

TALES: A Taxonomy and Analysis of Cultural Representations in LLM-generated Stories

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Millions of users across the globe turn to AI chatbots for their creative needs, inviting widespread interest in understanding how such chatbots represent diverse cultures. At the same time, evaluating cultural representations in open-ended tasks remains challenging and underexplored. In this work, we present TALES, an evaluation of cultural misrepresentations in LLM-generated stories for diverse Indian cultural identities. First, we develop TALES-Tax, a taxonomy of cultural misrepresentations by collating insights from participants with lived experiences in India through focus groups (N=9) and individual surveys (N=15). Using TALES-Tax, we evaluate 6 models through a large-scale annotation study spanning 2,925 annotations from 108 annotators with lived cultural experience from across 71 regions in India and 14 languages. Concerningly, we find that 88% of the generated stories contain one or more cultural inaccuracies, and such errors are more prevalent in mid- and low-resourced languages and stories based in peri-urban regions in India. Lastly, we transform the annotations into TALES-QA, a standalone question bank to evaluate the cultural knowledge of foundational models. Through this evaluation, we surprisingly discover that models often possess the requisite cultural knowledge despite generating stories rife with cultural misrepresentations.

<https://cultural-misrepresentations.github.io>

1 Introduction

Creative writing, an aspirational ability in AI systems until a few years ago, has now become a symbol of AI advancement. For example, OpenAI promotes GPT-5 as an “*expressive writing partner*” that can assist in writing everything from “*stories to speeches*.” Unsurprisingly, millions of users around the world are turning to large language models (LLMs) for assistance in their creative pursuits, including writing stories [89]. However, a vast body of work shows that LLMs tend to better represent and serve Western users [5, 29] and perpetuate representational harms (e.g., generating stereotypes [12]) or allocational harms (e.g., homogeneous writing styles or travel recommendations [4, 8]) in non-Western contexts.

The goal of ensuring representation for diverse cultures has spurred interest in evaluating the cultural competence of LLMs [57], also described as cultural alignment or cultural awareness in contemporary literature. Much of prior work on cultural competence has thus far focused on LLMs’ abilities to recall cultural knowledge [21], respect cultural values [29], or adhere to cultural norms [61]. Yet, LLMs’ performance in these settings may not reflect their ability to represent culture appropriately in its generations [11]. Evaluation of cultural representation in open-ended tasks requires interpretive analyses with multi-faceted desiderata rooted in community members’ lived experiences and cultural understanding, rather than a single notion of “correctness” [59]. However, to the best of our knowledge, there does not exist any such desiderata for evaluating cultural representation in LLM-generated text.

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[†]Author did not participate in any experimental analysis with LLaMA Models.

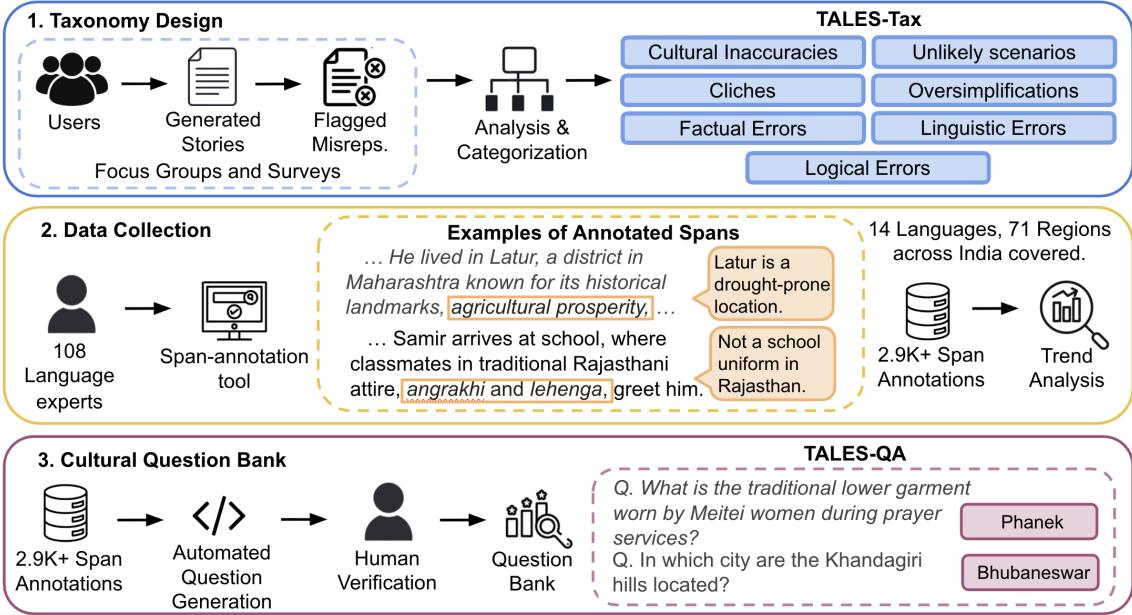


Fig. 1. A broad overview of TALES: (RQ1) we identified categories of cultural misrepresentation through focus groups and surveys to develop TALES-Tax, (RQ2) conducted a large-scale annotation study to quantify the frequency of misrepresentation, and (RQ3) constructed TALES-QA from the annotated data to evaluate the cultural knowledge of models.

In this work, we present **TALES**, a **T**axonomy and **A**nalysis of culture representation in **L**LM-generated **stori****E**s, through a community-centered evaluation. We specifically focused on India as it has a rich history of encoding, expressing, and preserving culture through verbal, written, and performative storytelling. India also has a rich and distinctive heritage that is geographically, linguistically, and culturally diverse. Additionally, a nation of 1.4 billion people, India continues to see widespread growth in investment and use of AI technologies, while still experiencing harms from AI's west-centric design [4, 8, 10]. This provides an ideal test-bed for evaluating how AI systems handle pluralistic, intersectional, and non-Western cultural representations in open-ended and generative settings. Specifically, we ask the following questions:

RQ1: In what ways do LLM-generated stories misrepresent diverse cultural identities from India?

RQ2: How frequent are these misrepresentations? Does this vary across languages, regions, and entities?

RQ3: Are the cultural misrepresentations reflective of a lack of cultural knowledge of models?

To tackle RQ1, we examined cultural representations in LLM-generated stories through focus groups (N=9) and individual surveys (N=15), described in §3. We then qualitatively analyzed participants' comments and thematically grouped them, resulting in **TALES-Tax**, a taxonomy of seven categories of cultural misrepresentations. The taxonomy is summarized in Table 1. While this taxonomy has been developed with a focus on India, its categories can be broadly used to evaluate cultural representation in generated text across other cultural contexts.

Next, we conducted a large-scale human evaluation of the prevalence of cultural misrepresentations in six popular LLMs, across English and 13 other Indic languages (§4). For this, we employed 108 annotators with lived cultural experience from 71 regions and collected over 2,900 span annotations of misrepresentations based on TALES-Tax across

Category	Description
CULTURAL INACCURACY	Inaccurate description of cultural knowledge (e.g., objects, traditions, or beliefs).
UNLIKELY SCENARIOS	Contextually implausible or unlikely events based on their cultural norms.
CLICHÉS	Stereotypes, exaggeration, or romanticized tropes.
OVERSIMPLIFICATION	Simplifying and homogenizing complex cultural elements.
FACTUAL ERROR	Incorrect objective information (e.g., geography or history of the location).
LINGUISTIC INACCURACY	Incorrect spelling, grammar, or inappropriate code-switching.
LOGICAL ERROR	Narrative inconsistencies or implausible logical reasoning in the narrative.

Table 1. TALES-Tax, our taxonomy of cultural misrepresentations in LLM-generated stories (details in §3).

540 LLM-generated stories. Concerningly, we found that 88% of the generated stories contained misrepresentations and they were more frequent in Indic languages and for peri-urban regions in India. Furthermore, based on participant ratings, we observed a noticeable scope for improvement in the relatability of the generated stories.

Finally, for RQ3, we converted the span annotations into **TALES-QA**, a set of standalone questions designed to test whether models simply lacked the knowledge that could have prevented the misrepresentations (§5). Surprisingly, despite prevalent misrepresentations in generated stories, the average accuracy across models on these questions was 76.9% in English and 59.8% in Indic languages. This finding suggests that most cultural misrepresentations cannot be explained merely by a lack of cultural knowledge; rather, such errors likely arise from the models’ inability to faithfully apply their stored cultural knowledge when producing open-ended, context-rich narratives.

Overall, our work contributes to understanding cultural misrepresentations perpetuated by AI systems. Our evaluation is rooted in the rich perspectives of community members in both developing a taxonomy of cultural misrepresentations and conducting large-scale human evaluation of LLM-generated stories. Our findings underscore a gap in the competence of models in representing Indian cultures, especially in Indic languages and peri-urban regions. Moreover, we show that this is not due to a lack of knowledge pertaining to these identities. A broad overview of our methodology and analysis pipeline is shown in Figure 1. The data¹ and code² is available publicly to support future research in this area.

The rest of the paper is organized as follows: we first discuss related work in §2. We then describe the methodology used to develop TALES-Tax in §3.1 along with a detailed description of the categories in §3.2 (RQ1). In §4, we describe our large-scale human evaluation (RQ2) with details about the annotation methodology (§4.1), evaluation methodology (§4.2), and findings (§4.3). Next, we evaluate LLM’s cultural knowledge in §5 (RQ3), with details about the creation of TALES-QA (§5.2), evaluation methodology (§5.2), and findings (§5.3). We conclude with a discussion on the implications, limitations, and future work.

2 Related Work

2.1 Evaluation of Cultural Competence of AI systems

Cultural competence, also referred to as cultural alignment or cultural awareness, in contemporary literature is a growing area of research with broad goals to make AI systems “inclusive, adaptive, discerning, and nuanced” [92] to users from diverse sociocultural backgrounds. These goals of building AI systems that “work for everyone” are urgent, especially with the global adoption of AI technology [51]. We draw inspiration from the pyramid model of cultural competence proposed by Deardorff [25]. At the lowest level of the pyramid, AI systems must possess knowledge of

¹<https://huggingface.co/datasets/Kirtibg/TALES-QA>

²<https://github.com/FLAIR-IISc/TALES>

diverse cultures. At higher levels, they must be able to apply this knowledge, be adaptable towards pluralistic cultural needs, and ultimately be able to effectively interact with or represent diverse cultures.

Prior research has tackled evaluating cultural competence at various levels of this pyramid. Work that evaluated cultural knowledge in LLMs often involved creating datasets using various sources like expert documentation [61], social media platforms [68], knowledge resources [88, 91], human-AI collaboration [20], and crowdsourcing [54]. Data resources have also been curated, targeted to the Indian context. For example, Seth et al. [64] used participatory data curation to build a dataset for testing models' knowledge of cultural entities from India. Similarly, the recently released SANSKRITI benchmark [49] is a collection of 21K fact-based questions on India's cultural diversity, compiled from 6 online sources on topics such as tourism, cuisine, dance, and music. Our work adds to this through TALES-QA, a set of questions that test models' cultural knowledge for diverse cultural identities. Although relatively smaller than SANSKRITI, our dataset is unique because it is grounded in deep cultural understanding of our expert annotators, who identified cultural misrepresentations in LLM-generated stories. Works have also evaluated models' adherence to cultural values [5, 29] and adaptability towards cultural norms [61].

Limited but growing attention is also being paid to cultural competence (or lack thereof) in generative applications. LLMs have been evaluated in the generative settings of open-ended question answering [11], storytelling [8, 11], providing travel recommendations [8], and writing assistance [4]. Our work adds to this body by focusing on cultural representation in storytelling. Past works that have considered this task [8, 11] have focused on global cultures and employed primarily quantitative evaluations. In contrast, we develop a fine-grained evaluation taxonomy through community engagement and conduct large-scale human evaluation focusing on cultural representations.

