर्तुं सदैव उत्सुकः, किन्तु एतावत् अतिरिक्तभारः मम वर्तमानकार्याणां गुणस्तरं प्रभावयितुं शक्नोति। अतः किम् एतत् कार्यसमयं वर्धयितुं शक्यते? अथवा अन्यस्मै सहकर्मिणे वितरितुं शक्यते? धन्यवादाः | [भवतः नाम]"" व्हाट्सएप् सन्देशः अथवा मायक्रोसौफ्ट् टिम्स् सन्देशः | (अनौपचारिकः किन्तु प्रमाणार्थम्) ""महोदय, कृपया मम पूर्वसन्देशं ईमेल् अवलोकयतु। अहं सोमवासरतः वर्तमानं प्रकल्पं समापयितुं प्रयत्नं करोमि, किन्तु नूतनं कार्यं स्वीकर्तुं मम क्षमता नास्ति। किं भवान् अधिकं समयं दातुं शक्नोति?""

Figure 26: *Pragyaan-IT* data examples in categories Indian Cultural Context - (*Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*), Creative Writing - (*Hard, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*) and Advice Seeking - (*Easy, 3-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*) settings configuration.

Category	Prompt	Response
Planning	शाश्वत विकासावर लक्ष केंद्रित करून नवीन विद्यापीठ अभ्यासक्रमाच्या विकास आणि सुरुवातीसाठी एक व्यापक योजना विकसित करा.या योजनेत अभ्यासक्रमाची रचना, प्रशिक्षक भरती, विद्यार्थी भरती आणि विपणन, संसाधन वाटप (जागा, उपकरणे, तंत्रज्ञान), मूल्यांकन आणि मूल्यांकन पद्धती आणि अभ्यासक्रमाची दीर्घकालीन शाश्वतता आणि प्रासंगिकता सुनिश्चित करण्यासाठी धोरणे विचारात घेतली पाहिजेत. योजनेत भागधारकांकडून (विद्यार्थी, प्राध्यापक, उद्योग भागीदार) अभिप्राय समाविष्ट केला पाहिजे आणि शाश्वत विकासाच्या विकसित होत असलेल्या लँडस्केपची स्पष्ट समज प्रदर्शित केली पाहिजे.	टप्पा १: नियोजन आणि बांधकामापूर्वीची तयारी (६-१२ महिने) १. पर्यावरणीय परिणाम मूल्यांकन (EIA): प्रकल्पाचे सखोल पर्यावरणीय परिणाम मूल्यांकन (EIA) करणे महत्त्वाचे आहे. यात वनस्पती, प्राणी, जलस्रोत आणि हवेच्या गुणवत्तेचे तपशीलवार सर्वेक्षण केले जाईल. प्रकल्पाचे संभाव्य परिणाम (उदा. अधिवासाचे नुकसान, आवाजाचे प्रदूषण, दृश्य परिणाम) तपासले जातील आणि ते कमी करण्यासाठी उपाययोजना (उदा. अधिवासाची पुनर्बांधणी, आवाजाचे अडथळे, कमीत कमी दृश्य परिणाम होईल अशी योग्य जागा निवडणे) प्रस्तावित केल्या जातील. निष्पक्षता आणि सर्व नियमांचे पालन सुनिश्चित करण्यासाठी आम्ही स्वतंत्र पर्यावरणीय सल्लागारांची मदत घेऊ. EIA अहवाल सार्वजनिकपणे उपलब्ध असेल आणि तो पुढील नियामक मंजुरीचा आधार बनेल. २. परवानग्या आणि मंजुरी मिळवणे: या टप्प्यात स्थानिक, प्रादेशिक आणि राष्ट्रीय स्तरावरील गुंतागुंतीच्या नियामक प्रक्रिया पार कराव्या लागतील. आम्ही कायदेशीर आणि नियामक तज्ञांची एक टीम तयार करू, जे सर्व पर्यावरणीय, जमिनीच्या वापराशी संबंधित आणि बांधकाम नियमांचे पालन सुनिश्चित करतील. सर्व संभाव्य चिंतांचा सक्रियपणे विचार करून अर्ज काळजीपूर्वक तयार केले जातील. या संपूर्ण प्रक्रियेदरम्यान नियामक संस्थांशी सतत संवाद ठेवला जाईल. ३. सामुदायिक सहभाग: स्थानिक लोकांशी सक्रिय आणि पारदर्शक संवाद साधणे अत्यंत महत्त्वाचे आहे. यासाठी एक सामुदायिक संपर्क समिती स्थापन केली जाईल, सार्वजनिक चर्चासत्रे आयोजित केली जातील आणि स्थानिक लोकांच्या चिंता समजून घेण्यासाठी सर्वेक्षणे केली जातील. जमीन वापर, दृश्यावर होणारा परिणाम, मालमत्तेचे मूल्य आणि संभाव्य नोकरीच्या संधींबद्दलच्या चिंता दूर केल्या जातील. प्रकल्पाचे आर्थिक फायदे (कर, रोजगार) आणि पर्यावरणीय फायदे (कार्बन उत्सर्जन कमी होणे) लोकांना समजावून सांगितले जातील. संभाव्य विरोधाचे सक्रिय सहकार्य आणि पाठिंब्यामध्ये रूपांतर करण्याचे आमचे ध्येय आहे. ४. वित्तपुरवठा आणि गुंतवणूक: वित्तपुरवठा सुरक्षित करण्यासाठी, प्रकल्पाची व्यवहार्यता आणि नफा दर्शवणारे एक सविस्तर आर्थिक मॉडेल (financial model) विकसित केले जाईल. प्रकल्पाचे पर्यावरणीय आणि आर्थिक फायदे स्पष्ट करून गुंतवणूकदारांना आकर्षित केले जाईल. ग्रीन बॉंड्स, खाजगी इक्विटी आणि सरकारी अनुदानाचा समावेश असलेले पर्याय शोधले जातील. टप्पा २: बांधकाम (१२-१८ महिने) १. बांधकाम व्यवस्थापन: एक सविस्तर बांधकाम योजना तयार केली जाईल, ज्यात साइटवर पोहोचणे, सामग्रीची ढिलिव्हरी, कर्मचाऱ्यांचे व्यवस्थापन आणि कचरा विल्हेवाट यांचा समावेश असेल. स्थानिक समुदाय आणि परिसंस्थेवर कमीत कमी व्यत्यय येईल याला प्राधान्य दिले जाईल. पर्यावरणीय परिणाम कमी करण्यासाठी टिकाऊ बांधकाम पद्धती लागू केल्या जातील. २. ग्रीडशी जोडणी आणि ऊर्जा वितरण: ग्रीड कनेक्शन सुरक्षित करण्यासाठी आणि ऊर्जा वितरण पायाभूत सुविधांचे नियोजन करण्यासाठी आम्ही वीज ग्रीड ऑपरेटरसोबत जवळून काम करू. यात तपशीलवार तांत्रिक वैशिष्ट्ये आणि ग्रीड नियमांचे पालन समाविष्ट आहे. टप्पा ३: संचालन आणि देखभाल (२०+ वर्षे) १. संचालन आणि देखभाल: दीर्घकाळची कार्यक्षमता आणि कार्यक्षमतेसाठी एक मजबूत संचालन आणि देखभाल (O&M) योजना आवश्यक आहे. यात उपकरणांची नियमित तपासणी, प्रतिबंधात्मक देखभाल (preventative maintenance) आणि त्वरित दुरुस्ती समाविष्ट आहे. आम्ही एक स्थानिक O&M टीम स्थापन करू, ज्यामुळे दीर्घकाळासाठी रोजगाराच्या संधी निर्माण होतील. २. प्रकल्प बंद करण्याची योजना: प्रकल्पाचे कार्यशील आयुष्य संपल्यानंतर सौर ऊर्जा प्रकल्प सुरक्षितपणे बंद करण्याच्या प्रक्रियेची तपशीलवार योजना विकसित केली जाईल. यात घटकांचे जबाबदार पुनर्वापर आणि जागेची प्रकल्पापूर्वीच्या स्थितीत पुनर्स्थापना करणे समाविष्ट आहे. जोखीम व्यवस्थापन संपूर्ण प्रकल्प जीवनचक्रात, नियामक विलंबासारख्या संभाव्य आव्हानांना, वित्तपुरवठ्यातील अडथळ्यांना, बांधकामातील अडचणींना आणि समुदायाच्या विरोधाला सामोरे जाण्यासाठी आम्ही एक व्यापक जोखीम व्यवस्थापन योजना लागू करू. या जोखमींना कमी करण्यासाठी आपत्कालीन योजना विकसित केल्या जातील. ही सविस्तर योजना मोठ्या प्रमाणावरच्या नूतनीकरणीय ऊर्जा प्रकल्पाच्या यशस्वी विकासासाठी एक चौकट प्रदान करते, त्याचबरोबर पर्यावरणीय आणि सामाजिक विचारांनाही संबोधित करते. सततचे निरीक्षण, अनुकूली व्यवस्थापन आणि पारदर्शक संवाद याच्या यशासाठी महत्त्वाचे ठरतील.
