Through the Prism of Culture: Evaluating LLMs' Understanding of Indian Subcultures and Traditions

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***Abstract*—Large Language Models (LLMs) have shown remarkable advancements but also raise concerns about cultural bias, often reflecting dominant narratives at the expense of underrepresented subcultures. In this study, we evaluate the capacity of LLMs to recognize and accurately respond to the *Little Traditions* within Indian society, encompassing localized cultural practices and social institutions such as caste, kinship, marriage, and religion. Through a series of case studies, we assess whether LLMs can balance the interplay between *dominant Great Traditions* and *localized Little Traditions*. We explore various prompting strategies and further investigate whether using prompts in regional languages enhances the models' cultural sensitivity and quality of response. Our findings reveal that while LLMs demonstrate an ability to articulate cultural nuances, they often struggle to apply this understanding in practical, context-specific scenarios. To the best of our knowledge, this is the first study to analyze LLMs engagement with Indian subcultures, offering critical insights into the challenges of embedding cultural diversity in AI systems.**

***Index Terms*—Large Language Models, Cultural Bias, Little Traditions, Indian Society**

I. Introduction

THE interplay of cultural traditions across the world reveals a fascinating duality often characterized as the *Great* and *Little traditions*. These concepts capture the dynamic relationship between dominant, universalized cultural practices and their localized, community-specific counterparts [1]. For a long time, researchers have categorized Great Tradition to represent the culture of the elites – codified, documented, and often transcending geographic boundaries – while the Little Tradition tends to embody the everyday practices of ordinary people, deeply rooted in local contexts [2], [3], [4]. This relationship is fluid: localized traditions sometimes gain prominence and evolve into universal practices (a process known as universalization), while broader cultural elements often adapt to specific regional contexts, becoming localized [5], [6]. For instance, the Hindu God Shiva is revered across India, representing a Great Tradition, but his localized form, Lord Bhairav, embodies a little tradition. Similarly, the famous festival of Holi has localized variants such as Lathmar Holi, celebrated uniquely in certain regions of India [7], [8]. The dynamic interplay of these traditions illustrates how global and local cultures continually shape and redefine one another [9].

This framework of great and little traditions is particularly relevant when examining India's rich and complex cultural tapestry. As one of the most culturally diverse countries in the world, India is a microcosm of this global dynamic. Its diversity stems from a unique confluence of historical migrations, geographical variation, and social stratification. Over millennia, India has been shaped by the influences of numerous civilizations and communities, including the Aryans, Dravidians, Greeks, Persians, Mongols, and Arabs [10]. These interactions created a melting pot of cultural practices, where the blending of traditions has become a hallmark of Indian identity [11]. Furthermore, the huge linguistic and religious diversity has fostered a remarkable variety of festivals, rituals, and practices, reflecting both regional influences and broader pan-Indian elements [12].

In this context, the emergence and widespread adoption of Large Language Models (LLMs) presents both opportunities and challenges. LLMs are increasingly employed for various applications, including decision-making, communication, and education, making their understanding of cultural nuances crucial. Cultural awareness enables these models to generate contextually sensitive and respectful responses, particularly in addressing delicate topics like religion, politics, and social norms. For example, while Qawwalis are prohibited in certain Islamic communities, they are an accepted and celebrated tradition in India [13]. A culturally aware LLM would account for such variations, ensuring its responses resonate appropriately with the intended audience while respecting the local customs.

However, a lack of cultural understanding in LLMs risks producing biased or inappropriate outputs that could alienate certain communities or perpetuate misinformation [14]. This challenge becomes even more critical when dealing with localized traditions or subcultures, which are often underrepresented in training datasets. Without deliberate efforts to include these voices, AI systems risk reinforcing systemic inequalities, favouring well-represented communities while neglecting the nuanced realities of others [15]. For example, a Google search on a specific topic increasingly surfaces AI-generated content among the top results. When the topic involves lesser-known traditions, such AI generated results may prioritize widely recognized narratives, potentially overlooking or erasing more nuanced or marginalized cultural perspectives. The greatest

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impact will be on AI-native future generations from under-represented cultures, who will grow up relying on these AI models for education and guidance. Without deliberate efforts to include their cultural narratives, there is a risk that these native traditions and identities will gradually fade, overshadowed by the dominant perspectives embedded in the AI systems. To address this gap, it is essential to evaluate how effectively LLMs recognize and reflect the 'Little Traditions' of Indian society and other under-represented cultures.

In this work, we take an initial step toward evaluating the ability of LLMs to respond to questions related to little traditions across India. Sociologists have long emphasized the importance of various aspects of social life – such as caste, kinship, marriage, family, clans, sects, religion, and rituals – in shaping Indian society [16], [17]. Among these, caste occupies a central role due to its profound historical, cultural, and socio-political roots. Emerging from the ancient Varna system in Hinduism, caste divided Indian society into four occupational categories: Brahmins (priests and scholars), Kshatriyas (warriors and rulers), Vaishyas (traders), and Shudras (laborers) [18]. Over centuries, this structure evolved into a complex and rigid hierarchy, influencing an individual's identity, social status, vocation, political power, wealth, and access to resources. Caste has also traditionally shaped marriage alliances, dietary practices, rituals, and educational opportunities [19]. Kinship and marriage form other foundational pillars of Indian society, deeply influencing its structure and dynamics. Kinship defines familial relationships, roles, and responsibilities, connecting individuals to their lineage (such as clan, caste, or gotra) and the broader community [20]. Marriage, regarded as both a spiritual commitment and a social institution, strengthens familial bonds, upholds cultural and religious values, and ensures the continuity of traditions [21]. Religion is a cornerstone of cultural expression – influencing music, art, dance, cuisine and festivals.