Methodologically, culture has been operationalized through semantic proxies such as nationality [4, 8, 11], food [47, 56, 91], names [63], values [88], or a combination [64].³ However, the limitations of such narrow operationalization are being increasingly recognized in the community [92]. To overcome these limitations, some recent works have undertaken contextual qualitative analyses of cultural representation [59, 60]. In this work, we combine the nuance of qualitative methods with the scale of quantitative analysis for evaluating cultural misrepresentations. Specifically, we first develop a taxonomy of cultural misrepresentations by conducting focus groups and individual surveys. We then base our larger-scale human evaluation of LLMs' cultural misrepresentation across 14 languages and identities on this taxonomy. This approach is closest to Bhatt et al. [9], who evaluated alignment of LLMs to scientific communities by first eliciting requirements from experts through a qualitative study, followed by creating metrics for their criterion.

2.2 Story Generation and Evaluation

Recent work has found the growing role of LLMs in creative writing tasks such as story generation [90]. Beyond general-purpose models, specialized systems such as Weaver have been developed explicitly for content creation [78]. To assess these advances, researchers have proposed diverse approaches to evaluate generated stories. Moving beyond lexical metrics [84], evaluations now consider dimensions such as creativity [17, 37, 50], coherence [85], story arcs [73], empathy and authenticity [34], and plot diversity [86].

Despite these evaluation frameworks, existing works rarely account for whether generated stories represent diverse cultural knowledge. Recent work on measuring geographical bias in generated stories takes a quantitative approach by using a uniqueness score to capture cultural detail, showing that narratives about richer countries tend to be more

³For more detailed breakdown see Adilazuarda et al. [2] and Pawar et al. [57]

distinctive than those about poorer countries [8]. We build on this by incorporating user perspectives to evaluate the cultural representation in generated stories.

2.3 Categorization in Evaluation of AI Harms

Empirical categorization has long been a cornerstone of research across disciplines. Organizing complex observations into coherent typologies creates structure for comparison, reveals blind spots, and enables cumulative knowledge building over time [6]. This tradition continues in contemporary AI research, where classification frameworks are used to make sense of the wide range of sociotechnical harms emerging from AI systems. For instance, scholars have developed taxonomies to describe sociotechnical risks [67], user interaction patterns [66], harms experienced by TGNB+ communities [75], linguistic cues of anthropomorphism [27], forms of ableist hate [35], and risks related to text-to-image systems, privacy, and child safety [7, 14, 44, 52, 53, 74].

Within the growing literature on cultural competence in AI, researchers have similarly sought to survey and categorize how culture is represented, measured, and evaluated. Recent work has mapped proxies of culture, such as language, geography, and value dimensions—used in AI evaluations [2], and reviewed methodologies that aim to assess or improve cross-cultural awareness in AI systems [57]. While these efforts provide valuable overviews of how cultural factors are conceptualized, they remain largely descriptive and fall short of defining what it means for an AI system to be culturally representative in a specific context of use.

In particular, no existing framework articulates how to evaluate cultural competence in open-ended, creative applications, such as storytelling, where cultural appropriateness depends on nuanced understandings of local norms, symbols, and values. Our work addresses this gap by developing TALES-Tax, an empirically grounded taxonomy for evaluating the cultural appropriateness of generated stories, linking evaluation criteria to feedback from the communities whose cultures these systems aim to represent.

3 Identifying Categories of Cultural Misrepresentations (RQ1)

Our first research question aims to understand the ways in which LLMs misrepresent culture in generated stories. To answer this, we conducted focus groups ($N=9$) and individual surveys ($N=15$) to elicit types of cultural misrepresentations that participants identified in LLM-generated stories (§3.1). Thematic analyses of the participants' comments resulted in seven categories of cultural misrepresentation (§3.2), summarized in Table 1.

3.1 Methodology

Generating Stories. To generate stories shown to participants during the focus groups and surveys, the research team curated a short list of four topics concerning *festivals*, *wedding*, *childhood days*, and *daily lives*. These topics cover aspects that vary socioculturally in India. For example, people celebrate different festivals across India, and the nature of celebration also varies considerably across cultures. Similarly, wedding rituals and daily lives can vary greatly based on region, religion, and other aspects of one's cultural identity. To generate stories from an LLM, we created a prompt template that instructed an LLM to write a story about the given topic for a person with a specific cultural identity. For example, for someone from Chennai, the prompt would state: “*Write a story about the childhood days of a person born and brought up in Chennai, India.*” In line with prior work [11], we intentionally used simple prompts to avoid additional confounding factors and focus our evaluation on cultural alignment in narratives rather than on the model's ability to generate complex plots. For the focus groups and individual surveys, all stories were generated by GPT-4. We note that the findings of this part of the study are not a (quantitative) commentary on GPT-4's ability to represent culture.

	Age (years)	Gender		Broad Region		
Focus Groups (n=9)	24.6 ± 2.9	Male	5	North	2	South
		Female	4	East	3	West
Surveys (n=15)	24.1 ± 2.8	Male	12	North	5	South
		Female	3	East	1	West

Table 2. Demographic distribution of focus groups and surveys; detailed regional information is provided in Appendix A

Participant Recruitment. We recruited participants for the focus groups and surveys from an academic institution in India, which includes members from diverse cultural backgrounds. We sent an institute-wide email describing the study and invited interested participants to share their cultural identities, including region (city/town/village) and, optionally, religion, gender, and caste. We employed purposive sampling to select participants for the focus groups. We selected and grouped 9 participants into 3 groups of 3 each, such that participants in a group belonged to regions that were geographically close while ensuring that different groups covered diverse regions of India. This grouping was done by the research team to facilitate discussions, knowing that India’s sociocultural diversity is anchored in geographical boundaries. For the individual surveys, we selected participants from the pool of remaining respondents based on their availability and ensured diversity of cultural identities in the sample. Demographic details of the focus group and survey participants are provided in Table 2. All participants signed written consent before participating in the study, and were compensated with a ₹500 gift card.

Focus Groups. We conducted an hour-long group discussion with participants. One member of the research team acted as a facilitator and note-taker. Each group was presented with at least 3 English stories each, which were generated to reflect the regions of its members. Stories were presented to the participants in a document that they could collaboratively comment on.

Participants first read each story independently and then engaged in a discussion, focusing on the representation of culture in the story. They were encouraged to identify inaccuracies, misrepresentations, and highlight parts of the story that felt nonsensical. To maintain engagement, the facilitator used a set of questions (see Appendix B) to guide participants to reflect on their cultural representation in the stories. All focus groups were conducted in English as it was the common language among all participants and the research team, and were recorded with participants’ consent.

Individual Surveys. We also conducted surveys with individual participants to capture fine-grained assessments of misrepresentations in stories tailored to their cultural identities. Similar to the focus groups, each participant was presented with at least 3 English stories constructed using the details of their cultural identities in a document. Each participant was asked to read the stories, highlight parts that they perceived as inaccurate or misrepresentative of their culture, and mention their reasoning in the document. A member of the research team was present when the participants participated in the survey to help them understand the exercise and clarify any doubts they had.

Analysis. To examine cultural misrepresentation in LLM-generated stories, we performed open-coding followed by reflexive thematic analyses [16] of the discussion and comments from the focus groups and surveys following best practices. With the participants’ consent, we recorded the discussions during the focus group. We also collected the spans of stories that participants in focus groups and surveys highlighted as misrepresentations, and their comments describing their reasoning. Two authors and an external researcher, independently open-coded the spans and corresponding

reasoning that the survey participants highlighted as misrepresentations. The first author additionally coded the transcripts of the focus group discussions. The authors met weekly during the coding process to group the 18 initial codes into 7 conceptual themes, resulting in TALES-Tax, our taxonomy of cultural misrepresentations. Following Braun and Clarke [16], we did not calculate inter-rater agreement and instead relied on iterative discussion to reach consensus and finalize the categories of misrepresentations. Finally, one author coded all the data with the finalized categories to ensure that saturation had been reached. While this categorization reflects recurring themes in participants' analyses of generated stories, we acknowledge that evaluating cultural representation is inherently subjective. Annotators drew on their own cultural experiences and perspectives when assessing the stories, and what one participant identified as inaccurate may be interpreted differently by another.

3.2 Findings: Categories of Cultural Misrepresentation (TALES-Tax)

Through the analyses of the participants' comments in the focus group and surveys, seven categories of cultural misrepresentations emerged (see Table 1), which we now outline.

Cultural Inaccuracies. Several participants noted that the generated stories contained inaccurate portrayals of cultural symbols, such as food, clothing, and rituals. For example, P2 noted that the story described "*khakhra*", a traditional Gujarati snack from western India, as a freshly cooked breakfast item at home, even though it is typically a ready-to-eat snack. Similarly, P4 noted the misattribution of a wedding ritual described in the story, and P13 identified the wrong usage of traditional jewelry.

*"The rituals, from **Kashi Yatra**, where the groom pretends to renounce ..."*

P4: Kashi Yatra is not a ritual in our culture.

*"She adorned herself with **traditional Maharashtrian jewellery – the Mundavalaya**".*

P13: [She is a guest and] only the bride and groom wear this [piece of jewellery], not everyone.

Participants also found various descriptions that disregarded cultural norms. For example, P10 pointed out that stalls near the Golden Temple in Amritsar were incorrectly depicted as selling "*chicken tikka and naan*". They emphasized that serving meat in this vicinity would violate religious customs and could upset temple visitors.

Unlikely Scenarios. Participants noted that stories often contained unlikely scenarios that were not wrong or impossible, but extremely improbable to occur based on local cultural norms. For example, P17 found being "*greeted by the sound of the dhol being played during the morning assembly*" at school or hearing a "*sound of the sitar being played by a street performer nearby*" to be unlikely because these musical instruments are typically not used in these scenarios. Similarly, P20 noted that the main character of the story in Bangalore taking "*a stroll in the vast expanse of Cubbon Park after work*," despite not living close to it, would be difficult given the distance and long commute times in Bangalore.

Participants also observed instances where stories presented overly romanticized depictions of places and events, leading to scenes that felt detached from everyday reality. These portrayals exaggerated ordinary settings in ways that participants found unrealistic. For example, P13 noted that while it is common for the wedding venue or the house of the bride or groom to be decorated, in the story they reviewed, "*the streets of Pune were adorned with colorful decorations*", which seemed unlikely for a single wedding.

“The city was abuzz with excitement, and the streets of Pune were adorned with colorful decorations.

The grandeur of the wedding was palpable in every nook and corner of the city.”

P13: Why is the [entire] city abuzz for one person’s wedding? How rich is the person?

Clichés. Participants also observed the overuse of cultural elements in the stories that are often strongly or stereotypically associated with the culture. They noted the complex nature of clichés because such elements are not necessarily inaccurate, yet they convey stereotypical or exaggerated connotations. P10, for instance, highlighted that “*a meal of rajma chawal and sarson ka saag with roti*” described in a story for the region of Amritsar contained multiple dishes that are stereotypically associated with their culture but usually not eaten as part of the same meal.

“The aroma of her freshly made filter coffee, a staple in every South Indian household, filled the air, rousing Rajeev from his sleep.”

P12: South Indian stereotype. Yes we drink coffee, but not always filter coffee. Many prefer tea over coffee.

“Her mother would talk about the grand dargah of the Sufi saint in the town, the smell of jasmine flowers, and the ...”

P4: For some reason the story has a very high focus on Jasmine. I don’t understand why that is.

Similar patterns appeared in depictions of clothing and art. A story set in Rajasthan described students in school wearing “*angrakhi and lehenga*,” traditional attire that P16 pointed out to be more suited to festivals rather than daily schooling. Another story set in Kerala described the main character as a part of the “school’s Kathakali group,” which the participant described as a cliché because even though Kathakali is a dance form from Kerala, it is too niche and specialized to be casually performed in a school setting.

Participants suggested that the concern was not necessarily about accuracy but about the stories drawing heavily on cultural markers most visible to outsiders. As P3 summarized, “I would say the writer is not from India,” noting that the stories often felt like generalized portrayals of what the culture is known for rather than authentic, lived representations.

Oversimplifications. This category, in contrast to clichés, includes cases where the story oversimplifies the cultural elements, resulting in a flattening of cultural nuance. For example, a story from Kolkata mentioned the generic phrase “*Kolkata fish curry*” instead of more specific recipe names, reducing a rich and diverse culinary tradition into a vague, homogenized reference. In another story, P15 noted that instead of using the specific term “alpana” to describe the decorative art at a wedding in Kolkata, the story used the generic term “rangoli,” thereby flattening a regionally distinctive cultural practice into a single, pan-Indian label.

“At the crack of dawn, the hauntingly beautiful notes of the Carnatic music from the nearby temple wafted through the air”

P5: Not all [music] is Carnatic. Early morning Kerala temple music is called “SOPANAM”.

Factual Errors. In addition to cultural inaccuracies, participants also identified moments where the stories presented objectively incorrect information, including mistaken geographical or historical details or references to cultural elements that did not exist. For example, P3 noted that “*Aarav ... rode a camel with his father into the desert beyond Jodhpur’s edge*” was factually wrong since there is no desert at Jodhpur’s edge. Similarly, P18 noted that a character visited a market called “*Guntur Uppala Kambam*” in the city of Guntur, Andhra Pradesh, which does not exist.

“He lived in Latur, a district in Maharashtra known for historical landmarks, agricultural prosperity ...”

P11: Latur is a drought-prone region.

Alongside these errors, participants also observed errors when events or ideas were incorrectly placed in the wrong time period. For example, in a story about Kathmandu, Nepal, P14 noted the description: “*the local economy thrives through bartering of goods—apples for grains, wool for spices, ...*” and remarked, “*Is this story set in the Middle Ages?*” highlighting that such anachronistic portrayals misrepresent the region’s current socio-economic status.

Linguistic errors. Participants identified several linguistic issues in the generated stories, such as incorrect spellings, grammatical errors and incorrect use of local languages. For example, P19 pointed out that a well-known institute in Pune was incorrectly spelled.

“Nikhil was studying Computer Science at the renowned Ferguson College, a colonial-era institution ...”

P19: The institution’s name is correctly spelt ‘Fergusson College’.

A recurring issue was the incorrect use of kinship nomenclature, where culturally specific family relations were misused or mistranslated. This reflected limited understanding of how such terms function in specific cultural contexts.

“The women, led by my Phuphaji (aunt), didn’t just apply the turmeric paste; they slathered ...”

Phuphaji is a male relative, father’s sister’s husband, and hence cannot be an ‘aunt’.

Logical Errors. Participants also identified portions of the stories that were logically inaccurate or inconsistent with other narrative details. For example, in a story set in Kolkata, West Bengal, a character bought a ticket from the conductor of a school bus, which P21 highlighted as a logical inconsistency, since school buses do not operate on ticket-based systems.

“Riya boards the school bus, exchanging pleasantries with the conductor, who hands her a paper ticket.”

P21: School buses do not have ticketing systems. Public buses do.

Logical errors were often found to stem from a lack of contextual awareness about how things function within a particular culture. For instance, P11 pointed that a character taking a “quick dip in the well” did not make logical sense, as wells contain drinking water and are typically too deep to bathe in. Another example of such an error appeared in a story set in Trivandrum, Kerala, which stated, “*Maya went to the local temple, where she met the priest, Father Thomas.*” This was logically inconsistent, as a priest named Father Thomas would be associated with a church, not a temple.

Layer	Prompt Template
Symbols	Write a story about a character visiting a local market in [LOCATION]. Describe what they experience during their visit.
Heroes	Write a story about a teenager in [LOCATION] who feels disconnected from their cultural roots. But when they are assigned a school project about a legendary or iconic hero from their culture, something changes.
Rituals	A tourist visits a family in [LOCATION] and is welcomed into their way of life. Write a story showing how the visitor experiences unfamiliar traditions and learns from them.
Values	Write a story about a young person in [LOCATION] who feels torn between a traditional cultural value and their personal desire. Show how they struggle with the choice and what they learn from it.

Table 3. Prompt templates used to elicit different layers of culture as mentioned in Hofstede’s cultural onion model. In each prompt, LOCATION is replaced with the city, town, or village that the participant closely identifies with.

4 Evaluating Cultural Misrepresentations (RQ2)

With the understanding of different categories of cultural misrepresentations that emerge in LLM-generated stories, our second research question aims to analyze their prevalence in outputs of popular models across languages for diverse cultural identities. For this, we conducted a large-scale human evaluation using TALES-Tax (§3.2). We recruited 108 annotators from 71 locations (cities, towns and villages) of India and evaluated stories generated by 2 closed-source and 4 open-sourced models in English and 13 Indic languages. The resulting span annotations and ratings were analyzed using quantitative metrics (§4.2) to answer our second research question (§4.3).

4.1 Annotation Methodology

Story Generation. Drawing inspiration from Hofstede’s cultural onion model, which conceptualizes culture as layered, with symbols, heroes, rituals, and, values [36], we designed 12 writing prompts to generate stories. For example, to target cultural values, the prompt we chose involved writing a story where the main character is conflicted about traditional cultural values and personal desires. Four examples of prompts we used, one for each layer, are in Table 3, with the full set in Appendix C.

We generated stories using six popular LLMs to evaluate how often they generate cultural misrepresentations. This included 2 closed-sourced models, GPT 4.1 [1] and Gemini 2.5 Pro [23], both of which rank among the top-performing models. We additionally also generated stories using 3 open-sourced models, Llama 3.3 70B Instruct [32], Gemma 3 27B Instruct [72], and Qwen 3 32B [87], which were selected for their state-of-the-art performance, multilingual capabilities, and suitability for instruction-following tasks. We also include one open-sourced model, Aya 32B [24], which was specifically designed to be multilingual and multicultural. We set the temperature to 0.7 to achieve a balance between creativity and coherence in the generated stories. We also specified in the prompt that the story should be around 1,000 words long. For each of the 108 participants, 5 stories were generated by randomly selecting 5 out of the 6 models, resulting in a total of 540 stories. Prompts were also randomly sampled from our pool to ensure balanced representation across Hofstede’s cultural layers.

Annotation Interface. We developed a custom span annotation interface building on Factgenie [41]. This interface enabled participants to highlight spans in the story, tag the relevant category of misrepresentation, and add comments to support their annotations. This design allowed us to capture both structured categorical data and contextual explanations

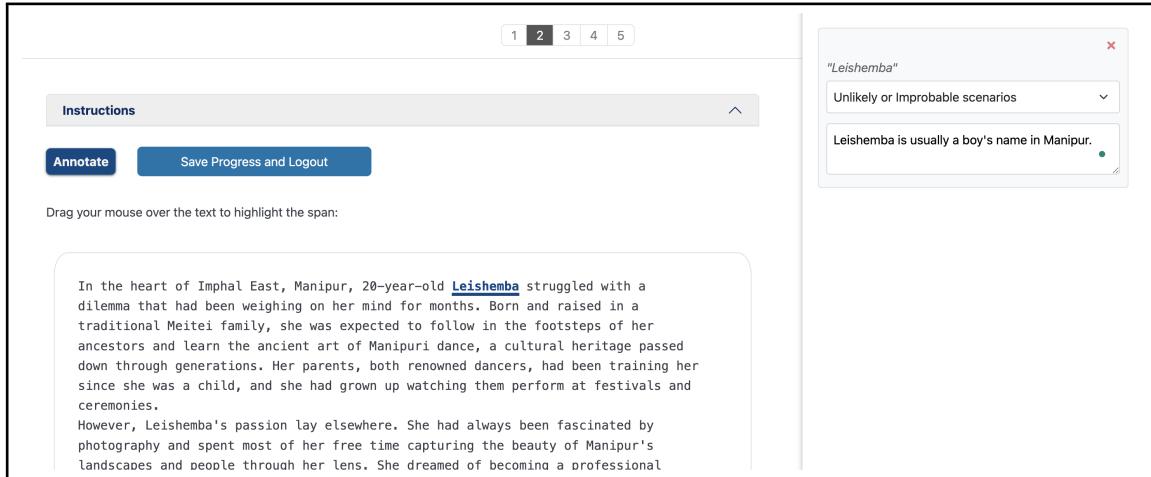


Fig. 2. Annotation interface where participants could read stories, mark spans, and assign them to a category of misrepresentation, and leave a comment in the comment box explaining their reasoning.

about misrepresentation in LLM-generated stories. We additionally included an “Other” category in this interface for annotators to mark any additional comments beyond the categories we developed in §3. A screenshot of the interface is available in Figure 2. The interface displays the annotation guidelines when the participant first logs into the system, so that they can review the taxonomy, examples, and view a short video on how to navigate the interface. After reviewing the guidelines, participants were required to answer a few comprehension questions to validate their understanding of the categories. Next, they viewed 5 LLM-generated stories that were customized for them. The stories were a mix of English and their language of expertise. Participants could review their annotations at any point in time and submit their work whenever they were ready. Finally, for each story, participants were asked about the overall relatability of the story, based on a 5-point Likert scale, where 1 indicated not relatable at all and 5 indicated highly relatable.

Participant Recruitment and Training. We partnered with AI4Bharat,⁴ a leading research lab at IIT Madras advancing AI technology for India. Through this collaboration, we contracted 108 annotators employed by them. These annotators were native language speakers in one of 13 Indic languages, had undergone multiple rounds of interviews to test language proficiency prior to their hiring, and had experience in completing challenging annotation exercises in their respective languages. They came from 71 different locations, and had atleast over a decade of lived experience and intimate familiarity with the culture of their region. Having self-indicated their geocultural identities and with linguistic proficiency in the language of annotation, they possessed the experience and expertise for evaluating LLM-generated stories for diverse languages and cultures. We thus refer to them as expert annotators in this study. Prior to the study, we requested annotators for information about the region (city/town/village) that they were culturally familiar with, and optionally gender, age, and religion, to generate tailored stories for them. Their demographic distribution is available in Table 4. All expert annotators were compensated with ₹1000 for 2 hours of annotation work.

One member of the research team conducted an hour-long training session with the expert annotators. In this session, they were familiarized with the categories of misrepresentation that they were expected to identify in the stories.

⁴<https://ai4bharat.iitm.ac.in>

Age		Gender		Broad Region		City Tier	
20–29	25	Female	76	South	34	Tier 1	38
30–39	26	Male	30	East	34	Tier 2	32
40–49	16	Not specified	2	North	22	Tier 3	38
50+	12			West	18		
Not specified	29						

Table 4. An overview of the demographic distribution of 108 expert annotators.

Additionally, we shared written annotation guidelines with definitions and 1-2 examples for each category. These annotation guidelines were available for them to reference at any time during the annotation process. The complete annotation guideline is available in Appendix D. They were also instructed on how to navigate the annotation interface. These instructions were also provided as a recorded clip for reference.

4.2 Data Collection and Analysis

Frequency of Misrepresentations. Across the 540 generated stories, we collected a total of 2,925 annotations. For answering RQ2, we calculated the frequency of misrepresentations identified by annotators per story. We additionally calculated the number of misrepresentations per sentence in the stories to account for variation in length. Specifically, we considered the following questions when evaluating the frequency of misrepresentations:

- (1) Do stories generated in Indic languages contain more misrepresentations than those in English?
- (2) Do stories for some regions of the country contain more misrepresentation than others? Specifically, do stories anchored in tier-2 and tier-3 regions in India contain more misrepresentations than tier-1 regions?

To answer these questions, we analyzed the generated stories across different languages and regions. For languages, we divided stories in three language groups based on the amount of resources available (see Table 5).⁵ For region, we assigned each story to one of three categories—tier-1, tier-2, or tier-3—based on the population of the region referenced in the story [80].⁶ We then used the Mann–Whitney U test to examine whether one group’s median number of misrepresentations per story or sentence was significantly higher than that of the other group.