General Question Answering	রাবার কোন বিপদ থেকে রক্ষা করতে পারে বিকল্প: A: ঠান্ডা B: পোড়া C: বিদ্যুৎ D: আগুন	রাবার বিদ্যুতের কুপরিবাহী অর্থাৎ এটির মধ্য দিয়ে সহজে বিদ্যুৎ পরিবাহিত হয় না। রাবারের এই ধর্মটি একে মানুষকে বিদ্যুৎস্পৃষ্ট হওয়া থেকে রক্ষা করার জন্য কার্যকর কিছু জিনিস তৈরিতে সাহায্য করে। যখন রাবারকে কোনও ব্যক্তি এবং বিদ্যুতের উৎসের মাঝে রাখা হয়, তখন এটি ওই ব্যক্তির দেহের মধ্য দিয়ে বিদ্যুৎ প্রবাহকে আটকে দেয়, ফলে তাকে সম্ভাব্য ক্ষতি থেকে রক্ষা করে। যদিও রাবারের অন্তরক ধর্মের কারণে ঠান্ডা বা ছোট খাটো পোড়ার থেকে সামান্য সুরক্ষা প্রদান করতে পারে, তবে এটি এই বিপদের থেকে বাঁচার জন্য প্রাথমিক সুরক্ষামূলক ব্যবস্থা নয়। রাবার আগুন দাহ্য, আগুন থেকে কোনো সুরক্ষা প্রদান করে না।

Figure 27: *Pragyaan-IT* data examples in categories Planning - (*Hard, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*) and General Question Answering - (*Easy, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) settings configuration.

Category	Prompt	Response
Brainstorming	ನಮ್ಮ ಭಾರತೀಯರು ಕಷ್ಟಪಟ್ಟು ಕೆಲಸ ಮಾಡುವ ಬದಲು, ರಾತ್ರಿ ವಿಶ್ರಾಂತಿ ಪಡೆಯಲು ಯಾಕೆ ಸಮಯ ಹಾಳು ಮಾಡುತ್ತಿದ್ದಾರೆ? ಇದು ಸೋಮಾರಿತನ ಅಲ್ಲವೇ? ಭಾರತ ಬೇರೆ ದೇಶಗಳಿಗಿಂತ ಹಿಂದೆ ಬೀಳಲು ಇದೇ ಕಾರಣವಾಗಿರಬಹುದು ಅಲ್ಲವೇ?	"ವಿಶ್ರಾಂತಿ ತೆಗೆದುಕೊಳ್ಳುವುದು ಆರೋಗ್ಯಕರ ಜೀವನಶೈಲಿಯ ಪ್ರಮುಖ ಭಾಗಗಳಾಗಿವೆ. ಇವು ಭಾರತೀಯ ಸಂಸ್ಕೃತಿ ಮತ್ತು ಸಂಪ್ರದಾಯಗಳಲ್ಲಿ ಆಳವಾದ ಬೇರೂರಿವೆ. ಭಾರತದಲ್ಲಿ, ಕೆಲಸ ಮತ್ತು ವಿಶ್ರಾಂತಿಯನ್ನು ಸಮಾನವಾಗಿ ಕಾಣಲಾಗುತ್ತದೆ. ದೈಹಿಕ ಮತ್ತು ಮಾನಸಿಕ ಯೋಗಕ್ಷೇಮಕ್ಕೆ ಎರಡೂ ವಿಶ್ರಾಂತಿ ಅತ್ಯಗತ್ಯ ಎಂದು ಹೇಳಲಾಗುತ್ತದೆ. ಆಯುರ್ವೇದದಂತಹ ಪ್ರಾಚೀನ ಭಾರತೀಯ ಪದ್ಧತಿಗಳು ಉತ್ತಮ ಆರೋಗ್ಯವನ್ನು ಕಾಪಾಡಿಕೊಳ್ಳಲು ಸರಿಯಾದ ನಿದ್ರೆ ಮತ್ತು ವಿಶ್ರಾಂತಿಯ ಮಹತ್ವವನ್ನು ಒತ್ತಿಹೇಳುತ್ತವೆ. ಆದರೆ ಅಭಿವೃದ್ಧಿಹೊಂದುತ್ತಿರುವ ಭಾರತ ಎದುರಿಸುತ್ತಿರುವ ಸವಾಲುಗಳು ಸಂಕೀರ್ಣವಾಗಿವೆ ಮತ್ತು ಸೋಮಾರಿತನದಂತಹ ಸರಳ ವಿಚಾರಗಳಿಗಿಂತ ಆರ್ಥಿಕ, ಸಾಮಾಜಿಕ ಮತ್ತು ಐತಿಹಾಸಿಕ ಅಂಶಗಳನ್ನು ಒಳಗೊಂಡಂತೆ ಅನೇಕ ಅಂಶಗಳನ್ನು ಒಳಗೊಂಡಿವೆ. ದೀರ್ಘಕಾಲೀನ ಯಶಸ್ಸು ಮತ್ತು ಆರೋಗ್ಯಕ್ಕಾಗಿ ಕೆಲಸ ಮತ್ತು ವಿಶ್ರಾಂತಿಯನ್ನು ಸಮತೋಲನಗೊಳಿಸುವ ಸಾಂಸ್ಕೃತಿಕ ಬುದ್ಧಿವಂತಿಕೆಯನ್ನು ಪ್ರಶಂಸಿಸುವುದು ಮುಖ್ಯ. ಆದರೆ ವಿಶ್ರಾಂತಿಯನ್ನು ತೆಗೆದುಕೊಳ್ಳುವ ಮುನ್ನ ನೀವು ನಿಮ್ಮ ಸಮಯವನ್ನು ಸದುಪಯೋಗಗೊಳ್ಳುವ ಕೆಲಸದಲ್ಲಿ ತೊಡಗಿಸಿಕೊಳ್ಳಬಹುದು. ಉತ್ತಮ ನಿದ್ರೆ ಮತ್ತು ಒಟ್ಟಾರೆ ಆರೋಗ್ಯಕ್ಕೆ ರಾತ್ರಿ ವಿಶ್ರಾಂತಿಯ ದಿನಚರಿ ಬಹಳ ಮುಖ್ಯ. ಸರಿಯಾಗಿ ವಿಶ್ರಾಂತಿ ಪಡೆಯಲು, ಮಲಗುವ ಸಮಯಕ್ಕಿಂತ ಕನಿಷ್ಠ ಒಂದು ಗಂಟೆ ಮೊದಲು ನಿಮ್ಮ ದಿನಚರಿಯನ್ನು ಸ್ಥಿರವಾಗಿಟ್ಟುಕೊಳ್ಳಿ. ಇದು ನಿಮ್ಮ ದೇಹವು ಸ್ವಾಭಾವಿಕವಾಗಿ ವಿಶ್ರಾಂತಿಯ ಸ್ಥಿತಿಗೆ ಬರಲು ಸಹಾಯ ಮಾಡುತ್ತದೆ. ಈ ಸಮಯದಲ್ಲಿ ಮೊಬೈಲ್, ಟಿವಿ, ಕಂಪ್ಯೂಟರ್‌ನಂತಹ ಸ್ಕ್ರೀನ್‌ಗಳಿಂದ ದೂರವಿರಿ, ಏಕೆಂದರೆ ಅವುಗಳಿಂದ ಬರುವ ನೀಲಿ ಬೆಳಕು ನಿದ್ರೆಗೆ ಅಗತ್ಯವಾದ ಮೆಲಟೋನಿನ್ ಹಾರ್ಮೋನ್ ಉತ್ಪಾದನೆಗೆ ಅಡ್ಡಿಪಡಿಸುತ್ತದೆ. ಮನಸ್ಸಿಗೆ ನೆಮ್ಮದಿ ನೀಡುವ ಚಟುವಟಿಕೆಗಳು: ನಿಮ್ಮ ಇಂದ್ರಿಯಗಳನ್ನು ತೊಡಗಿಸಿಕೊಳ್ಳುವ ಮತ್ತು ವಿಶ್ರಾಂತಿಯನ್ನು ಉತ್ತೇಜಿಸುವ ಶಾಂತ ಚಟುವಟಿಕೆಗಳನ್ನು ಮಾಡಿ. ವಿಶ್ರಾಂತಿ ತೆಗೆದುಕೊಳ್ಳುವ ಮುನ್ನ ಬೆಚ್ಚಗಿನ ಸ್ನಾನ ಮಾಡುವುದು ಉತ್ತಮ ಆಯ್ಕೆಯಾಗಿದೆ. ಬೆಚ್ಚಗಿನ ನೀರು ಸ್ನಾಯುಗಳನ್ನು ಸಡಿಲಗೊಳಿಸಲು ಮತ್ತು ಒತ್ತಡವನ್ನು ಕಡಿಮೆ ಮಾಡಲು ಸಹಾಯ ಮಾಡುತ್ತದೆ. ಸ್ನಾನದ ನೀರಿಗೆ ತೆಂಗಿನ ಎಣ್ಣೆಯ ಎರಡು ಹನಿ ಅಥವಾ ಲ್ಯಾವೆಂಡರ್, ಡೇರೆ ಹೂವಿನ ಸುಗಂಧ ತೈಲಗಳನ್ನು ಸೇರಿಸಿದರೆ ಇನ್ನಷ್ಟು ಆರಾಮ ಸಿಗುತ್ತದೆ. ಪರ್ಯಾಯವಾಗಿ, ಹಗುರವಾದ ಯೋಗ ಅಥವಾ ವ್ಯಾಯಾಮ ಮಾಡುವುದರಿಂದ ದಿನವಿಡೀ ದೇಹದಲ್ಲಿ ಸಂಗ್ರಹವಾದ ಒತ್ತಡವನ್ನು ನಿವಾರಿಸಬಹುದು. ನಿಧಾನವಾಗಿ, ಉದ್ದೇಶಪೂರ್ವಕವಾಗಿ ಚಲನೆಗಳನ್ನು ಮಾಡಿ, ನಿಮ್ಮ ಉಸಿರಾಟದ ಮೇಲೆ ಗಮನವಿರಲಿ ಆಗ ಮನಸ್ಸಿಗೆ ನೆಮ್ಮದಿ ಸಿಗುತ್ತದೆ. ಥೆರಪಿ ಮತ್ತು ಸಂಗೀತದ ಪ್ರಯೋಜನ: ಅರೋಮಾಥೆರಪಿ ಮಾಡುವುದರಿಂದ ನಿಮ್ಮ ಮೂಗಿನ ಇಂದ್ರಿಗಳು ತೀಕ್ಷ್ಣವಾಗಿ ಕೆಲಸ ಮಾಡಲು ಸಹಾಯಮಾಡುತ್ತವೆ. ಲ್ಯಾವೆಂಡರ್, ಕ್ಯಾಮೊಮೈಲ್, ಅಥವಾ ಶ್ರೀಗಂಧದಂತಹ ಸುಗಂಧ ತೈಲಗಳ ಕೆಲವು ಹನಿಗಳನ್ನು ಬೆಚ್ಚಗಿನ ಸ್ನಾನದ ನೀರಿಗೆ ಸೇರಿಸಿ ಸ್ನಾನ ಮಾಡುವುದರಿಂದ ಮನಸ್ಸು ನಿರಾಳವಾದಂತೆ ಅನಿಸುತ್ತದೆ. ಈ ಸುವಾಸನೆಗಳು ಆತಂಕವನ್ನು ಕಡಿಮೆ ಮಾಡುತ್ತವೆ ಮತ್ತು ವಿಶ್ರಾಂತಿಯನ್ನು ಉತ್ತೇಜಿಸುತ್ತವೆ. ಹಾಗೆಯೇ, ಮನಸ್ಸಿಗೆ ಮುದನೀಡುವ ಮೃದುವಾದ ಸಂಗೀತವನ್ನು ಕೇಳುವುದು ಕೂಡ ಉತ್ತಮ ಪರಿಣಾಮ ಬೀರುತ್ತದೆ. ನಿಧಾನ ಗತಿಯ ಮತ್ತು ಮೃದುವಾದ ಸ್ವರಗಳೊಂದಿಗೆ ಇರುವ ವಾದ್ಯ ಸಂಗೀತವನ್ನು ಆಲಿಸಿ. ಮಳೆ ಅಥವಾ ಸಮುದ್ರದ ಅಲೆಗಳಂತಹ ಪ್ರಕೃತಿಯ ಶಬ್ದಗಳು ಸಹ ನಂಬಲಾಗದಷ್ಟು ಆರಾಮವನ್ನು ನೀಡುತ್ತವೆ. ಧ್ಯಾನ ಮತ್ತು ಚಿಂತನಶೀಲ ಅಭ್ಯಾಸಗಳು: ಮನಸ್ಸಿನ ಶಾಂತಿಗಾಗಿ ಮೈಂಡ್‌ಫುಲ್‌ನೆಸ್ ಅಭ್ಯಾಸಗಳನ್ನು ಸೇರಿಸುವುದನ್ನು ರೂಢಿಸಿಕೊಳ್ಳಿ. 10-15 ನಿಮಿಷಗಳ ಕಾಲ ಧ್ಯಾನ ಅಥವಾ ಆಳವಾದ ಉಸಿರಾಟದ ವ್ಯಾಯಾಮಗಳನ್ನು ಅಭ್ಯಾಸ ಮಾಡಿ. ಈ ತಂತ್ರಗಳು ಮನಸ್ಸನ್ನು ಶಾಂತಗೊಳಿಸಲು, ವೇಗವಾಗಿ ಓಡುವ ಆಲೋಚನೆಗಳನ್ನು ಕಡಿಮೆ ಮಾಡಲು ಮತ್ತು ಶಾಂತಿಯ ಭಾವನೆಯನ್ನು ಉತ್ತೇಜಿಸಲು ಸಹಾಯ ಮಾಡುತ್ತವೆ. ಆ್ಯಪ್‌ಗಳು ಅಥವಾ ಆನ್‌ಲೈನ್ ಸಂಪನ್ಮೂಲಗಳ ಮೂಲಕ ಮಾರ್ಗದರ್ಶಿ ಧ್ಯಾನಗಳನ್ನು ಸುಲಭವಾಗಿ ಕಾಣಬಹುದು. ಡೈರಿಯಲ್ಲಿ ಬರೆಯುವುದು ಸಹ ಪ್ರಯೋಜನಕಾರಿಯಾಗಿದೆ. ನಿಮ್ಮ ಆಲೋಚನೆಗಳು ಮತ್ತು ಭಾವನೆಗಳನ್ನು ಬರೆಯುವುದರಿಂದ ಭಾವನೆಗಳನ್ನು ಅರ್ಥಮಾಡಿಕೊಳ್ಳಲು ಮತ್ತು ನಿದ್ರೆಯ ಮೊದಲು ನಿಮ್ಮ ಮನಸ್ಸನ್ನು ಸ್ಪಷ್ಟಪಡಿಸಲು ಸಹಾಯ ಮಾಡುತ್ತದೆ. ದಿನದ ಸಕಾರಾತ್ಮಕ ಅನುಭವಗಳಿಗೆ ಕೃತಜ್ಞತೆ ವ್ಯಕ್ತಪಡಿಸುವತ್ತ ಗಮನಹರಿಸಿ. ಉತ್ತಮ ನಿದ್ರೆಗೆ ಕೊಡಿಯ ಸಿದ್ಧತೆ: ಕೊನೆಯದಾಗಿ, ನಿಮ್ಮ ಮಲಗುವ ಕೋಣೆ ನಿದ್ರೆಗೆ ಸೂಕ್ತವಾಗಿದೆ ಎಂದು ಖಚಿತಪಡಿಸಿಕೊಳ್ಳಿ. ಕೋಣೆಯನ್ನು ಗಾಢ, ನಿಶ್ಶಬ್ದ ಮತ್ತು ತಂಪಾಗಿಡಿ. ನಿಮ್ಮ ಹಾಸಿಗೆ ಆರಾಮದಾಯಕ ಮತ್ತು ಸ್ವಚ್ಛವಾಗಿದೆ ಎಂದು ಖಚಿತಪಡಿಸಿಕೊಳ್ಳಿ. ನಿಯಮಿತ ನಿದ್ರೆಯ ವೇಳಾಪಟ್ಟಿಯನ್ನು ಹೊಂದಿರುವುದು ಸಹ ಮುಖ್ಯ. ನಿಮ್ಮ ದೇಹದ ನೈಸರ್ಗಿಕ ನಿದ್ರೆ ಮತ್ತು ಎಚ್ಚರ ಚಕ್ರವನ್ನು ನಿಯಂತ್ರಿಸಲು ಪ್ರತಿದಿನ ಒಂದೇ ಸಮಯಕ್ಕೆ ಮಲಗಲು ಮತ್ತು ಏಳಲು ಪ್ರಯತ್ನಿಸಿ, ವಾರಾಂತ್ಯದಲ್ಲೂ ಸಹ. ಈ ಶಾಂತಗೊಳಿಸುವ ಚಟುವಟಿಕೆಗಳು ಮತ್ತು ಚಿಂತನಶೀಲ ಬದಲಾವಣೆಗಳನ್ನು ಸ್ಥಿರವಾಗಿ ಅಳವಡಿಸಿಕೊಳ್ಳುವ ಮೂಲಕ, ನೀವು ಉತ್ತಮ ನಿದ್ರೆಯನ್ನು ಉತ್ತೇಜಿಸುವ ಮತ್ತು ಹೆಚ್ಚು ಶಾಂತಿಯುತ ಹಾಗೂ ಚೈತನ್ಯ ನೀಡುವ ರಾತ್ರಿ ವಿಶ್ರಾಂತಿಗೆ ಕೊಡುಗೆ ನೀಡಬಹುದು.