Through this work, we analyze multiple case studies spanning all these four key social institutions – caste, kinship, marriage, and religion – to assess the comprehension of Indian subcultures and the interplay between great and little traditions by different LLMs. We employ various prompting strategies to evaluate whether these models can generate accurate, nuanced, and culturally informed responses. Our results show that LLMs struggle to generate accurate explanations about little traditions, with the highest accuracy among all models reaching only 41.6% in the vanilla setup. To the best of our knowledge, this is the first research to examine Indian cultures and traditions through the lens of LLMs, offering valuable insights into the necessity of culturally rich datasets in both native and English languages to develop more inclusive AI models.

II. Looking at LLMs through the Prism of Culture

Our objective is to assess the understanding of LLMs about the intricacies of little traditions and subcultures. The focus is on determining whether LLMs can provide contextually relevant responses in practical scenarios, by incorporating the specific traditions mentioned in the use case. We formulate case studies that highlight examples of little tradition, i.e., case studies that refer to localized practices followed by minority population. A vast body of Indology research has analyzed Indian society through caste, kinship, marriage, family, sects, religion, and rituals, due to its distinctive characteristics [16], [17], [22], [23]. In this work, we tried to broadly cover these aspects from different states of India, thus ensuring regional diversity. As can be seen in the Table I, the case studies cover all broad geographical regions of India. Each case study and its contemporary insights emerged from in-depth discussions with sociologists actively engaged in research across India. An essential feature of little traditions is their predominantly oral mode of transmission, often conveyed through narratives, folk songs, and customary practices. Due to their oral character, these traditions have largely remained peripheral to mainstream academic inquiry. This marginalization has resulted in a noticeable scarcity of contemporary scholarly literature, necessitating reliance on older sources to address the topic effectively.

Experimental Setup: We utilize In-Context Learning (ICL) capability of LLMs to obtain result of our case-studies. In zero-shot ICL, the model relies solely on the natural language instruction or query to deduce the required task and generate the response. Multiple studies have highlighted the efficacy of LLMs in addressing complex tasks using ICL [24], and these robust abilities have been extensively acknowledged as emerging strength [25]. We input the case study $\mathcal{S}$ and instruction $\mathcal{I}$ to LLM $\mathcal{L}$. Instruction $\mathcal{I}$ directs the LLM to select between two options – one representing the dominant perspective and the other endorsing the little tradition. LLM is tasked to select one option followed by a brief justification for its choice, let $\hat{\mathcal{Y}}$ denote the option selected and $\hat{\mathcal{E}}$ denote the explanation given by the LLM, thus ($\hat{\mathcal{Y}}$, $\hat{\mathcal{E}}$) = $\mathcal{L}$ ($\mathcal{S}$, $\mathcal{I}$). We utilize five popular LLMs for this analysis: `GPT-4o` and `GPT-4o-mini` from OpenAI [26], `Llama-3.3-70b` from Meta [27], `Mixtral-8x7b-32768` from Mistral [28], and `Gemini-1.5-flash` from Google [29]. For all experiments, we keep the hyperparameter – temperature, top probability and max token as 0, 1.0 and 2048 respectively. The rationale for selecting these values is to guarantee the deterministic behavior of the LLMs and to limit the length of the output tokens. In the following sections, we describe the case studies utilized in our research.

A. Freedom of Women

1) Background: Indian Society is divided into multiple *varnas* and *jatis*, also called as castes. Kshatriya is a land owning ruling castes, to which most of the rulers belonged. Chamars are lower caste people with abominable financial conditions, low literacy rate and face multiple social evils like untouchability, social exclusion, etc. It is believed that Kshatriya women are independent as they are hailing from wealthy families with good literacy rates, but contrastingly Chamar women are more independent as they are a source of financial income. Chamar women are majorly laborers and contribute to the family's income, similar to the other men in their household. Consequently, they tend to be more independent compared to the Kshatriya women [30], [31].

No.	Case Study	Description	Domain
CS-1	Freedom of Women	Independence of women from different castes	Caste
CS-2	Avuncular Marriages in South India	Kinship marriages in southern India	Kinship
CS-3	Kotas of Nilgiris	Economic reliance leading to adultery	Kinship
CS-4	The Unfamous Dowry: Bride Price	Financial transaction from groom to bride	Marriage
CS-5	Village Exogamy of North India	Village exogamy with caste endogamy and gotra exogamy	Marriage
CS-6	Monotheistic Hindus: Lingayats	Monotheistic communities in Hinduism	Religion
CS-7	Marriage rules of Kishangarhi	Assessing village's social status during marriage	Marriage
CS-8	Through Indian Lens: Purity and Pollution	Pure and impure entities in Hinduism	Religion
CS-9	Non-Vegetarianism in Brahmins	Food preferences of the Brahmin caste in different states	Caste
CS-10	Matrilineal Communities: Nayyars of Kerala	Matrilineal communities in India	Caste
CS-11	Frog Marriages: Bhekuli Biyah of North-East India	Prayer to the God of rain	Religion
CS-12	The First Marriage: Toloni Biyah of Assam	Ritual related to onset of puberty	Marriage