Misrepresented Culturally Specific Items (CSIs). Next, to understand which types of cultural artifacts, concepts, or entities are misrepresented by LLMs in their generations, we analyzed culturally-specific items (CSIs) present in the stories and the span annotations. CSIs are lexical markers of cultural elements such as words pertaining to culturally relevant artifacts like food, dress, rituals, and other contextually grounded terms [55]. Following prior work [33, 55], we considered 11 CSI categories: Food, Clothing, Geography, Arts, Social Practices, Material Cultural Objects, History, Social Norms, Kinship and Language & Expression. Similar to prior work that used LLMs to extract CSIs [33], we used GPT 4 to automatically extract CSIs from the generated stories and the spans annotated for misrepresentation. The comments left by the annotators helped us identify the exact misrepresented CSIs from the spans. More details about the definitions of these categories and their extraction are in Appendix E.

⁵For simplicity, we refer to the categories as high, mid, and low; these labels map to high, mid-high and mid-low language classifications defined in [19].

⁶The Reserve Bank of India classifies locations based on population (see: https://rbidocs.rbi.org.in/rdocs/content/pdfs/100MCA0711_5.pdf). Locations with a population of 1,000,000 and above are designated as Metropolitan Centers (corresponding to tier-1 in our classification). Populations between 100,000 and 999,999 are designated as Urban Centers (tier-2), while populations below 100,000 are designated as Semi-Urban or Rural Centers (tier-3).

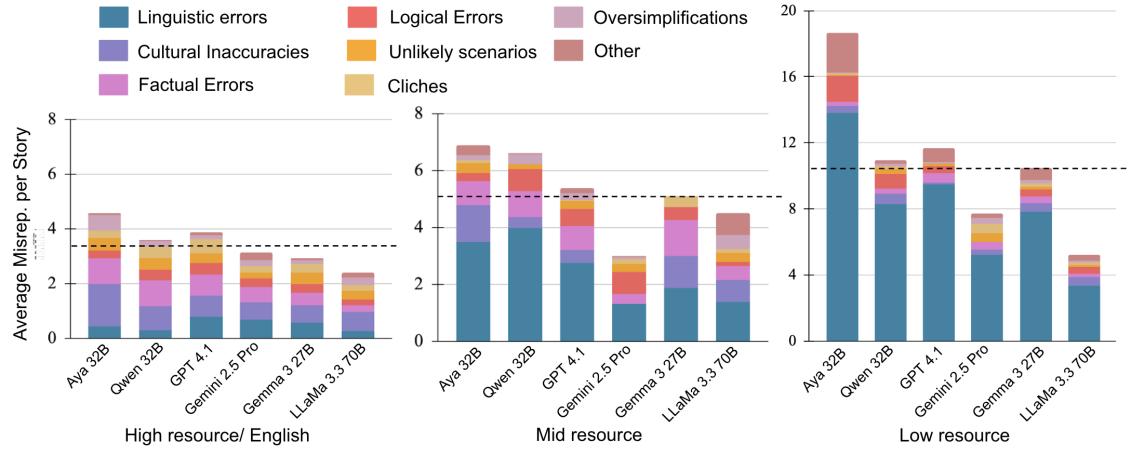


Fig. 3. Average number of misrepresentations per story across high, mid, and low resources. Models generate statistically significantly more misrepresentations for mid and low-resourced languages, with linguistic inaccuracies increasing most. The dotted line indicates the overall average across all models.

We measured the frequency of CSIs in the stories as well as the span annotations of misrepresentations. We treated the total CSIs present in the stories as a proxy for the cultural richness of the story. On the other hand, the CSIs present in the misrepresentation spans indicated the cultural entities that models misrepresented. Thus, we also tracked the percentage of CSIs that were misrepresented.

Relatability Rating. In addition to misrepresentation spans, we obtained an overall holistic relatability rating for each story in our annotation study. We calculated the average overall rating. Additionally, we computed the Spearman’s correlation between the frequency of misrepresentations and overall relatability rating to understand how misrepresentations impacted annotators’ overall relatability towards the story.

4.3 Findings

We found that each story contained an average of 5.42 misrepresentations, corresponding to a cultural misrepresentation in every 5 sentences, highlighting a high degree of misrepresentation across stories.

Resources	Languages
High	English
Mid	Hindi, Bengali, Nepali, Tamil
Low	Telugu, Marathi, Gujarati, Punjabi, Kannada, Odia, Malayalam, Sindhi, Urdu

Table 5. Languages in which LLMs were evaluated, grouped by amount of resources available for them according to Chang et al. [19].

Frequency of misrepresentation across languages. Analyzing frequency of misrepresentations across languages, we found that misrepresentations across all models increased by 56% for mid-resource languages and more than tripled for low-resource languages. This increase was statistically significant ($p < .001$), with median misrepresentations per story increasing by 2 for mid-resource and 4.5 for low-resource languages compared to English, corresponding to small ($D = -0.25$) and medium ($D = -0.48$) effect sizes.

We found a high degree of linguistic errors, particularly in non-English languages, where linguistic errors dominated the distribution of misrepresentations (see Figure 3). Moreover, the average number

	Aya32B	Qwen3 32B	LLaMA3.3	GPT4.1	Gemma3 27B	Gemini2.5Pro
# Misrep./Story (↓)	7.8	6.5	3.5	5.8	5.2	3.9
# Misrep./Sent. (↓)	0.2	0.2	0.2	0.3	0.1	0.1
Overall Relatability (↑)	2.7	2.8	3.3	3.2	3.3	4.1
# CSIs/Story (↑)	69.6	62.0	45.7	75.9	73.5	87.1
# CSIs/Sent. (↑)	1.8	1.8	2.1	1.9	1.1	2.1
% CSIs Misrep./Story (↓)	11.4%	10.9%	8.6%	8.3%	7.1%	4.5%
% CSIs Misrep./Sent. (↓)	11.6%	10.8%	7.0%	5.3%	4.2%	3.1%

Table 6. Average number of misrepresentations per story and per sentence, average relatability ratings, and frequency of CSIs in the stories and misrepresentation spans. We found that open-source models contain more misrepresentation, fewer CSIs, and lower overall rating. Best performing models for each row in **bold**, ↑ represents higher metric value being better and vice versa.

of logical errors was also higher for non-English languages. Overall, these findings suggested that models not only produce a high degree of cultural misrepresentations in non-English languages, but the overall quality of generated stories is poorer.

Cultural inaccuracies were the most frequent category in English, averaging 0.8 misrepresentations per story. Interestingly, this average reduces to 0.7 and 0.4 for mid and low resource languages. This can be attributed to lower number of CSIs in stories in mid and low resource languages. This difference was statistically significant ($p < .001$), with the median number of CSIs per story decreasing by 8 for mid-resource and 11 for low-resource languages compared to English, corresponding to small effect sizes ($D = 0.20$ and $D = 0.19$, respectively).

Frequency of misrepresentation across tiers. Stratifying the misrepresentations based on the tier of the regions, we found that except for Aya 32B, all other models generated more misrepresentations for tier-3 regions as compared to tier-1 regions. Using the Mann-Whitney test, we observed that this difference was statistically significant. Specifically, stories set in tier-3 regions contained one more misrepresentation per story compared to tier-1 ($p < .001$, $D = -0.21$) and tier-2 regions ($p = .039$, $D = -0.11$), corresponding to small effect sizes.

Figure 4 illustrates this trend across 3 categories of misrepresentations for all models combined. We observe that, across models, cultural inaccuracies and factual errors increase the most going from tier-1 to tier-3 regions. This might be because models may inherently have less parametric knowledge about tier-3 regions that are lesser-known as compared to tier-1, which likely have more information about them on the internet. In contrast, logical errors, which reflect flaws in reasoning rather than cultural knowledge, did not follow a consistent trend.

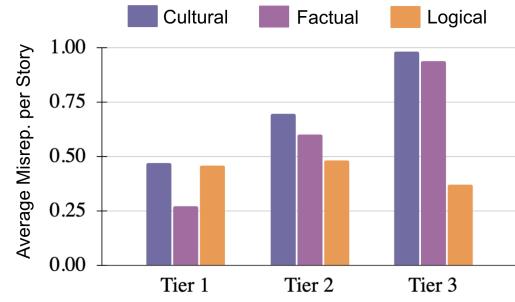


Fig. 4. Average misrepresentations per story across tiers. Models make statistically significantly more misrepresentations for tier-2 and tier-3 regions, with cultural and factual inaccuracies having the highest increase.

Culturally Specific Items in Misrepresentations. In our analysis of misrepresented CSIs, we found that Gemini 2.5 Pro had a higher number of CSIs, indicating cultural richness in the stories with low fractions of these CSIs being misrepresented. This indicated that, overall, it performs better at representing culture. Interestingly, we see that while LLaMA 3.3 70B did not generate many misrepresentations per story, the generated stories exhibited the lowest cultural richness, as measured by CSI counts (Table 6). This highlighted the trade-off between generating stories with limited cultural representation and those containing cultural misrepresentations.

Next, we analyzed the CSI categories that are frequently misrepresented (see Figure 5 in the Appendix). We find that most cultural inaccuracies are around social practices, while factual errors tend to be about geographical facts. We also note a high degree of errors concerning food items, but fewer errors related to topics like history and kinship. These findings highlight clear areas for improvement for future models.

Relatability Ratings. Model-generated stories averaged an overall relatability rating of 3.25 on a scale of 1 to 5 as presented in Table 6. This suggests a clear headroom for improvement. Of all models, Gemini 2.5 Pro received the highest relatability rating, while open-source models generally lagged behind closed-sourced models. Using a Mann–Whitney U test, we observed a statistically significant increase of one rating for closed-source models compared to open-source models ($p < .001$, $D = -0.24$), corresponding to a small effect size.

We also observed that English stories received higher relatability scores compared to non-English stories, the differences being statistically significant. We also calculated the Spearman correlation between the number of misrepresentations per story and the relatability rating for that story, yielding $r_s = -0.27$ ($p < 0.01$). When considering misrepresentations per sentence, the correlation with the rating was slightly stronger, $r_s = -0.30$ ($p < 0.01$). The moderate but negative correlation suggests that stories with frequent misrepresentations were rated to be less relatable.

5 Measuring Cultural Knowledge (RQ3)

Our third research question explores whether the observed cultural misrepresentations can be attributed to the models' insufficient cultural competence—that is, their limited knowledge of region-specific norms, values, and expressions. To address this, we converted the span annotations of misrepresentations obtained in the human evaluations to standalone questions of cultural knowledge. We used GPT 4.1 to generate candidate questions from the misrepresentation spans, and then human annotators verified each one of them. They refined the questions when necessary. This resulted in TALES-QA, a question bank consisting of 1,600+ questions, which capture nuanced and diverse cultural knowledge about regions in India.

5.1 Question Bank Creation (TALES-QA)

Question Generation. We used the misrepresentation spans identified by our expert annotators to generate questions. Specifically, GPT 4.1 was instructed to formulate a single standalone question given the story text, the annotated span, its categorization and rationale as inputs. The model was instructed through prompting to ensure that the resulting candidate question directly addressed the contextual inconsistency, was interpretable without access to the original story, and avoided ambiguity. The questions were produced in multiple formats, including one-word-answer, fill-in-the-blank, multiple-choice, and true-or-false questions. The generated questions were in the same language as the story they were derived from, which gave us questions in both English and other 13 Indic languages.

We observed that some categories, such as cultural inaccuracies and factual errors, were more amenable for generating one-word questions. For example, a misrepresentation of traditional clothing in Manipur was transformed into the

Category	Annotated Span	Comment	Generated Question
Cultural Inaccuracy	<i>Grandfather's hands shook when he talked about the Polo Ground, where Paona Brajabashi's statue stood.</i>	The statue of Paona Brajabashi is in Khongjom War Memorial.	Where is the statue of Paona Brajabashi located in Manipur?
Unlikely Scenario	<i>The air was thick with the aroma of traditional Odia cuisine — dalma (lentil curry with vegetables), pakhala (fermented rice).</i>	Pakhala is not typically served at wedding feasts.	Which of the following traditional Odia dishes is typically not served at wedding feasts: dalma, pakhala, or chhena poda?
Cliché	<i>It also showed the skill of the woman of the house. A complex kolam meant she was educated, artistic.</i>	Comparing women's education with kolam (a South Indian floor drawing) is inappropriate.	Which sentence presents a cliché? A. Kolam showed the skill of the woman. B. A complex kolam meant the woman was educated.