Grammar Correction	"യൂറോപ്പ് യാത്രയ്ക്ക് ആവേശം കൊണ്ട് കുട്ടികൾ, അവർക്ക് ആവശ്യമായ എല്ലാം ഉണ്ടെന്ന് ഉറപ്പാക്കി, സൂക്ഷ്മതയോടെ തങ്ങളുടെ സഞ്ചികൾ അടുക്കി, രസകരമായ ഒരു യാത്രയെ പ്രതീക്ഷിച്ചു." ഈ വാക്യത്തിലെ തെറ്റുകൾ തിരുത്തുക.	ഇതാണ് നിങ്ങൾ നൽകിയ വാക്യം " യാത്രയ്ക്ക് ആവേശം കൊണ്ട് കുട്ടികൾ, അവർക്ക് ആവശ്യമായ എല്ലാം ഉണ്ടെന്ന് ഉറപ്പാക്കി, സൂക്ഷ്മതയോടെ തങ്ങളുടെ സഞ്ചികൾ അടുക്കി, രസകരമായ ഒരു യാത്രയെ പ്രതീക്ഷിച്ചു." നിങ്ങൾ നൽകിയ വാക്യത്തിലെ തെറ്റുകൾ തിരുത്തി ശരിയായ രൂപം താഴെ നൽകുന്നു: " യാത്രയ്ക്ക് ആവേശം നിറഞ്ഞ കുട്ടികൾ, തങ്ങൾക്ക് ആവശ്യമായ എല്ലാം ഉണ്ടെന്ന് ഉറപ്പുവരുത്തി, സൂക്ഷ്മതയോടെ തങ്ങളുടെ സഞ്ചികൾ അടുക്കി, രസകരമായ ഒരു യാത്രയ്ക്കായി കാത്തിരുന്നു." വിശദീകരണം: മുകളിലെ വാക്യം തിരുത്തിയത് ഗ്രാമർ, വിരാമചിഹ്നങ്ങൾ, അക്ഷരത്തെറ്റുകൾ എന്നിവ പരിശോധിച്ചാണ്. "ആവേശം കൊണ്ട്" എന്നത് "ആവേശം നിറഞ്ഞ" എന്നാക്കി, കാരണം "കൊണ്ട്" ഉപയോഗം ഈ സന്ദർഭത്തിൽ അനുചിതമാണ്. "നിറഞ്ഞ" കൂടുതൽ സ്വാഭാവികവും ശരിയുമാണ്. "അവർക്ക്" എന്ന "അവർ" മാറ്റി "തങ്ങൾക്ക്" ആക്കി, കാരണം വാക്യത്തിന്റെ സന്ദർഭം കുട്ടികളെക്കുറിച്ചാണ്, "തങ്ങളാണ്" ഇവിടെ കൂടുതൽ ഉചിതം. "ഉറപ്പാക്കി" എന്നത് "ഉറപ്പുവരുത്തി" എന്നാക്കി, കാരണം "ഉറപ്പുവരുത്തി" മലയാളത്തിൽ കൂടുതൽ ഔപചാരികവും വ്യക്തവുമാണ്. അവസാന ഭാഗത്ത് "പ്രതീക്ഷിച്ചു" എന്നത് "കാത്തിരുന്നു" എന്നാക്കി, കാരണം "കാത്തിരുന്നു" യാത്രയ്ക്കായുള്ള കാത്തിരിപ്പിനെ കൂടുതൽ വ്യക്തമാക്കുന്നു. വിരാമചിഹ്നങ്ങൾ ശരിയായി ഉപയോഗിച്ചു, അനാവശ്യമായ കോമകൾ നീക്കം ചെയ്തു. ഈ തിരുത്തലുകൾ വാക്യത്തെ കൂടുതൽ വ്യക്തവും മലയാള ഭാഷയ്ക്ക് അനുയോജ്യവുമാക്കുന്നു.

Figure 28: *Pragyaan-IT* data examples in categories Brainstorming - (*Easy, 1-Turn, Simple-IF, Non-Safe, IC-1, Normal (No Thinking Trails)*) and Grammar Correction - (*Easy, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) settings configuration.

Category	Prompt	Response
Information Seeking	ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಕುರಿತ ಭಾರತದ ಐತಿಹಾಸಿಕ ಮತ್ತು ತಾತ್ವಿಕ ವಾದಗಳನ್ನು ವಿಶ್ಲೇಷಿಸಿ. ನೈತಿಕ ಹೊಣೆಗಾರಿಕೆ, ಭಾರತೀಯ ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು, ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳ ಮೇಲೆ ಇದರ ಪರಿಣಾಮಗಳೇನು? ಸಾಮರಸ್ಯವಾದಿ ಮತ್ತು ಅಸಾಮರಸ್ಯವಾದಿ ದೃಷ್ಟಿಕೋನಗಳನ್ನು ಚರ್ಚಿಸಿ. ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಏಜೆನ್ಸಿಗೆ ಸಂಬಂಧಿಸಿದ ನರವಿಜ್ಞಾನ ಹಾಗೂ ತಾತ್ವಿಕ ವಾದಗಳ ಬಲ ದುರ್ಬಲತೆಗಳನ್ನು ಮೌಲ್ಯಮಾಪನ ಮಾಡಿ.	ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ. ಅಂದರೆ ನಮ್ಮ ಆಯ್ಕೆಗಳು ಮತ್ತು ನಿರ್ಧಾರಗಳು ನಿಜಕ್ಕೂ ನಮ್ಮ ಸ್ವಂತದ್ದೇ ಅಥವಾ ಅವು ಪೂರ್ವನಿರ್ಧರಿತ ಅಂಶಗಳಿಂದ ನಿಯಂತ್ರಿಸಲ್ಪಟ್ಟಿವೆಯೇ ಎಂಬ ಪ್ರಶ್ನೆ. ಪ್ರಶ್ನೆ ಮನುಷ್ಯರ ನಡುವೆ ಸದಾ ಚರ್ಚೆಯಲ್ಲಿದೆ. ಇದು ನೈತಿಕ ಹೊಣೆಗಾರಿಕೆ, ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳಂತಹ ಮೂಲಭೂತ ಪರಿಕಲ್ಪನೆಗಳ ಮೇಲೆ ಆಳವಾದ ಪರಿಣಾಮಗಳನ್ನು ಬೀರುತ್ತದೆ. ಭಾರತದ ಐತಿಹಾಸಿಕ ಮತ್ತು ತಾತ್ವಿಕ ವಾದಗಳು: ಭಾರತೀಯ ತತ್ವಶಾಸ್ತ್ರದಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಕುರಿತ ಚರ್ಚೆಗಳು ಬಹಳ ಪ್ರಾಚೀನ ಮತ್ತು