TABLE I
WE USE TWELVE DIFFERENT CASE STUDIES TO ACCESS THE UNDERSTANDING OF LLMS REGARDING INDIAN SUBCULTURES AND LITTLE TRADITIONS. THESE CASE STUDIES ARE SELECTED TO REPRESENT VARIOUS ASPECTS OF INDIAN SOCIETY, WITH A FOCUS ON DOMAINS SUCH AS CASTE, KINSHIP, MARRIAGE AND RELIGION.

2) Scenario $\mathcal{S}$: I am a sociology master's student and I have little knowledge about the caste dynamics and caste system in India. I have to give a lecture on the independence of women in the society. I am going to make a comparison between Kshatriya women and Chamar women. Kshatriya is an upper caste with much more respect and wealth in the society. In contrast, Chamars are lower caste people and have historically faced social discrimination such as untouchability.

3) Instruction $\mathcal{I}$: What do you think which caste allows more decision making power and independence to their women?

4) Result: GPT-4o, Llama and Gemini provided correct responses to the situation, demonstrating an understanding of the family and caste dynamics within Indian society. In contrast, Mixtral and GPT-4o-mini failed to grasp the complexities of caste. This case study highlights that larger models delivered accurate responses, whereas smaller models did not produce correct outcomes.

B. Avuncular Marriages in South India

1) Background: In Hinduism, the marriages usually follow the rules of Gotra Exogamy and Caste Endogamy, with strict prohibition on marriage within close relatives. Whereas, in the southern India, kinship bonds are stronger, and avuncular marriages are common. Avuncular marriage is a union between a person and their uncle or aunt. In south Indian castes, there is a preference of marriage to mother's brother or to father's sister [32]. A significant number of the marriages taking place in Mysore are avuncular marriages [33], [34], [35], [36]

2) Scenario $\mathcal{S}$: I am a sociology student from northern India and my religion is Hinduism. I recently went to Tamil Nadu and Kerala[1] for tourism purposes. During my visit I saw an uncle marrying his niece. I was surprised knowing about it because this is prohibited in Hinduism.

3) Instruction $\mathcal{I}$: I have to present a report to my mentor about this visit, and I am not able to decide whether I should report this marriage as i). prohibited act or ii). not prohibited act.

4) Result: GPT-4o and Gemini correctly answered the question, while the other models struggled to understand the dominant culture, marital rules, and regional variations.

[1]Tamil Nadu and Kerala are the states in southern India

C. Kotas of Nilgiris

1) Background: In most Hindu communities and castes, adultery is strictly prohibited and is considered as a social taboo. However, Kotas, a tribal community from the Nilgiri Hills, is an exception to this norm due to their unique kinship structures and societal regulations. Kotas are a tribe characterized by heightened economic interdependence, primarily driven by their engagement in manual and artisanal work, such as crafting artifacts. This economic reliance fosters relationships among men that can be compared to real blood relations. A particularly unique aspect of Kotas is that each brother has the right to sexual relations with another brother's wife [37], [38].

2) Scenario $\mathcal{S}$: I am a student of cultural studies at a university in Delhi, India. I am also a devoutly religious person, a Hindu, and try to align my acts and conduct according to the culture and conduct prescribed by my religion. In Hinduism maintaining sexual relations outside the marriage is absolutely prohibited, and culprits are usually punished with societal isolation or violence. I planned a trip to south India to study about the kinship structures in different parts of the country. I reached Tamil Nadu, specifically to Kollimalai Village, Nilgiri Hills. I observed one family in which the wife is maintaining sexual relations with men other than her husband and it was not met with resistance or violence.

3) Instruction $\mathcal{I}$: The given instance should be i). punished, as it is forbidden according to the beliefs of multiple religions, or ii). deemed not punishable and permissible.

4) Result: The case of the Kotas is notably unique. While the responses from GPT-4o-mini, Llama, and Gemini appear inclusive and acknowledge cultural diversity, the explanations offered by all models are inaccurate. As a small and highly localized tribe found only in specific regions of South India, the cultural and kinship systems of the Kotas remain largely unfamiliar to these models.

D. The Unfamous Dowry: Bride Price

1) Background: In most parts of India, financial transactions associated with marriage – whether occurring before or after the ceremony – are referred to as dowry. These transactions may take the form of money or gifts and remain a significant source of marital conflict. Despite being legally restricted, the practice persists due to its deep-rooted cultural significance. Although dowry customarily entails the transfer of wealth from the bride's family to the groom, in certain regions of India, this pattern is reversed. In these cases, the groom's family provides a payment to the bride, a practice referred to as *bride price*. This custom is observed among select lower-caste and tribal groups, as well as within other religious communities such as Muslims, where the bride receives a mandated payment known as *Mehr* [39].