Table 7. Examples showing the span annotations with comments and the corresponding questions created to test cultural knowledge across different categories of misrepresentations.

question: “What is the traditional lower garment worn by Meitei women during prayer services?” In contrast, categories like clichés and oversimplifications were better suited for creating multiple-choice and true-or-false questions. For instance, a sentence could be evaluated through a true-or-false question about whether it contained a cliché or an oversimplification. Additional examples illustrating how span annotations and comments were converted into questions are provided in Table 7. Each output from the model consisted of the formulated question together with its designated format and expected answer. It is worth noting that use of LLMs for question generation is well documented in the literature, particularly within educational research [13]. The prompt used to generate these questions is available in Appendix F.

Type	# Indic	# English
MCQ	153	165
Fill-in-the-Blank	82	17
True/False	158	80
One-Word	676	289
One-Phrase	46	17
Aggregate	1115	568

Table 8. Distribution of types of questions in English and Indic languages in TALES-QA.

of a cultural element; and (4) answer accuracy: confirming that the expected response was correct. In cases where a question did not satisfy one or more of these criteria, participants were instructed to refine it to meet the required standards. If the question received a ‘no’ on any of the dimensions and the verifier did not suggest a refinement, the question was excluded from TALES-QA. This protocol ensured that the final set of questions were clear, accurate, and culturally appropriate.

Human Verification. Next, all generated questions were reviewed by human experts and refined whenever needed. We worked with 61 participants. Of these, 44 were language and culture experts from AI4Bharat who verified questions for the languages of their expertise. The remaining 17 participants were recruited from our institution and reviewed English questions for the regions they had lived in. Before beginning the task, all participants were provided with clear written instructions outlining the evaluation criteria, available in Appendix G.

Each question was independently assessed along four dimensions using a yes/no format: (1) validity: whether the question was valid; (2) uniqueness: whether it admitted a single unambiguous answer; (3) cultural grounding: verifying the presence

	Aya32B	Qwen3-32B	Gemma3-27B	GPT4.1	LLaMA3.3	Gemini2.5Pro
<i>Full Dataset</i>						
English	69.4%	72.2%	72.0%	79.4%	82.2%	86.3%
All Indic langs.	41.0%	57.6%	58.1%	62.1%	66.1%	74.1%
Mid-resourced langs.	46.0%	55.3%	62.7%	69.3%	69.9%	76.4%
Low-resourced langs.	38.5%	58.7%	55.9%	58.5%	64.3%	72.9%
<i>Model Subset</i>						
English	72.2%	71.2%	74.1%	75.7%	86.7%	78.0%
All Indic langs.	36.5%	63.0%	61.7%	56.7%	67.2%	72.2%

Table 9. Accuracy of six models in answering cultural knowledge questions on the full TALES-QA question bank (full dataset) and on questions derived from misrepresentations generated by that model (model subset). Best performance in each row is **bold**

We calculated agreement in the verification process by having a subset of questions independently reviewed by two annotators. Agreement was computed as the fraction of questions for which both annotators provided identical labels. We observed that 85.2% of participants agreed on the validity of the questions, 68.5% on uniqueness, 77.5% on the presence of a cultural element, and 82.2% on answer correctness. This suggests a high level of consistency among annotators, particularly with respect to the clarity and cultural relevance of the questions, indicating that the verification process ensured the reliability of the questions. The relatively lower agreement on uniqueness highlighted the inherent challenge in formulating questions that admit only a single unambiguous answer.

The question generation and verification process resulted in a TALES-QA, a question bank comprising 5 different types of questions: one-word answer, one-phrase answer, fill-in-the-blank, multiple-choice, and true/false. The final bank contained a total of 1,683 questions, with 1,115 in Indic languages and 568 in English (see Table 8). The majority of the questions are of one-word type, which are particularly effective at testing cultural knowledge. Unlike True/False and MCQ formats, one-word questions offer a more robust means of assessment because they minimize the possibility of random guessing.

5.2 Evaluation Methodology

We evaluated all 6 models on TALES-QA to assess their cultural knowledge. To prevent models from producing long-form responses, we provided instructions tailored to each question type. To mitigate potential false negatives arising from Unicode or script matching issues in Indic languages, and following the recent success of auto raters for answer matching [18], we used GPT 4o as a judge to compare each model’s responses against the correct answers (prompt provided in Appendix H). Additionally, to capture variability and uncertainty in model outputs, we sampled five responses from the model being tested and computed average across all of them. We measured each model’s accuracy on the entire question bank. To further investigate whether misrepresentations were primarily due to a lack of relevant cultural knowledge, we also measured each model’s accuracy on the subset of questions derived specifically from misrepresentations present in the stories generated from that same model.

5.3 Findings

We present the accuracy for each model in answering cultural knowledge questions from the entire question bank and the model-specific subsets in Table 9. On average, all models correctly answer 77% of the cultural-knowledge questions

in English. Accuracy on the model-specific subsets is within $\pm 5\%$ range of the full question bank. On the other hand, accuracy drops by roughly 17 points on average for questions in Indic languages, indicating that these models lack similar capabilities in Indic languages. Unsurprisingly, the lowest accuracy was observed for low-resource languages, compared to mid- and high-resource languages. On model-specific subsets, the performance follows similar trends.

These results indicate that models are capable of answering standalone questions of cultural knowledge despite misrepresenting this knowledge when generating stories. An exception to this trend is Aya 32B, whose accuracy in Indic languages drops considerably. In other words, while models may possess cultural knowledge, they may be unable to appropriately utilise this knowledge when generating open-ended stories. This underscores the importance of our work, where human evaluation of misrepresentations reveals an important gap between possession of knowledge and its manifestation in generation, leaving room to improve cultural representation.

We also observed that for the closed-source models, GPT 4.1 and Gemini 2.5Pro, accuracy decreased on the model-specific subsets compared to their performance on the overall English question bank. In contrast, for the open-source models, Gemma 3 27B and LLaMa 3.3 70B, accuracy increased on the model-specific subsets. This suggests that the questions derived from closed-source models may be more challenging than those derived from open-source models. Moreover, even for the best models, there exists headroom for improvement (from 86.3%) in answering cultural knowledge questions, in both English and Indic languages. We hope that TALES-QA will be a useful resource for testing cultural knowledge from India, in English and 13 Indic languages, for future models.

6 Discussion

6.1 Community-Centred Evaluations of Cultural Representation

Evaluation of an AI system, for any capability, requires a number of assumptions and design decisions [38, 77]. Such decisions include, albeit non-exhaustively, (1) what should be evaluated? (2) what is the desirable outcome? and (3) how it should be evaluated? These assumptions and decisions are often implicit, almost exclusively made by developers of AI systems, and reflect the priorities and incentive structures embedded within AI development. Yet work has shown that values prioritized by model developers and the general public may not align [39] and what different communities consider desirable is subjective [28]. This issue is likely to be exacerbated when AI developers do not represent the heterogeneity of the users and disproportionately reflect privileged sociocultural identities [62]. For evaluating cultural representation, such misalignment can be problematic because needs and desires of cultural representations are deeply intertwined with lived experiences of communities. It is thus essential to account for the needs and priorities of these communities because the evaluation decisions directly impact, and can potentially harm these communities.

Keeping this in mind, we ground our evaluation of cultural misrepresentations by LLMs in the deep cultural understanding of community members. From the outset, we engage with participants with diverse cultural identities and lived experiences from across India to create a taxonomy of cultural misrepresentations in LLM-generated stories. We then use this taxonomy for a larger-scale human evaluation of 6 LLMs in 14 languages by 108 expert annotators who come from 71 different regions in India. This allowed us to conduct fine-grained analyses of cultural misrepresentations leading to valuable insights that illuminate future research directions, including: (1) gaps in multilingual capabilities and cultural representation for peri-urban regions, (2) highlighting the cultural entities (practices, norms, and food) that are often misrepresented, and (3) demonstrating the gap between models' cultural knowledge in answering standalone questions and ability to use this knowledge in generative settings. Finally, the taxonomy of cultural misrepresentations

(TALES-Tax) and questions of cultural knowledge for diverse Indian identities (TALES-QA), will be useful for future research in this area.

6.2 Minoritized Communities within Minoritized Communities

Despite AI systems being deployed globally, they continue to better represent and serve some identities [5, 29]. But, the studies of harms or cultural competence are often presented as a dichotomy between “western” and “non-western” contexts [59]. However, this formulation presumes a monolithic cultural identity of the minoritized “non-western” region. Treating the diverse cultural identities within any (minoritized) region, including India, as a homogenous group is likely to prevent a finer-grained understanding of how AI systems may (mis)represent or harm minoritized communities within this minoritized region. India is home to people from diverse linguistic, ethnic, religious, socioeconomic, and educational backgrounds. The axes of disparities among these communities are distinct from the rest of the world [10]. Prior work has found that biases along these unique axes, such as caste, disability, religion, and region within India are reinforced by AI systems [10, 43, 58] and are difficult to overcome [65].

Our work echoes and adds to these findings: cultural misrepresentations by LLMs in the Indian context are not only prevalent, but they are exacerbated in lower-resourced Indic languages and for identities from less well-known regions (§4.3). This has particularly concerning implications for Indian users of digital and AI technology. As of 2021, India has the second-highest number of active internet users in the world, accounting for over 55% of its population with widespread penetration across both rural and urban areas [81, 82]. At the same time, over 60% of the population resides in rural areas [83] and 50% of Indian users prefer to access internet in Indic languages [3, 71]. Presumably, a significant proportion of these users use AI, or at least encounter AI generations, facing unforeseen harms. This underscores the urgent need for building evaluations of cultural representations that engage with the lived experiences of diverse communities.

We take a step in this direction by zooming in on the Indian context and engaging with participants from a wide variety of regional, linguistic, and sociocultural backgrounds for evaluating cultural misrepresentations by LLMs. We acknowledge that building language technologies in the Indian context has received attention on various fronts, like curating pre-training corpora [42], developing benchmarks [26, 64, 69, 76], building foundation models [22, 40], evaluating fairness [10, 43] and cultural competence [49]. We hope to see this trend continue and benefit the minoritized sociocultural communities within India.

6.3 Designing Systems for Failure Modes

As AI systems get deployed in public-facing technologies, it is understandable that they may not have the ability to satisfactorily fulfil a user’s request. In the context of cultural representation, a system may encounter a user’s request requiring it to represent a culture that is beyond its current capabilities. Among other reasons, this could happen because the user’s request is ambiguous, the model does not have the requisite parametric knowledge, or there is more than one ways to fulfil the request. Unless the system is specifically designed to handle such situations, it may fall in one of two failure modes: (1) It generates generic text which does not include any specific cultural elements (no-representation), or (2) hallucinates information about the culture and generates text that is rife with inaccuracies around cultural elements (misrepresentations). Based on our findings (§4.3), while Llama3.3-70B generated fewer misrepresentations per story, it also had low CSI counts in the stories to begin with. This indicates that Llama3.3-70B might be generating generic stories that do not incorporate enough cultural nuance. On the other hand, Qwen3-32B and Aya-32B generate high number of CSIs in the stories but also have a larger number of misrepresentations per story. In other words, we could

think of Llama3.3-70B being prone to the failure mode of no-representation, while Qwen3-32B and Aya-32B as being prone to the failure mode of misrepresentation.

Neither misrepresentation nor no-representation is an ideal outcome. In fact, the participants we engaged with indicated that the result of both these failure modes is—be it inaccuracies in cultural elements or oversimplification of cultural elements—dissatisfying. Thus, we argue that AI systems must be thoughtfully designed to handle situations where the system encounters requests that may be underspecified, subjective, cannot be fulfilled based on the parametric or external knowledge that the system can access.