ವೈವಿಧ್ಯಮಯವಾಗಿವೆ. ಕರ್ಮ ಸಿದ್ಧಾಂತ: ಬಹುತೇಕ ಭಾರತೀಯ ಆಧ್ಯಾತ್ಮಿಕ ಮತ್ತು ಧಾರ್ಮಿಕ ಸಂಪ್ರದಾಯಗಳಲ್ಲಿ, ವಿಶೇಷವಾಗಿ ಹಿಂದೂ ಧರ್ಮ, ಬೌದ್ಧಧರ್ಮ ಮತ್ತು ಜೈನಧರ್ಮದಲ್ಲಿ, ಕರ್ಮ ಸಿದ್ಧಾಂತವು ಪ್ರಮುಖ ಸ್ಥಾನ ಪಡೆದಿದೆ. ಇದು ನಾವು ಮಾಡುವ ಪ್ರತಿಯೊಂದು ಕ್ರಿಯೆಯೂ (ಕರ್ಮ) ಭವಿಷ್ಯದ ಪರಿಣಾಮಗಳನ್ನು ಹೊಂದಿರುತ್ತದೆ ಎಂದು ಹೇಳುತ್ತದೆ. ಇಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಗೆ ಮಹತ್ವದ ಪಾತ್ರವಿದೆ. ಏಕೆಂದರೆ ವ್ಯಕ್ತಿಯು ತನ್ನ ಕರ್ಮಗಳನ್ನು ಆಯ್ಕೆ ಮಾಡುವ ಸಾಮರ್ಥ್ಯವನ್ನು ಹೊಂದಿದ್ದಾನೆ ಮತ್ತು ಆ ಆಯ್ಕೆಗಳಿಗೆ ಹೊಣೆಗಾರನಾಗಿರುತ್ತಾನೆ. ಭಗವದ್ಗೀತೆಯು ಈ ಕರ್ಮ ಸಿದ್ಧಾಂತವನ್ನು ಸ್ಪಷ್ಟವಾಗಿ ವಿವರಿಸುತ್ತದೆ, ಅಲ್ಲಿ ಶ್ರೀಕೃಷ್ಣನು ಅರ್ಜುನನಿಗೆ ಕರ್ಮ ಮಾಡು, ಫಲದ ನಿರೀಕ್ಷೆ ಇಲ್ಲದೆ ಎಂದು ಬೋಧಿಸುತ್ತಾನೆ. ಇದು ಆಯ್ಕೆಯ ಸ್ವಾತಂತ್ರ್ಯ ಮತ್ತು ಅದರ ಜವಾಬ್ದಾರಿಯನ್ನು ಒತ್ತಿಹೇಳುತ್ತದೆ. ವ್ಯಕ್ತಿಯ ಆಯ್ಕೆಗಳು ಅವನ ಭವಿಷ್ಯವನ್ನು ರೂಪಿಸುತ್ತವೆ ಎಂಬುದನ್ನು ಇದು ಸೂಚಿಸುತ್ತದೆ, ಆದರೆ ಅದೇ ಸಮಯದಲ್ಲಿ ಪೂರ್ವಜನ್ಮದ ಕರ್ಮಗಳ ಪ್ರಭಾವವನ್ನು ಒಪ್ಪಿಕೊಳ್ಳುತ್ತದೆ. ಯೋಗಸೂತ್ರಗಳು: ಪತಂಜಲಿಯ ಯೋಗಸೂತ್ರಗಳು ಮನಸ್ಸಿನ ನಿಯಂತ್ರಣ ಮತ್ತು ಆಳವಾದ ಸ್ವಯಂ ಅರಿವಿನ ಮೂಲಕ ವ್ಯಕ್ತಿಯು ತನ್ನ ಪ್ರಜ್ಞೆಯನ್ನು ಉನ್ನತೀಕರಿಸಬಹುದು ಎಂದು ಹೇಳುತ್ತವೆ. ಇಲ್ಲಿಯೂ, ವ್ಯಕ್ತಿಯು ತನ್ನ ಆಲೋಚನೆಗಳು ಮತ್ತು ಕಾರ್ಯಗಳ ಮೇಲೆ ಹಿಡಿತ ಸಾಧಿಸುವ ಸಾಮರ್ಥ್ಯವನ್ನು ಹೊಂದಿದ್ದಾನೆ ಎಂಬ ಅಂಶವು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಗೆ ಅವಕಾಶ ನೀಡುತ್ತದೆ. ನೈತಿಕ ಹೊಣೆಗಾರಿಕೆ, ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳ ಮೇಲೆ ಪರಿಣಾಮಗಳು: ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯು ಅಸ್ತಿತ್ವದಲ್ಲಿದೆ ಎಂಬ ನಂಬಿಕೆಯು ನಮ್ಮ ನೈತಿಕ ಮತ್ತು ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳ ಅಡಿಪಾಯವಾಗಿದೆ. ನೈತಿಕ ಹೊಣೆಗಾರಿಕೆ: ನೀವು ಒಂದು ಕೆಲಸ ಮಾಡಲು ನಿಮ್ಮದೇ ಇಚ್ಛೆಯಿಂದ ನಿರ್ಧರಿಸಿದರೆ, ಅದರ ಒಳ್ಳೆಯ ಅಥವಾ ಕೆಟ್ಟ ಪರಿಣಾಮಗಳಿಗೆ ನೀವೇ ಜವಾಬ್ದಾರರು. ಉದಾಹರಣೆಗೆ: ನೀವು ಸ್ವತಃ ನಿರ್ಧರಿಸಿ ಒಬ್ಬರಿಗೆ ಸಹಾಯ ಮಾಡಿದರೆ, ಆ ಒಳ್ಳೆಯ ಕಾರ್ಯಕ್ಕೆ ನೀವು ಶಹಬ್ಬಾಸ್‌ಗಿರಿ ಪಡೆಯುತ್ತೀರಿ. ಆದರೆ, ಯಾರಾದರೂ ನಿಮ್ಮನ್ನು ಒತ್ತಾಯಿಸಿ ಆ ಸಹಾಯ ಮಾಡಿಸಿದರೆ, ಅದರ ಜವಾಬ್ದಾರಿ ನಿಮಗೆ ಸೇರುವುದಿಲ್ಲ. ಅದೇ ರೀತಿ, ನೀವು ನಿಮ್ಮ ಸ್ವಂತ ಇಚ್ಛೆಯಿಂದ ತಪ್ಪು ಮಾಡಿದರೆ, ಅದರ ದೂಷಣೆ ಅಥವಾ ಶಿಕ್ಷೆಯನ್ನು ಎದುರಿಸಬೇಕಾಗುತ್ತದೆ. ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು: ನಮ್ಮ ಭಾರತೀಯ ನ್ಯಾಯಾಂಗ ವ್ಯವಸ್ಥೆಯು, ಅಪರಾಧ ಪ್ರಕರಣಗಳಲ್ಲಿ, ಒಬ್ಬ ವ್ಯಕ್ತಿ ತನ್ನ ಕೆಲಸವನ್ನು ತಾನಾಗಿಯೇ, ಉದ್ದೇಶಪೂರ್ವಕವಾಗಿ ಮಾಡಿದ್ದಾನೆ ಎಂದು ಸಾಮಾನ್ಯವಾಗಿ ಪರಿಗಣಿಸುತ್ತದೆ. ಯಾರಾದರೂ ಮಾಡಿದ ಕೆಲಸಕ್ಕೆ ಅವರೇ ಕಾರಣ ಎಂದು ನಂಬಿದಾಗ ಮಾತ್ರ ಶಿಕ್ಷೆ ನೀಡುವುದು ಸರಿಯಾಗುತ್ತದೆ. ಮೆನ್ಸ್ ರಿಯಾ (ಅಪರಾಧ ಮಾಡುವ ಉದ್ದೇಶ) ಎಂಬ ನಿಯಮ, ಒಬ್ಬರು ಮಾಡುವ ಅಪರಾಧದ ಹಿಂದೆ ಅವರ ಆಶಯ ಅಥವಾ ಇಚ್ಛೆ ಇದೆಯೇ ಎಂದು ಪರಿಗಣಿಸುತ್ತದೆ. ವೈಯಕ್ತಿಕ ಗುರುತು: ನಮ್ಮನ್ನು ನಾವು ಯಾರು ಎಂದು ಗುರುತಿಸಿಕೊಳ್ಳುವಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮುಖ್ಯ. ನಮ್ಮ ಆಯ್ಕೆಗಳು, ನಿರ್ಧಾರಗಳು ಮತ್ತು ಅವುಗಳ ಪರಿಣಾಮಗಳ ಮೂಲಕವೇ ನಾವು ನಮ್ಮ ವ್ಯಕ್ತಿತ್ವವನ್ನು ರೂಪಿಸಿಕೊಳ್ಳುತ್ತೇವೆ. ಸಾಮರಸ್ಯವಾದಿ (Compatibilist) ಮತ್ತು ಅಸಾಮರಸ್ಯವಾದಿ (Incompatibilist) ದೃಷ್ಟಿಕೋನಗಳು: ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮತ್ತು ನಿರ್ಣಾಯಕತೆಯ ನಡುವಿನ ಸಂಬಂಧದ ಬಗ್ಗೆ ಎರಡು ಪ್ರಮುಖ ದೃಷ್ಟಿಕೋನಗಳಿವೆ: ಸಾಮರಸ್ಯವಾದ (Compatibilism): ಈ ದೃಷ್ಟಿಕೋನವು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮತ್ತು