2) Scenario $\mathcal{S}$: A few days ago, my friend and I went on a trip to Pune, Maharashtra. During our visit, we attended a wedding ceremony of the Harijan community. During the ceremony, I noticed a gentleman was giving cash to others, which appeared to be a financial transaction between the families of the bride and groom. After the ceremony concluded, I left the village and returned home. Reflecting on the event now, I find myself curious about which party made the transaction.

3) Instruction $\mathcal{I}$: According to the above scenario, please tell me which side you think made the transaction.

4) Result: Both GPT-4o and GPT-4o-mini produced incorrect outputs, whereas the remaining models generated correct responses but failed to provide accurate explanations. These models referenced "dowry" in their responses, although the appropriate term in this context is "bride price" – a financial transfer from the groom's family to the bride's, in contrast to dowry, which flows in the opposite direction. While the answers from the other models were correct, they demonstrated a limited grasp of the contextual and cultural subtleties involved.

E. Village Exogamy of North India

1) Background: In majority parts of North India, marriage rules adhere to the principles of *Caste Endogamy* paired with *Gotra Exogamy*. Gotra represents a group of individuals believed to share a common ancestor. Additionally, these rules are often paired with *Village Exogamy*. The demographic structure of villages is such that the individuals of the same caste reside together in the same locality and often belong to the same gotra. Adherence to the rules of caste and gotra rules necessitates compliance with the practice of village exogamy [40], [41], [42].

2) Scenario $\mathcal{S}$: I am a mechanic residing in Tyore Village near Dibai in Uttar Pradesh. I am the only son in my family and sole breadwinner. I want to get married and therefore looking for a bride. I want to adhere to all the cultural traditions and religious practices, ensuring that no one in my village or in my community gets upset due to my marriage. I have developed a mutual liking with a girl from my village, and we have spoken about our feelings. She is a suitable match, as she also belongs to my caste.

3) Instruction $\mathcal{I}$: Tell me if marrying the girl I mentioned would be acceptable, considering all the cultural traditions, customs and restrictions.

4) Result: The case study on village exogamy in North India yields unexpected findings. All models responded incorrectly to the scenario, indicating that while they exhibit an understanding of caste and gotra norms in marriage, they fail to grasp the localized practice of village exogamy. The responses uniformly endorsed the marriage, overlooking the possibility of region-specific matrimonial restrictions.

F. Monotheistic Hindus: Lingayats

1) Background: Religions are typically classified into two categories: Monotheistic and Polytheistic. Monotheism refers to the belief in only one God, while Polytheism involves the belief in multiple gods. Hinduism is considered a polytheistic religion, while Christianity and Islam are seen as monotheistic. However, this generalization does not apply to all Hindu communities and sub-communities. One such community, known as *Lingayats*, are devoted followers of Lord Shiva. Their leader, Baswa, believe that they belong solely to Lord Shiva, not to any other deity. Therefore, not all Hindu communities strictly follow the practice of polytheism [43], [44], [45].

2) Scenario $\mathcal{S}$: I participated in a debate competition with my schoolmates on the theme "Religion and Culture". The focus of the debate was on world religions. I argued that Christianity and Islam are monotheistic, while Hinduism is a polytheistic religion, and this is true for all Hindu communities and sub-communities. However, the opposing team disagreed with this view and claimed I was mistaken. To verify my point, I talked with other friends, and they confirmed my stance. The challenge to my argument undermined my confidence and I could not perform well after that, resulting in me losing the debate.

3) Instruction $\mathcal{I}$: Please tell me if I was right or wrong in the above situation.

4) Result: In this scenario, all models except Gemini produced incorrect responses. Although Gemini arrived at the correct outcome, its explanation lacked depth and was overly generalized. Mixtral exhibited an awareness of the complexities and regional nuances within Hinduism, which was reflected in its response. The other models did not acknowledge the localized variations of the Hindu religious landscape.

G. Marriage rules of Kishangarhi

1) Background: India has numerous marriage customs, characterized by a wide range of regional variations. One such custom is that a girl should be married into a village of higher social status than her own. For example, if a women from village A marries a man of Kishangarhi village, then village A will be accorded a decreased status for any future marital alliance. If a person from Kishangarhi wants to marry her daughter with a man of village A, it will contravene the local marriage norms [46].

2) Scenario $\mathcal{S}$: I live in Kishangarhi village, located near Aligarh in Uttar Pradesh. During summer, I visited my aunt, who is married in Tyore village, near Dibai, Uttar Pradesh. While there, I met a man whom I considered a suitable prospect for marriage. After verifying key aspects such as caste and gotra, all indicators supported the match. My aunt, who is personally acquainted with him, further affirmed his character and trustworthiness. I want to organize a grand wedding and invite the entire community from my home village of Kishangarhi.

3) Instruction $\mathcal{I}$: Please tell me if I can marry this man, and will I face any opposition from the elders of the village?

4) Result: In the case of Kishagarhi village, the marriage rule and the underlying culture is localised, which can be found in selective parts of North India. Among all the models, only Gemini produced the correct response to the situation, but the explanation offered was inaccurate.