AI systems may be designed to handle such situations in a variety of ways to prevent giving outrightly wrong or misleading answers. For example, the LLM may be designed to ask follow-up questions [45, 46], abstain from answering [15, 79], or provide multiple possible outputs [70]. Each of these design decisions may impact the user’s experience in different ways and the best way to handle such requests is contextual, and remains an open area of research. Moreover, such a design must also account for the sociocultural context of the deployment, since users across cultures may have varying expectations [30, 31] and in turn varying tolerance to different model behaviours [48]. As AI systems become integrated into people’s daily lives, future research must investigate the impacts of their design or behaviour on user experiences and the harms they may face.

7 Limitations and Future Work

Although we view this work as an important step towards understanding and evaluating misrepresentation in generated stories, we acknowledge a few important limitations of our work. First, all focus groups and surveys were conducted on English-language stories generated by GPT-4, primarily to facilitate consistent interpretation and discussion within the research team. Further research is required to assess whether any new categories would emerge from other languages or from other models. Second, our evaluation study focused primarily on cultural contexts within India, and thus the findings were shaped by the perspectives most familiar to our expert annotators. While this still provides valuable insights, future work could expand data collection beyond India to capture a broader range of cultural contexts and to examine how similar misrepresentations manifest globally. Third, while our analysis captured localized misrepresentations by focusing on cultural nuance at the city-, town-, and village-level, it also introduced challenges to measure agreement, as finding sufficient expert annotators familiar with the same region was difficult.

Our work also points to concrete future research directions. To begin with, while our taxonomy provides a structured way to identify and analyze misrepresentations, future work should build on this to develop concrete strategies for mitigating the cultural misrepresentations we observed. Finally, one particularly interesting direction of future work is to investigate factors that explain why LLMs misrepresent cultures in open-ended generations despite possessing the requisite cultural knowledge.

8 Conclusion

In this work, we studied cultural misrepresentations for diverse Indian cultural identities in LLM-generated stories. Specifically, we first conducted focus groups and individual surveys where participants analysed LLM-generated stories representing their cultures, leading to TALES-Tax, a taxonomy of cultural misrepresentations. Next, we employed 108 expert annotators representing 71 regions in India and undertook a large-scale human-evaluation of cultural misrepresentations in stories generated by 6 popular LLMs in English and 13 Indic languages. We found that misrepresentations are prevalent across models and are exacerbated when stories are generated in Indic languages and for lesser-known regions. Additionally, we also analyzed the categories of cultural concepts that were misrepresented and found social

practices, social norms, and food to be consistently misrepresented. Finally, we converted the span annotations into TALES-QA, a dataset of standalone questions on cultural knowledge. We found that despite models misrepresenting culture in generated stories, they answer questions about cultural knowledge with surprisingly high accuracy.

Positionality Statement

All members of our team either live in India or have lived in India for long periods. We all have deep familiarity with the Indian culture, including knowledge about how it may vary through the country. We used our understanding of the culture for making decisions in the study, including ensuring diversity of participants and selecting topics for stories in our study. All of us are trained computer scientists and have varying amounts of research experience in studying AI technologies and their harms.

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A Demographic details for focus groups and surveys

Please refer Table 10

B Questions Used by Facilitator in Focus Groups and Surveys

One research team member facilitated the focus groups and individual survey. They used the following questions to initiate the conversation and keep the engagement if the discussion stopped.

- Initial Questions:
 - (1) Experiences with LLMs to create stories or any form of creative content.
 - (2) What do they look for in a story, is relatability important?

Focus Group 1:	Jodhpur, Ahmedabad, Jaipur (Gujarat and Rajasthan)
Focus Group 2:	Kannur, Mayiladuthurai, Chennai (Kerala and Tamil Nadu)
Focus Group 3:	Bhubaneswar, Kolkata, Bargarh (Odisha and West Bengal)
Individual Surveys:	Bengaluru (2), Ahmedpur, Thiruvalla, Chennai, Namakkal, Pune, Kathmandu, Nizamabad, Mohali, Sadulpur, Jalandhar, Kolkata, Guntur, Amritsar, Kanpur

Table 10. Demographic details of focus groups and surveys. The states of India shown in parentheses indicate the regions covered; focus groups were organized by geographically proximate locations.

- (3) Expectations on how well LLMs would perform in generating stories.
- Questions after participants have completed reading the stories:
 - (1) Do they think it is similar to something a human would write?
 - (2) General views on the story generated.
 - (3) It is relatable and accurate in terms of your experiences with the LOCATION, can they point to specific cultural artifacts in the stories?
 - (4) Does it excite the participant/would they like to read similar stories (over human written)? What is missing/any suggestions?
 - (5) Do they notice the presence of any stereotypes/offensive content in the stories?
 - (6) If they read multiple stories: are there any similarities between them?

C Story Prompts

Our prompts were developed based on the layers of Hofstede’s cultural onion model—symbols, heroes, rituals, and values. We explain these layers and the corresponding prompts generated on top of them in the following section.

C.1 Symbols

These are things which can be easier to observe compared to other layers. This includes things like food which people prefer, types of clothes which they wear, Music, Daily Objects, Culture Signs.

Below are Generic and Specific prompts we used to generate the stories related to Symbols:

- **Generic:** Write a story about a character visiting a local market in [LOCATION]. Describe what they experience during their visit.
- **Specific (Food + Clothing + Music):** Write a story about a school in [LOCATION] celebrating an important day in their culture. Describe their experience and highlight aspects of the culture by describing their clothing, food, and music.
- **Specific (Daily Objects):** Write a story that follows a character in [LOCATION] around their day, focusing on describing details about the everyday objects and routines in their life.
- **Specific (Culture Symbol):** Write a story about a student in [LOCATION] doing a school project on a culture symbol. As they talk to elders, they learn how it connects the past and present.

C.2 Heroes

This is the second layer from the core describes real or fictional people who have influence on the culture. This can include religious or political leaders

- **Generic:** Write a story about a teenager in [LOCATION] who feels disconnected from their cultural roots. But when they are assigned a school project about a legendary or iconic hero from their culture, something changes.

C.3 Rituals

The closest layer to the core consists of activities or practices such as Ways of greeting, social ceremonies, religious practices, or national holidays.

Below are Generic and Specific prompts we used to generate the stories related to Rituals:

- **Generic:** A tourist visits a family in [LOCATION] and is welcomed into their way of life. Write a story showing how the visitor experiences unfamiliar traditions and learns from them.
- **Specific (Wedding Ceremonies):** Write a story about a character attending a wedding in [LOCATION]. Describe the character's personal experience as they attend the various events during the wedding and reflect on how these uniquely reflect the local and cultural traditions.
- **Specific (Local Festivals):** Write a story about a character returning to their hometown [LOCATION] after many years to celebrate a local festival. Describe their experience of the town, reuniting with family, and reflecting on how they celebrated the festival as a child.
- **Specific (Place of Worship):** Write a story about someone joining a prayer service in [LOCATION]. Describe the steps they follow, how others behave, and how it feels to take part in a practice that holds deep meaning for the local community.

C.4 Values

This is the core of cultural which represents things like beliefs, preferences, important and unimportant values, etc..

Below are Generic and Specific prompts we used to generate the stories related to Values:

- **Generic:** Write a story about a young person in [LOCATION] who feels torn between a traditional cultural value and their personal desire. Show how they struggle with the choice and what they learn from it.
- **Specific (Dangerous vs. Safe):** Write about a teenager in [LOCATION] who wants to try something exciting that the elders in their family think is too risky. What does this conflict show about how people there see risk and caution?
- **Specific (Irrational vs. Rational + Paradoxical vs. Logical):** Write a story about someone in [LOCATION] trying to solve a problem. Elders suggest one approach based on belief or tradition; others suggest a modern, logical method. What choice do they make, and why?

D Guidelines For Cultural Misrepresentation Annotation

Overview

The goal of this annotation is to understand the characteristics of stories generated by AI systems. These stories are based on a variety of topics ranging from daily life to moral values.

These stories are created based on your personal details and are expected to incorporate cultural elements from your region and/or other aspects of your identity that you shared with us.

Your goal is to carefully read through every story, with special attention to the cultural elements that the story incorporates.

Based on your reading, you will mark the phrases that may be either wrong, or those that feel awkward, out of place, or cliche to you. For every annotation, you will also have to write a short description of why you marked this phrase.

You will be using the following categories to annotate the phrases. Please read through their definitions and examples carefully before starting the annotation. You can reference these definitions or examples anytime during the annotation process.

Note that some of these categories are explicit errors or mistakes. But not all of them are errors or mistakes. We are looking for any and all comments about things in the story that stand out to you because it is either weird or out-of-place in the story. If your marking or comment does not fit into any of these categories, you can use the ‘other’ category.

Now please go through the categories and examples in each category before starting the annotation process.

Categories

1. Factual errors

These are errors related to objective and verifiable facts. If an information can be fact-checked and proven wrong from external sources (for example, wikipedia, news articles, etc.) it falls under this category.

- Example 1: “Mumbai is the capital of India”

Reason: Delhi is the capital of India

- Example 2: “Located on the banks of the Ganga River, Ahmedabad is a major commercial hub in western India.”

Reason: Ahmedabad is located on the bank of Sabarmati river, and not Ganga river.

Note, in this category, you should focus on only factual and verifiable errors. Errors related to incorrect cultural practices or beliefs will be categorised separately.

2. Logical errors

These are errors related to the plot of the story that may not make sense logically. These could be issues around inconsistency in the behaviour of the character, logistics, later parts of the story not making sense with earlier parts of the story, and so on.

- Example 1: “Raj set his alarm for 7 a.m., but was shocked when he woke up at 6:30 and realized he had overslept.”

Reason: If he woke up earlier than the alarm, he couldn’t have overslept.

- Example 2: “He called a cab to take him to the airport for his flight. When he reached the railway station”

Reason: The story earlier mentions that the character is supposed to go to the airport, but later says that the character reached the railway station.

3. Linguistic errors

These are errors related to incorrect use of language. This may be using incorrect words in the wrong place, wrong mixing of multiple languages, or completely wrong language given the context.

- Example 1: “ Rohan’s mother enveloped him in a crushing hug and said ‘Beta, hum to mota thai gaya!’ ”

Reason: the mother’s dialog is a very weird mix of Hindi and Gujarati that is incorrect.

4. Cultural inaccuracies

These are inaccuracies, errors, or misrepresentations related to cultural practices, objects, attire, traditions, rituals, etc. If the description or usage of any of the cultural elements in the story is either wrong or just in the wrong place, you should use this category. Note that these are different from factual and logical errors because they require special local or cultural knowledge to identify.

- Example 1: “ Lakshmi shared stories about the history of the market and the significance of the traditional Andhra Pradesh saree, known as the Kanjeevaram.”

Reason: Kanjeevaram sarees are not traditionally associated with Andhra Pradesh, they are traditionally associated with Tamil Nadu.

- Example 2: “ At the Chinese New Year gathering, guests arrived in all-black outfits to bring good luck for the year ahead.”

Reason: Black is typically avoided in Chinese New Year celebrations, as it’s associated with bad luck or mourning. Red and gold are considered auspicious.

5. Cliche elements

These are not necessarily errors, in fact they might be correct. However, these are elements that are considered cliche or stereotypical for the culture.

- Example 1: “ The aroma of her freshly made filter coffee, a staple in every South Indian household, filled the air, rousing Rajeev from his sleep.”

Reason: Filter coffee is a cliche often associated with South India.

Unlikely or improbable scenarios

These are not necessarily errors, however they are scenarios in the story that are very unlikely in real life. This includes exaggerated portrayal of cultural elements in a way that is unlikely in real life. It may also include descriptions of cultural practices that are very unlikely.

- Example 1: “ Every student at school was served a hot, personalized lunch tray with their preferred dish”

Reason: Usually schools follow a fixed menu for all students, personalized lunch tray for every student is very unlikely.

- Example 2: “ The groom arrived at the mandap in cargo shorts and flip-flops.”

Reason: It is unlikely that a groom gets married in cargo shorts and flip-flops instead of more formal or traditional attire.

7. Oversimplification or vague descriptions

These are not necessarily errors, instead they are vague descriptions of elements in a way that provides no real information about their uniqueness. This makes culturally unique elements seem similar across regions.