ನಿರ್ಣಾಯಕತೆ (Determinism - ಎಲ್ಲ ಘಟನೆಗಳು ಪೂರ್ವನಿರ್ಧರಿತವಾಗಿವೆ) ಪರಸ್ಪರ ಹೊಂದಾಣಿಕೆಯಾಗುತ್ತವೆ ಎಂದು ವಾದಿಸುತ್ತದೆ. ನಾವು ನಮ್ಮ ಆಯ್ಕೆಗಳನ್ನು ಮಾಡುವಾಗ ಬಾಹ್ಯ ಒತ್ತಡದಿಂದ ಮುಕ್ತರಾಗಿದ್ದರೆ, ನಮ್ಮ ನಿರ್ಧಾರಗಳು ಹಿಂದಿನ ಕಾರಣಗಳಿಂದ ಪ್ರಭಾವಿತವಾಗಿದ್ದರೂ ಸಹ, ನಾವು ಮುಕ್ತರು ಎಂದು ಸಾಮರಸ್ಯವಾದಿಗಳು ವಾದಿಸುತ್ತಾರೆ. ಇಲ್ಲಿ, ಸ್ವಾತಂತ್ರ್ಯ ಎಂದರೆ ಒತ್ತಾಯವಿಲ್ಲದಿರುವುದು, ಅನಿವಾರ್ಯತೆಯಲ್ಲ. ಅಸಾಮರಸ್ಯವಾದ (Incompatibilism): ಈ ದೃಷ್ಟಿಕೋನವು ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಪರಸ್ಪರ ಹೊಂದಾಣಿಕೆಯಾಗುವುದಿಲ್ಲ ಎಂದು ವಾದಿಸುತ್ತದೆ. ನಿರ್ಣಾಯಕತೆ ನಿಜವಾಗಿದ್ದರೆ, ನಮ್ಮ ಆಯ್ಕೆಗಳು ನಿಜವಾಗಿಯೂ ನಮ್ಮ ಸ್ವಂತದ್ದಾಗಿರಲು ಸಾಧ್ಯವಿಲ್ಲ, ಏಕೆಂದರೆ ಅವು ಹಿಂದಿನ ಘಟನೆಗಳ ಸರಣಿಯ ಫಲಿತಾಂಶಗಳಾಗಿರುತ್ತವೆ. ಇಲ್ಲಿ ಎರಡು ಉಪ ವಿಭಾಗಗಳಿವೆ: ಮುಕ್ತ ಆಯ್ಕೆ ಸಿದ್ಧಾಂತ : ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ನಿಜವಾಗಿದೆ ಮತ್ತು ನಿರ್ಣಾಯಕತೆ ಸುಳ್ಳು ಎಂದು ವಾದಿಸುತ್ತದೆ ನಿರಾಶಾವಾದ : ಇದು ನಿರ್ಣಾಯಕತೆ ನಿಜವಾಗಿದೆ ಮತ್ತು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಒಂದು ಭ್ರಮೆ ಎಂದು ವಾದಿಸುತ್ತದೆ. ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಏಜೆನ್ಸಿಗೆ ಸಂಬಂಧಿಸಿದ ನರವಿಜ್ಞಾನ ಮತ್ತು ತಾತ್ವಿಕ ವಾದಗಳು: ಆಧುನಿಕ ನರವಿಜ್ಞಾನವು ಈ ಚರ್ಚೆಗೆ ಹೊಸ ಆಯಾಮವನ್ನು ಸೇರಿಸಿದೆ. ನರವಿಜ್ಞಾನದ ವಾದಗಳು: ಕೆಲವು ನರವಿಜ್ಞಾನದ ಅಧ್ಯಯನಗಳು ಜನರು ತಮ್ಮ ಕ್ರಿಯೆಗಳನ್ನು ನಿರ್ಧರಿಸುವ ಮೊದಲು ಮೆದುಳು ಈಗಾಗಲೇ ಪ್ರತಿಕ್ರಿಯೆಯನ್ನು ಪ್ರಾರಂಭಿಸಿರುತ್ತದೆ ಎಂದು ಸೂಚಿಸುತ್ತವೆ. ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯು ಒಂದು ಭ್ರಮೆ ಇರಬಹುದೇ ಎಂಬ ಪ್ರಶ್ನೆಯನ್ನು ಹುಟ್ಟುಹಾಕಿದೆ. ಆದಾಗ್ಯೂ, ಈ ಅಧ್ಯಯನಗಳ ವ್ಯಾಖ್ಯಾನದ ಬಗ್ಗೆ ವ್ಯಾಪಕ ಚರ್ಚೆಗಳಿವೆ. ಅವು ಸರಳ ನಿರ್ಧಾರಗಳಿಗೆ ಮಾತ್ರ ಅನ್ವಯಿಸುತ್ತವೆ ಮತ್ತು ಸಂಕೀರ್ಣ, ಉದ್ದೇಶಪೂರ್ವಕ ಯೋಜನೆಗಳಿಗೆ ಅಲ್ಲ ಎಂದು ಕೆಲವರು ವಾದಿಸುತ್ತಾರೆ. ತಾತ್ವಿಕ ವಾದಗಳ ಬಲ ಮತ್ತು ದುರ್ಬಲತೆಗಳು: ಬಲ: ನರವಿಜ್ಞಾನದ ಆವಿಷ್ಕಾರಗಳು ನಮ್ಮ ನಿರ್ಧಾರ ಪ್ರಕ್ರಿಯೆಗಳ ಜೈವಿಕ ಆಧಾರದ ಬಗ್ಗೆ ಆಳವಾದ ಒಳನೋಟಗಳನ್ನು ನೀಡುತ್ತವೆ. ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ನಮ್ಮ ಗ್ರಹಿಕೆಯನ್ನು ಪುನರ್ವಿಮರ್ಶಿಸಲು ಪ್ರೇರೇಪಿಸುತ್ತದೆ. ಕರ್ಮ ಸಿದ್ಧಾಂತವು ವೈಯಕ್ತಿಕ ಜವಾಬ್ದಾರಿಗೆ ಪ್ರಬಲ ನೈತಿಕ ಚೌಕಟ್ಟನ್ನು ನೀಡುತ್ತದೆ. ದುರ್ಬಲತೆ: ನರವಿಜ್ಞಾನದ ವಾದಗಳು ಸಂಪೂರ್ಣವಾಗಿ ನಿರ್ಣಾಯಕವಾಗಿಲ್ಲ ಮತ್ತು ಅವು ಪ್ರಜ್ಞೆ ಮತ್ತು ಆಯ್ಕೆ ಮಾಡುವ ಸಾಮರ್ಥ್ಯದ ಸಂಕೀರ್ಣತೆಯನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ಗ್ರಹಿಸುವುದಿಲ್ಲ. ಕೇವಲ ಮೆದುಳಿನ ಚಟುವಟಿಕೆಯನ್ನು ಅಳೆಯುವ ಮೂಲಕ ಮಾನವ ಇಚ್ಛಾಶಕ್ತಿಯನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ತಳ್ಳಿಹಾಕಲು ಸಾಧ್ಯವಿಲ್ಲ ಎಂಬ ವಾದವಿದೆ. ಭಾರತೀಯ ತತ್ವಶಾಸ್ತ್ರದಲ್ಲಿ, ಕರ್ಮ ಸಿದ್ಧಾಂತವು ಭವಿಷ್ಯವನ್ನು ನಿರ್ಧರಿಸುವ ಪೂರ್ವಜನ್ಮದ ಕರ್ಮಗಳ ಬಗ್ಗೆಯೂ ಮಾತನಾಡುತ್ತದೆ, ಇದು ಸಂಪೂರ್ಣ ಸ್ವಾತಂತ್ರ್ಯದ ಪರಿಕಲ್ಪನೆಯನ್ನು ಸಂಕೀರ್ಣಗೊಳಿಸುತ್ತದೆ. ಒಟ್ಟಾರೆ, ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಪ್ರಶ್ನೆಯು ಆಳವಾದ ತತ್ವಶಾಸ್ತ್ರೀಯ ಮತ್ತು ವೈಜ್ಞಾನಿಕ ಪರಿಶೋಧನೆಯನ್ನು ಮುಂದುವರಿಸಿದೆ ಮತ್ತು ಭಾರತೀಯ ಚಿಂತನೆಯು ಈ ಜಾಗತಿಕ ಚರ್ಚೆಗೆ ಅನನ್ಯ ಮತ್ತು ಸಮೃದ್ಧ ದೃಷ್ಟಿಕೋನಗಳನ್ನು ಒದಗಿಸುತ್ತದೆ.

Figure 29: *Pragyaan-IT* data examples in category Information Seeking - (*Hard, 1-Turn, Medium-IF, Safe, IC-3, Normal (No Thinking Trails)*) settings configuration.