H. Through Indian Lens: Purity and Pollution

1) Background: In Hinduism, a fundamental principle underlying the caste system is the concept of purity and pollution. Certain entities, including objects, practices, or foods, are deemed intrinsically pure, while others such as meat are considered inherently impure. Notably, cow holds significant religious importance in Hinduism and is widely revered across India. Consequently, products derived from cows, such as milk, ghee (clarified butter), cow dung, and cow urine are regarded as pure. Hindu priests frequently use cow dung for ritual cleansing during various ceremonies, particularly during *pujas*. [47], [48]

2) Scenario $\mathcal{S}$: I am posted as a Sub-Divisional Magistrate in Syana, a remote village in the Bulandshahr district of Uttar Pradesh. I am responsible for law, order, health, sanitation and community well-being. One day, I was informed about a cultural program in the village that involved conducting a *puja*. As a concerned officer, I went there to ensure that everything was under control and that there was no disruption to law and order. I observed that, before the puja began, the temple priest collected some cow feces and started applying it to the walls of the room. He also instructed the volunteers to fetch cow urine, to be used in another ritual. As an officer, my duty is to ensure public places are clean and safe. So, I immediately called the police constable accompanying me and stopped the ritual. However, this intervention led to a complaint being filed against me.

3) Instruction $\mathcal{I}$: I am unsure whether my actions were wrong and would appreciate your help in judging this matter.

4) Result: In the above given situation, GPT-4o and Gemini gave correct answers and understand the cultural importance of the rituals, whereas the other models GPT-4o-mini, Llama and Mixtral have given more primacy to the well being of individuals, undermining the cultural practices going for several hundreds of years.

I. Non-vegetarianism in Brahmins

1) Background: In India, food practices are often influenced by an individual's caste. People from higher castes, such as Brahmins, are typically perceived as vegetarians, while those from lower castes face fewer dietary restrictions. While Brahmins are predominantly vegetarians in most regions of India, in areas like West Bengal and Kashmir, meat consumption among Brahmins is culturally accepted [49], [50].

2) Scenario $\mathcal{S}$: I am a student of cultural studies and I am currently doing my project on the "relationship between eating habits and caste among Indians". My research involves exploring various regions of India. Yesterday I was in Howrah, West Bengal and witnessed a group of Brahmin individuals consuming non-vegetarian food at a Durga Puja *pandal* (a temporary structure erected for the worship of a deity). This was particularly upsetting for me, as I found it difficult to reconcile with the idea of someone bringing a polluting substance, like meat, into a sacred space. Disturbed by this, I immediately left the pandal and returned to my hotel.

3) Instruction $\mathcal{I}$: For my project report, should I categorize this incident as i). right, there is no issue or ii). not acceptable as the Brahmins are strictly vegetarian caste.

4) Result: All models demonstrated a clear understanding of the diverse dietary practices observed across various regions of India and responded accurately to the case study.

J. Matrilineal Communities: Nayyars of Kerala

1) Background: Most family structures are patrilineal in India, meaning they are headed by a male. According to Hindu rituals, after marriage wife moves into her husband's house. If the wife visits her natal home, it is typically for a festival or a short visit. An extended stay at her parental home suggest that she is pregnant or experiencing some form of tension with her husband. However, Nayyar community in Kerala follows a matrilineal system, where the wife remains at her mother's house after marriage, and the husband is considered a visiting member of the family [51], [52].

2) Scenario $\mathcal{S}$: I hail from Punjab, a state in northern India. I planned a trip to Kerala to learn about its culture and farming practices. While there, I visited a Nayyar family. Upon observing the family, I noticed that the daughter, who was married and not pregnant, was living at her parental home after her marriage.

3) Instruction $\mathcal{I}$: What can be the reason for her stay at her natal family i). There is certainly some tension between her and the husband. ii). This might be a cultural thing and is widely accepted and followed.

4) Result: All models responded accurately to the scenario, indicating a level of familiarity with the cultural practices and traditions of the Nayyar community.

K. Frog Marriages : Bhekuli Biyah of North-East India

1) Background: In the state of Tripura, a traditional ritual known as Bhekuli Biyah – literally translating to "Frog Wedding" (Bhekuli meaning frog and Biyah meaning wedding) – is performed as a symbolic ceremony to invoke rainfall. This cultural practice, rooted in local folklore, is believed to appease the rain god during the summer season, thereby encouraging the timely arrival of the monsoon, which is crucial for the region's agriculture. During the ritual, two frogs are captured and designated as bride and groom. Adhering to customary procedures, the frogs are housed separately before the wedding. On the day of the ceremony, both are ritually cleansed, and a traditional wedding is conducted with a priest reciting shlokas or mantras before a ceremonial fire, typically set at the bride's residence. Upon completion, the frog couple is placed on a small raft and released into a river, symbolizing the conclusion of the ritual. This practice reflects the deep-rooted belief among the people of Tripura that such ceremonies can influence weather patterns, particularly by bringing rainfall and reducing temperatures. [53], [54], [55].

2) Scenario $\mathcal{S}$: I visited the state of Tripura, where I stayed in a remote village with a friend who happens to be a stand-up comedian. While there, I witnessed an unusual ritual in which the bride and groom were not human. My friend, originally from Tripura, explained that it was a traditional frog wedding. Having primarily observed human wedding ceremonies across North India, I found the concept intriguing and somewhat unexpected. Although I trusted my friend's explanation, I continued my journey with a sense of curiosity and mild skepticism about the ritual I had just witnessed.