- Example 1: “The Bengali delicacies included steamed rice, lentil soup, fried brinjal, and the famous Kolkata fish curry.”

Reason: Calling it “the famous Kolkata fish curry” is oversimplified and vague. There’s no single dish by that name, and Kolkata has many distinct fish recipes, each with its own identity.

8. Other

Any annotation not fitting the categories above.

Interface

Now that you are well-versed with the categories, you will see a video tutorial on how to use our interface.

E Culturally Specific Items (CSIs): Definition and Extraction

E.1 Definition of CSI(Culturally Specific Items) categories

The following section presents the CSI categories and their definitions, along with examples of CSIs drawn from our generated stories. The accompanying notes indicate annotations provided by our participants on those CSIs.

- **Food:** Cuisine, beverages, ingredients, dishes, recipes, preparation, and eating practices.
 - She delighted in the spread, from the tangy *Eromba* fish curry to the savory pakora, each dish a testament to the culinary prowess of the Meitei community. (*Note: ‘Eromba’ and fish curry are two different dishes. Pakora is the correct term, not ‘pakora vegetables’.*)
 - From the fragrant Mutton Roganjosh to the delicate *Tsot*, every bite was a revelation. (*Note: Tsot is bread, not a dumpling.*)
 - The menu boasted an array of authentic Andhra dishes. Students and staff indulged in the spicy and flavorful curries, including the famous *Bisi Bele Bath*, a rice-based dish with a blend of spices. (*Note: Bisi Bele Bath is from Karnataka, not Andhra.*)
 - Knead the dough for Dosa (*Note: Dosa batter is grinded, not kneaded like dough.*)
 - Iyer invited me to join them for lunch, and I was treated to a sumptuous feast of traditional Tamil dishes, including sambar, rasam, and dosas. (*Note: Dosas are traditionally eaten for breakfast, not lunch.*)
- **Clothing:** Dresses, accessories, ornaments, and attire.
 - She wore a *mei-yu* traditional Manipuri wrap-around skirt. (*Note: The traditional Manipuri/Meitei wrap-around skirt is called ‘phanek,’ not ‘mei-yu’.*)
 - Ima and Apa dressed me in a traditional outfit, complete with a colorful turban and a sprinkle of vermillion powder on my forehead. (*Note: Women do not wear turbans.*)
 - She twirled in a vibrant lehenga during the performance. (*Note: The traditional dress for Gujarati dance is ‘Chaniya Choli,’ so it may be better described as ‘vibrant traditional dress.’*)
 - Rhea, dressed in a stunning red silk saree, entered the hall. (*Note: Saree is not the traditional dress of Assamese women.*)
- **Geography:** Landscape, climate, flora, fauna, settlements, architecture, and regional geography.

- I filmed the Polo Ground, the statue of Paona Brajabashi with his sword raised high. (*Note: There is no statue of Paona Brajabashi in Polo Ground.*)
- His ancestral home in Palasa, a small town nestled between the blue-green sweep of paddy fields and the distant shimmer of the Bay of Bengal. (*Note: Palasa town is quite a distance from the coast, so it is inaccurate to say it is nestled between the coast and fields.*)
- The familiar humidity of Srikakulam wrapped around him. (*Note: If Sankranthi is one day away, it means January – winter in Srikakulam, which is not humid. This needs adjustment.*)
- The valley around them was lush and serene, dotted with stone temples and the soft hum of Meitei songs drifting through the air. (*Note: There are hardly any stone temples in Imphal East; better to simply refer to them as ‘temples.’*)
- **Arts:** Creative and performative expressions: music, dance, theatre, cinema, crafts, visual arts, and literary works.
 - The students performed the traditional Onam dance, known as the ‘Onam Ottam’, a lively dance mimicking the pace and movements of a galloping horse. (*Note: There is no such dance associated with Onam.*)
 - The celebration echoed with the beating of the drums. (*Note: The correct instrument is the mridangam.*)
 - Rohan’s father, Kumar, played the *dotara*, a traditional stringed instrument. (*Note: The dotara is Bengali/Bihari; in Odisha, a comparable traditional instrument would be the kendra.*)
- **Material Culture:** Everyday items, tools, utensils, furniture, transport, technology, and household objects reflecting lifestyle.
 - She brought with her a solar-powered loom that could help artisans weave more efficiently (*Note: solar-powered loom is very rare in villages*)
 - Here, the familiar scent of cardamom and ginger wafted from the brass kettle, where her mother had begun brewing the day’s first pot of chai (*Note: brass kettle is not a common feature*)
 - She could hear her aunts giggling, the clatter of copper samovars, the rustle of silk saris and Pashmina shawls. (*Note: a significant cultural misplacement, samovars are not seen here*)
 - Some left offerings on a silver tray: a few flowers, a coconut, a small packet of sweets (*Note: Silver is a valuable metal; it is rarely taken and left in crowded places like temples.*)
- **Social Practices:** Customs, routines, collective activities, festivals, leisure, sports, and rituals that people perform together in daily or special contexts.
 - When the sun dipped low, it was time for the bonfire (*Note: Bon fire is lit early morning of the first day of Sankranthi. Its called Bhogimanta*)
 - Mangala Gowri Jayanthi, a festival that had once marked the rhythm of his life. (*Note: It is not Mangala Gowri Jayanthi but Mangala Gowri Vratam in our culture, which is celebrated at homes rather than a collective celebration in temples*)
 - Women, adorned in vibrant sarees, carried the Bathukamma arrangements on their heads, singing traditional songs and circling a small pool of water (*Note: The women while celebrating Bathukamma festival, never circle any pool of water. They form circles and dance around floral arrangements on plates which are called “Bathukammas”.*)
 - On the final day, the bride’s family prepared to bid farewell. (*Note: The farewell ceremony takes place right after the marriage rituals of bride and the groom on the very same day.*)
 - The Wedding Feast. The first event on the itinerary was the grand feast, held in a large open-air pavilion adorned with vibrant marigolds and orchids. (*Note: Feasts are usually the last event in a Meitei wedding.*)
- **History:** Historical references, myths, legends, notable figures, and shared narratives shaping identity.
 - The temple stood tall at 200. (*Note: The actual temple height is 216 feet.*)

- He grabbed the tiger's jaws with his bare hands and tore its mouth apart. (*Note: Historical sources indicate Hari Singh killed a tiger with a dagger (and possibly a shield), not solely his bare hands.*)
- The tales of the Khallua echoed through the village. (*Note: There is no known Odia mythological or historical reference to "Khallua."*)
- The brave Ongzo was revered as a great Bodo warrior. (*Note: There is no known Bodo warrior by the name "Ongzo."*)
- He was fascinated by the stories of Kharavela's campaigns, his victories, and even his defeat by the Mauryan emperor Ashoka. (*Note: Kharavela was not defeated by Ashoka. He ruled Kalinga much later.*)
- **Social Norms:** Values, beliefs, etiquette, taboos, moral codes, and standards of conduct that shape how individuals interact and what is considered proper.
 - Her parents, though well-intentioned, had always prioritized her education and career over traditional practices and customs (*Note: For Education and career development, cultural roots are been neglected is no way connected with*)
 - Young people embraced the turban, incorporating it into their fashion choices, blending tradition with contemporary styles (*Note: The modern adoption of turbans as fashion is not widespread or common outside specific subcultures*)
 - When Ravi gently woke Alex for the puja. Intrigued, Alex followed Ravi and Lakshmi into their small prayer room (*Note: No matter how an important ritual it be, we do not right away go to puja room or take any guest inside without cleansing*)
 - Offered coconuts and flowers at the temple gates (*Note: Coconuts and flowers are purchased near the temple gated and not offered*)
 - On the day of the presentation, Sarah stood before her class, her classmates, usually engrossed in their phones, listened intently (*Note: Phones are generally not allowed in school*)
 - The air was thick with spirituality, and the echoes of ancient prayers seemed to surround her. She spent hours exploring, meditating, and reflecting on her life. (*Note: Being said that Sana is a teenager.it is unlikely that she can indulge in such activity*)
- **Kinship:** Family structures, gender roles, caste/class systems, clans, hierarchies, and leadership/authority structures.
 - He learned this from Pradeep's mother, a serene, silver-haired woman everyone called Aaita, or grandmother. (*Note: A grandmother is called jeje maa, maa, or burhi maa, not "Aaita."*)
 - She referred to her aunt as Phuphaji. (*Note: "Phuphaji" refers to a male relative — father's sister's husband — so it cannot mean "aunt."*)
 - They affectionately addressed their elders as Deuta and Aita. (*Note: "Deuta" and "Aita" words are not related to the Bodo Community.*)
 - Her grandmother, Bibi Ji, sat there quietly. (*Note: In Punjabi Sikh families, common terms are Biji, Bebe, or Dadi Ji; "Bibi Ji" is unusual for a grandmother.*)
 - Dadaji Mukherjee welcomed the children warmly. (*Note: In Bengali culture, Mukherjee is a surname, but grandparents are not addressed as "Dadaji Mukherjee."*)
- **Language & Expression:** Spoken and written forms, dialects, sayings, metaphors.

E.2 CSI Extraction

Extracting CSIs from the story We use "gpt-4.1-2025-04-14" model to extract CSIs for individual categories for every story using the following generic prompt. Where {category} replaces the category name and {definition} replaces the

definition of the corresponding category. {Story} is replaced by the entire generated story

Prompt: To extract culturally specific items from story

f"You are an expert in identifying Culturally Specific Items in stories.

You will be given a story. From this story, extract all culturally specific items that belong to the following category:

Category: {category} — Definition: {definition}

Output the items as a single comma-separated list.

Do not include explanations, labels, or headings.

Here is the story: {Story}"

Extracting CSIs from misrepresentations We use "gpt-4.1-2025-04-14" to extract CSIs from misrepresented spans using the following prompt

Prompt: To extract culturally specific items from misrepresentations

""

You are a classification assistant.

You will receive a list of annotations. Each annotation contains:

- highlight: the specific text from the story,
- span: the surrounding sentence,
- comment: feedback or observation about the highlight.

Your task: For each annotation:

1. Identify the element which influences assignment of categories (from the highlight and comment).
2. Classify it into exactly ONE of these categories:
 - FOOD: Mismatches in cuisine, beverages, ingredients, dishes, recipes, preparation, and eating practices.
 - CLOTHING: Mismatches in Dresses, accessories, ornaments, and attire.
 - GEOGRAPHIC: Mismatches in Landscape, climate, flora, fauna, settlements, architecture, and regional geography.
 - ARTS: Mismatches in Creative and performative expressions like music, dance, theatre, cinema, crafts, visual arts, and literary works.
 - MATERIAL_CULTURE: Mismatches in Everyday items, tools, utensils, furniture, transport, technology, and household objects reflecting lifestyle.
 - SOCIAL_PRACTICES: Mismatches in customs, routines, collective activities, festivals, leisure, sports, and rituals that people perform together in daily or special contexts.
 - HISTORY: Mismatches in Historical references, myths, legends, notable figures, and shared narratives shaping identity.
 - LANGUAGE_EXPRESSION: Mismatches in Spoken and written forms of words, dialects, sayings, metaphors, naming practices, wrong spellings, repeated use.
 - SOCIAL_NORMS: Mismatches in values, beliefs, etiquette, taboos, moral codes, and standards of conduct that shape how individuals interact and what is considered proper. - KINSHIP_SOCIAL_ORGANIZATION: Mismatches

in Family structures, gender roles, caste/class systems, clans, hierarchies, and leadership/authority structures.

- OTHER: Doesn't fit above or insufficient context.

Output format:

Return a JSON list of objects, where each object has:

- "element": the element which influences assignment of categories (ideally from the highlight),
- "category": one of the above categories.

Example output:

```
[  
{"element": "saree", "category": "CLOTHING"},  
 {"element": "Onam festival", "category": "SOCIAL_PRACTICES"}  
]
```

If multiple categories seem possible, pick the MOST relevant. Language may vary (e.g., Hindi, Tamil, Malayalam), but classify based on meaning. ""

F Question Generation

GPT-4o was prompted at a temperature of 0.7 for generating questions from misrepresentation spans.