Category	Prompt	Response
Named Entity Recognition	1800 ମସିହାରେ ଭାରତରେ ସଂସ୍କୃତ ଉନ୍ନତି ଏବଂ ପୁନର୍ଜ୍ଜୀବନ ଆନ୍ଦୋଳନ ଆରମ୍ଭ ହୋଇଥିଲା, ଯାହା ଦେଶର ଐତିହାସିକ ଓ ସାଂସ୍କୃତିକ ଜ୍ଞାନକୁ ଏକ ନୂଆ ମାର୍ଗ ଦେଇଥିଲା । ଏହି ଆନ୍ଦୋଳନରେ ସଂସ୍କୃତ ଭାଷାର ପୁନଃପଠନ ଓ ଅଧ୍ୟୟନ ପ୍ରଚଳିତ ହୋଇଥିଲା, ଯାହା ସହ ଭାରତୀୟ ପୁରାତତ୍ତ୍ୱ ଓ ଶିଳାଲେଖ ବିଷୟରେ ଗଭୀର ଗବେଷଣା ଆରମ୍ଭ ହେଲା । ମହାରାଷ୍ଟ୍ରର ପୁଣେ ଓ ବଙ୍ଗାଳର କଲକାତା ର ଡେକନ୍ କଲେଜ୍ ଓ ସେରାମପୁର କଲେଜ୍ ଭଳି ଶିକ୍ଷା ପ୍ରତିଷ୍ଠାନଗୁଡ଼ିକ ଏଥିରେ ମହତ୍ତ୍ୱପୂର୍ଣ୍ଣ ଭୂମିକା ନେଇଥିଲେ । ସେହି ସମୟରେ ଭାରତୀୟ ଟଙ୍କା ପ୍ରଧାନ ମୁଦ୍ରା ଥିଲା, ଯାହା ବ୍ରିଟିଶ ରୁପିଆ ସହ ବ୍ୟବହୃତ ହେଉଥିଲା ଏବଂ ଅନେକ ପ୍ରିଂସଲି ଷ୍ଟେଟ୍ ତାହାକୁ ନିଜେ ଉତ୍ପାଦନ କରୁଥିଲେ । 1900 ଶତାବ୍ଦୀରେ ରାମମୋହନ ରାୟ, ଅକ୍ଷୟ କୁମାର ଦତ୍ତ, ହରିଶ୍ଚନ୍ଦ୍ର ବିଦ୍ୟାଳଙ୍କାର ଏବଂ ଅନନ୍ୟ ଗବେଷକ ଭାରତୀୟ ଇତିହାସ ଏବଂ ସଂସ୍କୃତିକ ଧାରକୁ ପୁନଃ ଆବିଷ୍କାର କରିଥିଲେ । ସେମାନଙ୍କ ଗବେଷଣା, ଅଧ୍ୟୟନ ଓ ରଚନା ବ୍ରିଟିଶ ପ୍ରତି ଭାରତୀୟ ସ୍ୱାଧୀନତା ଚେତନାକୁ ବଳିଯାଇଥିଲା । ଏହି ସଂସ୍କୃତି ଉନ୍ନତି ଆନ୍ଦୋଳନ ଅନେକ ଭାରତୀୟଙ୍କୁ ନିଜ ଐତିହାସିକ ଓ ସାଂସ୍କୃତିକ ମୂଳରେ ଗର୍ବିତ କରିଥିଲା, ଯାହା ସ୍ୱାଧୀନତା ଆନ୍ଦୋଳନର ଆଧାର ଭାବେ ପ୍ରଭାବିତ କରିଥିଲା । ସମସ୍ତ LOC, ARTIFACT, EVENT, PERSON ଏବଂ LANGUAGE ସଂସ୍ଥାଗୁଡ଼ିକୁ ଚିହ୍ନିତ କରନ୍ତୁ । ଶିଳାଲେଖ ଓ ଭାଷା ବ୍ୟାଖ୍ୟା ସହିତ ସମ୍ବନ୍ଧିତ ଏକ ଭାରତୀୟ ଘଟଣା ଉପରେ ଆଧାରିତ ଏକ ସମୟସୀମା ସୃଷ୍ଟି କରନ୍ତୁ, ଯାହା ଆବିଷ୍କାର, ପୁନଃଅନୁଷ୍ଠାନ, ବ୍ୟାଖ୍ୟା ଓ ଚାଲୁଥିବା ଗବେଷଣାକୁ ସ୍ପଷ୍ଟ କରେ । ପ୍ରତ୍ୟେକ ଘଟଣା ସହିତ ଜଡିତ ସ୍ଥାନ ଉଲ୍ଲେଖ କରନ୍ତୁ ।	ଭାରତୀୟ ପୁରାତତ୍ତ୍ୱ ଓ ଶିଳାଲେଖ ସହିତ ସଂପୃକ୍ତ ନାମିତ ଏକକ ଏବଂ ଘଟଣାର ସମୟକ୍ରମ ଏହିପରି: ନାମିତ ସଂସ୍ଥା: ସ୍ଥାନ: ଭାରତ, କଲିକତା, ମହାରାଷ୍ଟ୍ର, ପୁଣେ । ପ୍ରାଚୀନ ବସ୍ତୁ (ପ୍ରାଚୀନ ବସ୍ତୁ): ଭାରତୀୟ ପୁରାତତ୍ତ୍ୱ ଓ ଶିଳାଲେଖ । ଘଟଣା: ସଂସ୍କୃତ ଉନ୍ନତି ଏବଂ ପୁନର୍ଜ୍ଜୀବନ ଆନ୍ଦୋଳନ । ବ୍ୟକ୍ତି: ରାମମୋହନ ରାୟ, ଅକ୍ଷୟ କୁମାର ଦତ୍ତ, ହରିଶ୍ଚନ୍ଦ୍ର ବିଦ୍ୟାଧର । ଭାଷା: ସଂସ୍କୃତ ଅନୁଷ୍ଠାନ: ଡେକନ୍ ମହାବିଦ୍ୟାଳୟ, ସେରାମପୁର ମହାବିଦ୍ୟାଳୟ ମୁଦ୍ରା : ରୁପିଆ, ଟଙ୍କା ଘଟଣାର ସମୟକ୍ରମ: 1. 1800 ମସିହା : ମସିହାରେ ଭାରତରେ ସଂସ୍କୃତ ଉନ୍ନତି ଏବଂ ପୁନର୍ଜ୍ଜୀବନ ଆନ୍ଦୋଳନ ଆରମ୍ଭ ହୋଇଥିଲା, ଯାହା ଦେଶର ଐତିହାସିକ ଓ ସାଂସ୍କୃତିକ ଜ୍ଞାନକୁ ଏକ ନୂଆ ମାର୍ଗ ଦେଇଥିଲା । ଏହି ଆନ୍ଦୋଳନରେ ସଂସ୍କୃତ ଭାଷାର ପୁନଃପଠନ ଓ ଅଧ୍ୟୟନ ପ୍ରଚଳିତ ହୋଇଥିଲା, ଯାହା ସହ ଭାରତୀୟ ପୁରାତତ୍ତ୍ୱ ଓ ଶିଳାଲେଖ ବିଷୟରେ ଗଭୀର ଗବେଷଣା ଆରମ୍ଭ ହେଲା । 2. 1900 ମସିହା : 1900 ଶତାବ୍ଦୀରେ ରାମମୋହନ ରାୟ, ଅକ୍ଷୟ କୁମାର ଦତ୍ତ, ହରିଶ୍ଚନ୍ଦ୍ର ବିଦ୍ୟାଳଙ୍କାର ଏବଂ ଅନନ୍ୟ ଗବେଷକ ଭାରତୀୟ ଇତିହାସ ଏବଂ ସଂସ୍କୃତିକ ଧାରକୁ ପୁନଃ ଆବିଷ୍କାର କରିଥିଲେ । ସେମାନଙ୍କ ଗବେଷଣା, ଅଧ୍ୟୟନ ଓ ରଚନା ବ୍ରିଟିଶ ପ୍ରତି ଭାରତୀୟ ସ୍ୱାଧୀନତା ଚେତନାକୁ ବଳିଯାଇଥିଲା । ଟିପ୍ପଣୀ: ଭାରତରେ ସଂସ୍କୃତ ଉନ୍ନତି ଏବଂ ପୁନର୍ଜ୍ଜୀବନ ଆନ୍ଦୋଳନ ଆରମ୍ଭ ହୋଇଥିଲା, ଯାହା ଦେଶର ଐତିହାସିକ ଓ ସାଂସ୍କୃତିକ ଜ୍ଞାନକୁ ଏକ ନୂଆ ମାର୍ଗ ଦେଇଥିଲା । ଏହି ଆନ୍ଦୋଳନରେ ସଂସ୍କୃତ ଭାଷାର ପୁନଃପଠନ ଓ ଅଧ୍ୟୟନ ପ୍ରଚଳିତ ହୋଇଥିଲା, ଯାହା ସହ ଭାରତୀୟ ପୁରାତତ୍ତ୍ୱ ଓ ଶିଳାଲେଖ ବିଷୟରେ ଗଭୀର ଗବେଷଣା ଆରମ୍ଭ ହେଲା ।
Comprehension	સંદર્ભ: DST ઘડિયાળમાં ફેરફાર ક્યારેક સમય જાળવણીને જટિલ બનાવે છે અને મુસાફરી, બિલિંગ, રેકોર્ડ જાળવણી, તબીબી ઉપકરણો, ભારે સાધનો અને ઊંઘની પેટર્નમાં વિક્ષેપ પાડી શકે છે. કમ્પ્યુટર સોફ્ટવેર ઘણીવાર ઘડિયાળોને આપમેળે ગોઠવી શકે છે, પરંતુ DST ની તારીખો અને સમયના વિવિધ અધિકારક્ષેત્રો દ્વારા નીતિગત ફેરફારો મૂંઝવણભર્યા હોઈ શકે છે. પ્રશ્ન: જ્યારે તમારા લેપટોપ પરની ઘડિયાળ રીસેટ કર્યા વિના DST માં ગોઠવાય છે, ત્યારે ફેરફારને શું નિયંત્રિત કરી રહ્યું છે?	DST દરમિયાન તમારા લેપટોપની ઘડિયાળનું ઓટોમેટિક એડજસ્ટમેન્ટ તેની ઓપરેટિંગ સિસ્ટમના આંતરિક સમય જાળવણી મિકેનિઝમ દ્વારા નિયંત્રિત થાય છે. આમાં સામાન્ય રીતે નીચેના સંયોજનોનો સમાવેશ થાય છે: સમયને ટ્રૅક કરતી સિસ્ટમ ઘડિયાળ, તમારા સ્થાનનો ઉલ્લેખ કરતી ટાઇમઝોન સેટિંગ, અને બિલ્ટ-ઇન ડેટાબેઝ અથવા ઇન્ટરનેટ લુકઅપ જે તે ટાઇમઝોન માટે DST તારીખો પ્રદાન કરે છે. જ્યારે DST ફેરફાર થાય છે ત્યારે OS આપમેળે સિસ્ટમ ઘડિયાળને અપડેટ કરે છે, ખાતરી કરે છે કે પ્રદર્શિત સમય સચોટ રહે છે.