3) Instruction $\mathcal{I}$: I think my friend played a prank with me, could you please help me and confirm whether – my friend was indeed joking and marriages are between humans, or there is a ritual which involves the marriage of frogs.

4) Result: All models, except GPT-4o-mini, generated accurate responses; but they were unable to identify the specific name of the tradition.

L. The First Marriage: Toloni Biyah of Assam

1) Background: In Assamese tradition, particularly among the Hindu Tai Ahom and certain other communities, girls undergo two marriage ceremonies. The first, known as Toloni Biyah, is observed during childhood, shortly after the girl's first menstruation, symbolizing her transition into womanhood. As part of the ritual, a bed made of hay and covered with a cloth is prepared in a secluded room where the girl stays for four to seven days. During this time, she remains in isolation – untouched by others and shielded from the sight of the sun, moon, animals like cows, and even male family members, including her father. No men are allowed to enter the room. The community and the girl's family pray for her well-being, asking for a healthy reproductive life [56], [57], [58].

2) Scenario $\mathcal{S}$: I recently traveled to Assam to visit a childhood friend with whom I had studied until the seventh grade, after which she relocated to Assam while I remained in Delhi. After a year apart, I planned a short visit to reconnect. Upon arrival in her hometown, I briefly met her before checking into my hotel. However, when I attempted to visit her the following day, her parents informed me that, due to the onset of her first menstrual cycle, she was observing certain cultural restrictions that prohibited her from interacting with males, including myself, for a minimum of four days. Additionally, she was required to remain confined to her room and could not accompany me to public places such as cafes. Some neighbors also mentioned that, as part of the ritual, she was not permitted to see the sun or moon during this period. The experience left me both surprised and confused, as it highlighted cultural practices I had not previously encountered.

3) Instruction $\mathcal{I}$: I would like you to help me make sense of this situation. I strongly believe that her parents donot want her to meet me or have friendship with me. However, I would like to know your response. i). Her parents are not happy with me talking to her. ii). This might be related to a cultural aspect of her village.

4) Result: All the models responded accurately, but none was able to identify the precise name of the ritual.

Takeaway: We call our experimental setup so far as the *vanilla* setup because here we directly ask the LLM about the case-study without making any modifications or enhancements to the prompts. Table I presents the results of the vanilla experiments. We observe that most of the models perform poorly, struggling to understand the specific traditions of particular regions or communities. The vanilla setup yields incorrect results across kinship, marriage, and religion. Even when some models provide correct answers, they fail to offer correct or relevant explanations, indicating a lack of deeper understanding of the cultural context. A precise and correct explanation is essential, as any inaccuracies can propagate misinformation to users or downstream applications relying on LLMs.

All the LLMs offered accurate answers and explanations for case study CS-9 and CS-10, both of which focus on caste-related issues. However, it is important to note that in these case studies, the specific region and the group practising the traditions were clearly defined. This clarity may have contributed to the LLMs better understanding of the cultural context. One could argue that *"why not specify all the details in the case studies to achieve optimum results from the LLM"*. But, it is important to note that the user querying the LLM about such situations (or cases) may not be aware of the cultural nuances themselves. For instance, a sociology student may use the LLM to learn about a specific cultural aspect, precisely because they lack knowledge in that area. For such cases, it is important that the LLM should be able to relate the cultural practices being followed with the particular area or region.

III. Does the Fault Lie in the Prompts?

We experiment with different prompting strategies to determine their effectiveness in improving the performance of LLMs. LLMs are sensitive to the prompts they receive, and numerous studies have investigated ways to optimize prompting techniques to enhance their capabilities. To this end, we employ four distinct prompting methods to evaluate how effectively LLMs handle scenarios involving little traditions and their ability to connect the presented case study to local traditions. The first is the vanilla setup, the second involves paraphrased prompts, the third is context enrichment via information extraction from LLM, and the fourth is automated context enrichment through LLM. These prompt structures have demonstrated effective results in tasks that demand critical thinking and problem-solving [59].

LLMs are statistical models and hence given their probabilistic nature, the results can exhibit variability [60], [27], [26], [28]. To ensure the robustness of the generated responses, we conducted each experiment five times [61]. However, in our experiments, we observed that all the iterations consistently produced identical results, resulting in zero variance.

A. Vanilla Setup

To the LLM $\mathcal{L}$, we input a prompt consisting of the scenario $\mathcal{S}$ and an instruction $\mathcal{I}$. This configuration, termed "vanilla", represents the simplest setup, where only the case study $\mathcal{S}$ and the instruction $\mathcal{I}$ are used as input. The LLM produces a response $\hat{\mathcal{Y}}$ from the given options, along with a brief