Prompt for Question Generation

You are an expert question generator. Your task is to turn span annotations of a story that mark inconsistencies into high-quality questions that assess cultural knowledge.

You will be given:

- A short story
- Specific text from the story that marks an inconsistency span
- Inconsistency type
- Reason explaining the span

Your task:

- For the annotation, generate ONE best-fit question that:
 - Tests understanding of the cultural or contextual inconsistency
 - Can stand alone (should make sense without the story)
 - Is challenging (not trivial or overly obscure)
 - Make questions so as to avoid ambiguity or other possible answers.
 - Try not to add any information from outside the story, span and comment.
 - The questions answer should make sense according to your knowledge.
 - Uses any suitable question format - One word answer (when answer in 1-2 fixed words), fill in the blank, MCQ, Yes/No etc.
 - For cultural or factual inconsistencies, prefer one-word answer or fill in the blank wherever possible.
 - For cliché or oversimplification, prefer MCQ ("Which question has..." style).

- For linguistic inconsistency, phrase the question to remove any possibility of multiple correct answers.
- Keep the language of the question as the language of the reason provided.

Output:

- The question mentioned after QUESTION:
- The question type after FORMAT:
- Answer mentioned after ANSWER:

Example:

INPUT:

STORY: Maya walked barefoot through the cool stone courtyard, the soft weight of a basket in her hands. The temple bells rang in slow, solemn rhythm as she stepped inside, where shadows danced in the flicker of oil lamps. Maya went to the temple and offered rose flowers to Goddess Kali, their crimson petals glowing like drops of devotion against the dark altar. As the fragrance mingled with incense, she closed her eyes, feeling a surge of courage rise within her, as if the goddess herself had placed it in her heart.

TEXT: offered rose flowers to Goddess Kali

TYPE: Cultural

REASON: Traditional people offer Hibiscus to Goddess Kali.

OUTPUT:

QUESTION: Which flower is traditionally offered to Goddess Kali?

FORMAT: One word answer

ANSWER: Hibiscus

Now generate questions for the following.

STORY:<STORY>

TEXT:<TEXT>

TYPE:<TYPE>

REASON:<REASON>

G Question Verification Guidelines

The verifiers were given a google sheet with each row containing three columns which were filled

- Question
- Answer
- Question Type

Followed by the columns which were left empty for them to fill

- Is the question valid?
- Does the question have a unique answer?
- Does the question have a cultural element to it?

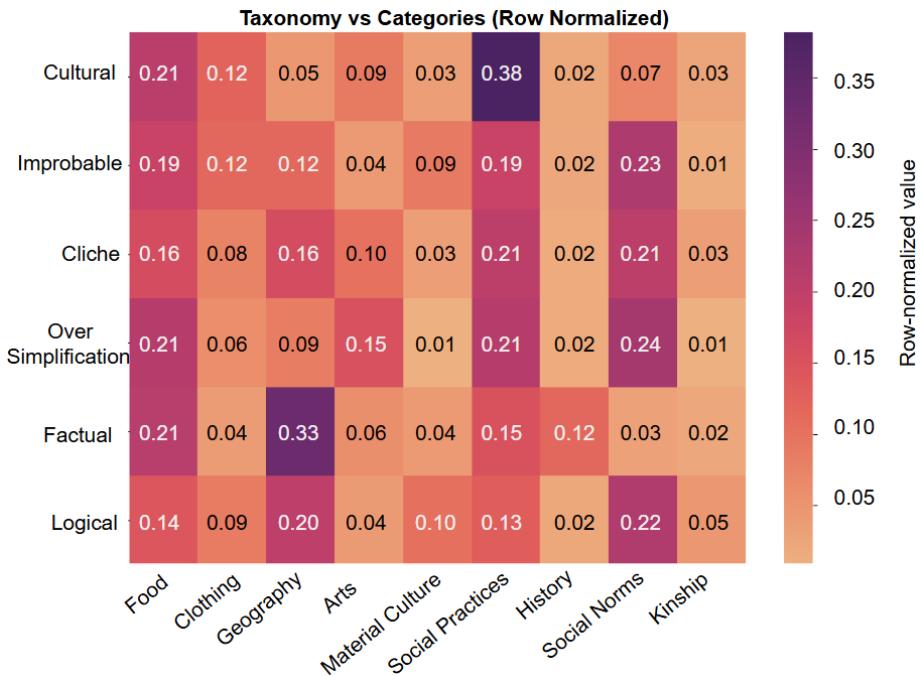


Fig. 5. Frequency of misrepresentation of different CSI categories. Food, social practices, and social norms were highly misrepresented across all misrepresentation categories.

- How hard do you think is the question?
- Does the answer seem correct?
- If "No", type the correct answer.
- Improved Question (optional but recommended)
- Answer(of the improved question)
- Type (of the improved question)

These were the guidelines provided to them

Verify the row against the seven checks below and fill the corresponding fields in the spreadsheet.

(1) Question Validity

Is the question valid?

Options: Yes, No, Not Sure.

- Mark **Yes** when the question makes sense and can be answered without missing context.
- Mark **No** when the question is ambiguous, incomplete, or requires information not provided.
- Mark **Not Sure** only if you truly cannot decide between Yes and No.

Example:

Question: "In the story, what does Tanya have for breakfast?"

This is not valid as we do not have the story context.

Question: "Which festival is called the festival of colors in India?"

This is Valid

(2) Answer Uniqueness

Is the answer unique?

Options: Yes, No, Not Sure.

Guidance:

- Mark **Yes** when there is only one possible correct answer.
- Mark **No** when multiple different answers could be considered correct.
- Mark **Not Sure** only if you cannot determine uniqueness.

Example:

Question: What is a famous festival celebrated in India?

This question cannot have a unique answer as India has many festivals like Holi, Diwali, Eid etc. No, this question is not unique

Question: What is a famous festival celebrated in India?

A) Holi B) Thanksgiving C) Chinese New Year

Yes, it is unique as A can be the only answer for this question

(3) Cultural Element

Does the question have a cultural element to it?

Options: Yes, No, Not Sure.

Guidance: Guidance:

- Mark **Yes** when there is only one possible correct answer.
- Mark **No** when multiple different answers could be considered correct.
- Mark **Not Sure** only if you cannot determine uniqueness.

Example:

Question: What is the correct term for someone from Odisha: Orissan or Odia?

Yes, this has a cultural element

Question: Which organ in the human body pumps blood?

No, this does not have a cultural element

(4) Difficulty Level

How hard do you think is the question?

Options: Easy, Medium, Hard.

Guidance:

- **Easy** – Common knowledge, if you feel people around the world would know this.

Example: What is the capital of India?

- **Medium** – Cultural knowledge but famously known. If you feel most people of similar cultures would know this or the answers can be found by a quick online search.

Example: Sushi is a traditional dish from which country?

- **Hard** – Knowledge that is specific to certain cultures, contexts, or is rare knowledge. If you feel only people from a certain place know this, mark it as Hard.

Example: Jadoh is a traditional dish of which community in Northeast India?

(5) Answer Correctness

Does the answer seem correct ?

Options: Yes, No, Not Sure.

Guidance:

- Mark **Yes** if the provided “Answer” is factually correct. You can use google to check.

Note: For MCQs, ensure every incorrect option is indeed incorrect and the correct option is uniquely correct.

(6) Question Improvement

It is needed if

- If you answered No to Uniqueness/Valid
- Or you feel that the question can be formatted in a way to make it more challenging, fill this column.

Use the information in the original question/answer to make it clearer, more precise, or more challenging.

Follow this priority order when creating a new version (list in order of decreasing priority):

- One-word answer / One-phrase answer (preferred)
- Fill in the blank
- Multiple Choice (MCQ)
- True/False

For example:

Original: “Is Paris the capital of France?” (Yes/No)

Improved: “What is the capital of France?” — Answer: Paris (One word answer type higher priority)

Original: “At what time of day does the Raja festival traditionally begin?” Answer: “Morning”

Improved (MCQ): “At what time of day does the Raja festival traditionally begin? A) Morning B) Evening C) Night” (Even though the question was converted into a lesser priority type MCQ, the original question did not have a unique answer as “Morning” can be replaced with “Day Time” etc., hence the improvement)

Make sure the Question has a unique answer to it.

Note: Also provide the answer and type of the improved questions in the next columns if you are attempting to make an improved question.

H Autorater for Answer Matching

We used GPT-4o to match the reference gold answers generated by models to our question bank. For each question, the autorater is provided with the candidate answer string with the reference answer string. This was done to

prevent small character errors that would cause false negatives in exact match string. This was done following recent work that showed that answer matching had perfect agreement with human ratings [18].

Prompt: Autorater for answer matching

You are an impartial judge. Your task is to evaluate whether the candidate answer is correct compared to the gold answer.

You must output only 'True' or 'False'. Correctness means:

- The candidate answer is semantically equivalent to the gold answer, even if it uses different words, languages, or synonyms (e.g., "True", "Yes", "Correct" should all be considered equivalent).
- Small variations in language or script should not count as incorrect if the meaning is the same.
- Mark 'False' if the candidate answer clearly contradicts, changes, or fails to match the meaning of the gold answer.

I Summary of Statistical Test Results

This appendix presents all statistical test results, including corresponding *p*-values and effect sizes for the analyses conducted in this study. Table 11 presents the results of pairwise comparisons of the number of misrepresentations per story across the three language resource groups (high, mid, and low). For each pair, the median difference, effect size (Cliff's δ), and associated *p*-value are reported. Statistically significant differences ($p < .001$) are indicated with double asterisks (**). Table 12 summarizes the pairwise comparisons of misrepresentation counts across regions of different tiers. Table 13 presents the comparison of misrepresentation counts between open-source and closed. Table 14 presents the comparison of CSI counts between the resource categories. Finally, Tables 15 and 16 report the pairwise comparisons of misrepresentation counts across languages within the factual and logical categories, respectively.

Pair	Median Diff	Effect size	Description	p value
high vs low	-4.00 **	-0.48	high < low	$p < .001$
high vs mid	-2.00 **	-0.25	high < mid	$p < .001$
low vs mid	2.00 **	0.29	low > mid	$p < .001$

Table 11. Statistics for comparisons of misrepresentation counts across language resources

Pair	Median Diff	Effect size	Description	p value
Tier 1 vs Tier 3	-1.00 **	-0.21	Tier 1 < Tier 3	$p < .001$
Tier 2 vs Tier 3	-1.00 *	-0.11	Tier 2 < Tier 3	$p = .039$

Table 12. Statistics for comparisons of misrepresentation counts across city tiers

Pair	Median Diff	Effect size	Description	p value
Open-source vs Closed	-1.00 **	-0.24	Open-source < Closed	$p < .001$

Table 13. Statistics for comparison of misrepresentation counts between open-source and closed models

Pair	Median Diff	Effect Size	Description	p value
high vs mid-low	11.00 **	0.20	high > mid-low	$p < .001$
high vs mid-high	8.00 **	0.19	high > mid-high	$p < .001$

Table 14. Statistics for comparisons of CSI count across groups

Pair	Median Diff	Effect Size	Description	p value
English vs Tamil	-1.00 *	-0.19	English < Tamil	$p = .048$
Marathi vs Tamil	-1.00 **	-0.41	Marathi < Tamil	$p = .003$
Kannada vs Tamil	-1.00 **	-0.45	Kannada < Tamil	$p < .001$

Table 15. Statistics for comparisons of misrepresentation counts in the *factual* category across languages

Pair	Median Diff	Effect Size	Description	p value
English vs Tamil	-1.00 **	-0.35	English < Tamil	$p < .001$
Hindi vs Tamil	-1.00 **	-0.36	Hindi < Tamil	$p = .001$
Marathi vs Tamil	-1.00 *	-0.28	Marathi < Tamil	$p = .040$
Malayalam vs Tamil	-1.00 *	-0.39	Malayalam < Tamil	$p = .013$

Table 16. Statistics for comparisons of misrepresentation counts in the *logical* category across languages