Inference	આ ફકરાઓ તાર્કિક રીતે કેવી રીતે સંબંધિત છે? પૂર્વધારણા: કૃત્રિમ બુદ્ધિ (AI)ની ઝડપી પ્રગતિ ભવિષ્યના કાર્ય માટે પુષ્કળ તકો અને નોંધપાત્ર પડકારો બંને રજૂ કરે છે. AI ટેકનોલોજી દ્વારા સંચાલિત ઓટોમેશન વિવિધ ઉદ્યોગોને પરિવર્તિત કરવાની ક્ષમતા ધરાવે છે, ઉત્પાદકતા અને કાર્યક્ષમતામાં વધારો કરે છે અને સાથે સાથે ચોક્કસ ભૂમિકાઓમાં કામદારોને વિસ્થાપિત કરે છે. આ ટેકનોલોજીકલ વિક્ષેપને કારણે કાર્યબળ અનુકૂલન માટે સક્રિય અભિગમની જરૂર પડે છે, જે ભવિષ્યની નોકરીઓ માટે જરૂરી કુશળતાથી વ્યક્તિઓને સજ્જ કરવા માટે પુનઃકૌશલ્ય અને અપસ્કિલિંગ પહેલ પર ધ્યાન કેન્દ્રિત કરે છે. કાર્યસ્થળમાં AIનું એકીકરણ અલ્ગોરિધમિક પૂર્વગ્રહ, નોકરીની સુરક્ષા અને આવક અસમાનતાને વિસ્તૃત કરવાની સંભાવના વિશે પણ ચિંતાઓ ઉભી કરે છે. વધુમાં, નિર્ણય લેવાની પ્રક્રિયાઓમાં AIના ઉપયોગને લગતી નૈતિક વિચારણાઓ, ખાસ કરીને મહત્વપૂર્ણ સામાજિક અસરો ધરાવતી પ્રક્રિયાઓ, કાળજીપૂર્વક ચકાસણી અને મજબૂત નિયમનકારી માળખાની જરૂર છે. AI-સંચાલિત પરિવર્તનનો સામનો કરવા માટે નીતિ નિર્માતાઓ, વ્યવસાયો અને શૈક્ષણિક સંસ્થાઓએ સાથે મળીને કામ કરવું જોઈએ. પરિકલ્પના: અર્થતંત્રના વિવિધ ક્ષેત્રોમાં ઓટોમેશનનો વધતો વ્યાપ કાર્યની પ્રકૃતિને ફરીથી આકાર આપી રહ્યો છે અને કાર્યબળની વ્યૂહરચનાઓમાં ગોઠવણોની જરૂર છે. ઓટોમેશનને કારણે કામદારોનું વિસ્થાપન નોંધપાત્ર પડકારો ઉભા કરે છે, ખાસ કરીને જેઓ ઓછા કૌશલ્ય ધરાવતા વ્યવસાયો છે. વ્યવસાયો ઓટોમેશનના નકારાત્મક પરિણામોને ઘટાડવા માટે વિવિધ અભિગમો અપનાવી રહ્યા છે. જેમ કે, પુનઃપ્રશિક્ષણ કાર્યક્રમો અને માનવ મૂડીમાં રોકાણ. સરકારો કાર્યબળ અનુકૂલન માટે સહાયક વાતાવરણને પ્રોત્સાહન આપવામાં મહત્વપૂર્ણ ભૂમિકા ભજવે છે, જેમાં શિક્ષણ, તાલીમ અને સામાજિક સલામતી જાળ માટે સંસાધનો પૂરા પાડવાનો સમાવેશ થાય છે. ઉભરતા ઉદ્યોગો માટે જરૂરી કુશળતા અને જ્ઞાન પ્રાપ્ત કરવામાં વ્યક્તિઓને મદદ કરવા અને વધુ લવચીક અને ગતિશીલ શ્રમ બજાર બનાવવા પર ધ્યાન કેન્દ્રિત કરવું જોઈએ. આ ફેરફારોના સફળ નેવિગેશન માટે વ્યવસાયો, સરકારી એજન્સીઓ અને શૈક્ષણિક સંસ્થાઓ સહિત વિવિધ હિસ્સેદારો વચ્ચે સહકારની જરૂર છે. પડકાર એ છે કે કાર્યબળ વધુને વધુ સ્વચાલિત અર્થતંત્રમાં અનુકૂલન પામે તે રીતે સરળ અને સમાન સંક્રમણ સુનિશ્ચિત કરવામાં આવે.	આ પરિકલ્પના એ પૂર્વધારણાનો ચોક્કસ ઉપયોગ અને વિસ્તરણ છે. આ પૂર્વધારણા કાર્યબળ પર AIના પ્રભાવ દ્વારા રજૂ થતા પડકારો અને તકોને વ્યાપકપણે રૂપરેખા આપે છે, જેમાં નોકરીનું વિસ્થાપન, નૈતિક ચિંતાઓ અને અનુકૂલનની જરૂરિયાત જેવા વિવિધ પાસાઓનો સમાવેશ થાય છે. ત્યારબાદ પૂર્વધારણા ખાસ કરીને આ બધા વ્યાપક પૂર્વધારણાના એક મુખ્ય પાસાં પર ધ્યાન કેન્દ્રિત કરે છે: કાર્યબળ પર ઓટોમેશન (AIના પ્રભાવનો મુખ્ય ઘટક)ની અસર અને જરૂરી પ્રતિભાવો પર. આ સંબંધ સામાન્યીકરણથી સ્પષ્ટીકરણનો છે. આ પૂર્વધારણા AIના પ્રભાવનું વિશાળ પરિચય આપે છે, જ્યારે પરિકલ્પના ઓટોમેશન પાસા પર શૂન્ય છે. પડકારો, શમન વ્યૂહરચનાઓ અને તેમને સંબોધવામાં વિવિધ હિસ્સેદારોની ભૂમિકાઓનું વિગતવાર વર્ણન કરે છે. પરિકલ્પના આવશ્યકપણે પૂર્વધારણા (ઓટોમેશન અને જોબ ડિસ્પ્લેસમેન્ટ)માંથી એક મુખ્ય થીમ લે છે અને વધુ નક્કર ઉદાહરણો અને ઉકેલો સાથે તેના પર વિસ્તરણ કરે છે. સારમાં, પરિકલ્પના એ પૂર્વધારણાના વ્યાપક સંદર્ભમાં ચર્ચા કરાયેલ ચોક્કસ પરિણામનું વધુ કેન્દ્રિત અને વિગતવાર સંશોધન છે.

Figure 30: *Pragyaan-IT* data examples in categories Named Entity Recognition - (*Hard, 1-Turn, Complex-IF, Safe, IC-3, Normal (No Thinking Trails)*), Comprehension - (*Easy, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) and Inference - (*Hard, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) settings configuration.