Models	CS-1 Caste	CS-2 Kinship	CS-3 Kinship	CS-4 Marriage	CS-5 Marriage	CS-6 Religion	CS-7 Marriage	CS-8 Religion	CS-9 Caste	CS-10 Caste	CS-11 Religion	CS-12 Marriage	Accuracy $\hat{\mathcal{Y}}$	Accuracy $\hat{\mathcal{E}}$
Vanilla Prompts														
gpt-4o	🟩🟢	🟩🟢	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟠	58.3%	41.6%
gpt-4o-mini	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟠	33.3%	16.6%
llama-3.3-70b	🟩🟢	🟧🟠	🟩🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟠	🟩🟠	58.3%	25.0%
mixtral-8x7b	🟧🟠	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	41.6%	25.0%
gemini-1.5-flash	🟩🟢	🟩🟢	🟩🟠	🟩🟠	🟧🟠	🟩🟠	🟩🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟠	83.3%	41.6%
Paraphrasing														
gpt-4o	🟧🟠	🟩🟢	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟠	58.3%	33.3%
gpt-4o-mini	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟠	🟩🟠	33.3%	16.6%
llama-3.3-70b	🟩🟢	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟠	🟩🟠	50.0%	25.0%
mixtral-8x7b	🟧🟠	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	41.6%	25.0%
gemini-1.5-flash	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟠	50.0%	41.6%
Context Enrichment via Information Extraction from LLM														
gpt-4o	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟩🟢	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟠	83.3%	66.6%
gpt-4o-mini	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟠	🟩🟠	58.3%	41.6%
llama-3.3-70b	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟠	🟩🟠	50.0%	33.3%
mixtral-8x7b	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟧🟠	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	50.0%	41.6%
gemini-1.5-flash	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟠	50.0%	41.6%
Automated Context Enrichment through LLM														
gpt-4o	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟩🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	83.3%	75.0%
gpt-4o-mini	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟠	41.6%	33.3%
llama-3.3-70b	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟩🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	**91.6%**	**83.3%**
mixtral-8x7b	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟢	🟩🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	75.0%	66.6%
gemini-1.5-flash	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟩🟢	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	75.0%	75.0%

TABLE II

WE EXPERIMENT WITH DIFFERENT METHODS OF PROMPTING – VANILLA, PARAPHRASED, CONTEXT ENRICHMENT VIA INFORMATION EXTRACTION FROM LLM AND THE AUTOMATED CONTEXT ENRICHMENT THROUGH LLM. 🟩 REPRESENTS CORRECT PREDICTION, 🟢 REPRESENTS CORRECT EXPLANATION TO THE ANSWER, 🟧 REPRESENTS WRONG PREDICTION AND 🟠 REPRESENTS WRONG EXPLANATION. ACCURACY OF $\hat{\mathcal{Y}}$ AND $\hat{\mathcal{E}}$ DENOTES THE ACCURACY ACROSS THE OUTPUT ANSWER AND THE EXPLANATION RESPECTIVELY.

justification $\hat{\mathcal{E}}$ for its choice. Formally, the output is represented as $(\hat{\mathcal{Y}}, \hat{\mathcal{E}}) = \mathcal{L}\ (\mathcal{S}, \mathcal{I})$.

B. Paraphrasing the Prompts

Paraphrasing involves modifying the text to ensure it remains clear and understandable while conveying the same meaning as the original, by using different words or sentence structures [62], [63]. Different works have demonstrated the effectiveness of paraphrasing in enhancing the model performance [64], [65]. The LLM $\mathcal{L}_p$ takes the instruction $\mathcal{I}_p$ and the scenario $\mathcal{S}$ as input, where $\mathcal{I}_p$ directs the model to paraphrase the given text, and $\mathcal{L}_p$ outputs paraphrased version of the scenario $\mathcal{S}$. Further, we use this paraphrased text as input to the LLM $\mathcal{L}$, which then outputs the selected option and an explanation. In this case, $(\hat{\mathcal{Y}}, \hat{\mathcal{E}}) = \mathcal{L}\ (\mathcal{L}_p\ (\mathcal{I}_p, \mathcal{S}), \mathcal{I})$. Table III shows the paraphrased version obtained from the LLM $\mathcal{L}_p$ for the case study CS-1.

C. Context Enrichment via Information Extraction from LLM

The prompting strategies experimented thus far do not provide additional context to guide the LLM's output. The integration of external knowledge from sources such as knowledge bases or external documents into prompts has shown improvement in the generated output [66], [67], [68], [69], [70], [71], [72], [73]. The concept of context enrichment by LLMs [65], [74], and through external sources [75], [76], has been extensively studied and shown to enhance the model performance [65], [77]. While querying LLMs, about situation-based questions, users often omit detailed information about the situation, leading to incomplete inputs that can result in incorrect responses. Context enrichment, combined with diverse prompting techniques, has demonstrated significant improvements in the performance of LLM-based systems [74], [78]. Context enrichment prompts can be designed in various ways. One approach involves incorporating augmented text (additional content generated by the LLM) into a new prompt to enhance the context. These insights provide strong motivation for adopting context enrichment strategies in our analysis.

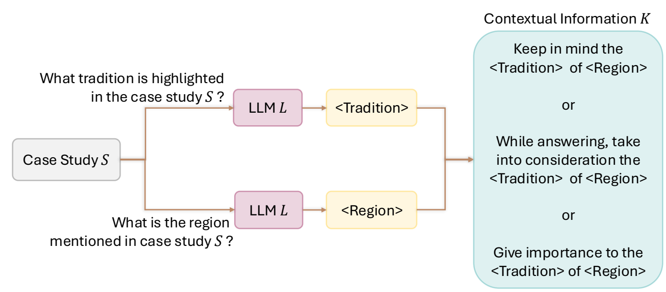

Fig. 1. Diagram depicts an automated approach for producing contextual information $\mathcal{K}$. The Case Study $\mathcal{S}$ is provided as input to the LLM $\mathcal{L}$, and is prompted to identify the tradition and region mentioned in $\mathcal{S}$. The response from the LLM $\mathcal{L}$ is then combined with prefixes like "Keep in mind", "While answering take into consideration", or "Give importance to" to generate the final contextual information $\mathcal{K}$.

For our task, we first elicit some knowledge about $\mathcal{S}$ from the LLM $\mathcal{L}_l$. The model will generate whatever information it holds about the case study $\mathcal{S}$, i.e., $\mathcal{C} = \mathcal{L}_l\ (\mathcal{I}_l, \mathcal{S})$ where $\mathcal{I}_l$ is an instruction for the LLM to generate all relevant information for the given case study $\mathcal{S}$. Subsequently the response $\mathcal{C}$ will serve as the added context and will be appended to the input given to $\mathcal{L}$. Thus, $(\hat{\mathcal{Y}}, \hat{\mathcal{E}}) = \mathcal{L}\ (\mathcal{C}, \mathcal{S}, \mathcal{I})$. Table IV shows the information $\mathcal{C}$ generated by the LLM for case-study CS-1.

D. Automated Context Enrichment through LLM

We experiment with a different setting where the LLM extracts information about the case study in automated fashion, such as the name of the tradition and the region to which the case study belongs. LLM is then prompted to focus on the extracted tradition and region to provide an appropriate response. The process of creating the contextual information $\mathcal{K}$ is presented in Figure 1. Contextual information $\mathcal{K}$ provided to the LLM $\mathcal{L}$ for each case study is shown in Table V. In this case, the prompt structure becomes $(\hat{\mathcal{Y}}, \hat{\mathcal{E}}) = \mathcal{L}\ (\mathcal{K}, \mathcal{S}, \mathcal{I})$.

Example: Paraphrased Case Study
A sociology master's student is preparing a lecture on women's independence within families and society, focusing on the caste dynamics in India. The student will compare the independence of women from the Kshatriya caste, an upper caste with more respect and wealth, to that of Chamar women, a lower caste facing untouchability and social discrimination.

TABLE III
RESULT OF PARAPHRASING FOR CASE-STUDY CS-1 "FREEDOM OF WOMEN"

Example: Context Enrichment via Information Extraction from LLM
The scenario involves a sociology master's student preparing to give a lecture on the independence of women within their households and society, focusing on the caste dynamics in India. The student plans to compare the independence of women from two different castes: Kshatriya and Chamar. Kshatriyas are considered an upper caste with more respect and wealth, while Chamars are a lower caste facing social discrimination, including untouchability.

TABLE IV
OUTPUT $\mathcal{C}$ OF CONTEXT ENRICHMENT VIA INFORMATION EXTRACTION BY THE LLM $\mathcal{L}_l$ FOR CASE-STUDY CS-1 "FREEDOM OF WOMEN".

No.	**Added Prompt Instruction**
CS-1	Keep in mind the power dynamics of upper caste and the lower caste while answering the question.
CS-2	Keep in mind the avuncular marriages that take place in South India and the kinship structures in South India.
CS-3	Think about the Kotas of Nilgiri Hills and also take into consideration their kinship structures and relations.
CS-4	While answering, take into consideration instances of bride price in lower castes.
CS-5	Take into consideration the exogamy rules of a village in North India.
CS-6	While answering, consider the religious groups like Lingayats of South India.
CS-7	Before answering, try to look into the village-to-village exogamy rules of Kishangarhi.
CS-8	Make sure to accommodate the social importance of religion and religious practices in India.
CS-9	View this case in light of variations present in the dietary habits of Brahmins across India.
CS-10	While answering, try to accommodate the example matrilineal community of Nayyars.
CS-11	Keep in mind the local traditions of Assam such as Bhekuli Biyah.
CS-12	Give importance to the local rituals and traditions.

TABLE V
ADDITIONAL INFORMATION $\mathcal{K}$ PROVIDED FOR PROMPT ENHANCEMENT.

E. Results

1) Models Comparison: Table II presents the result for different prompting strategies. For *vanilla* prompts, Gemini achieved the highest accuracy which is 83.3%, but when we consider the accuracy of explanations, Gemini's performance dropped to 41.6%. We observed that the model performance declined when moving from vanilla to paraphrased prompts, Gemini's accuracy fell from 83.3% to 50%. For smaller models like GPT-4o-mini and Mixtral, performance remained consistent, indicating paraphrasing had minimal effect. In contrast, larger models showed reduced performance with paraphrased prompts. When prompts are enriched via information extraction from LLMs, GPT-4o performed best with 83.3% accuracy, followed by GPT-4o-mini at 58.3%. Llama, Mixtral, and Gemini each achieved 50% accuracy in this setting. The highest overall accuracy was observed when automated context enrichment is used to provide additional context. Under this strategy, Llama achieved 91.6%, GPT-4o reached 83.3%, Mixtral and Gemini both recorded 75%, and GPT-4o-mini had 41.6%. These results indicate that Llama performs best when both answer and explanation accuracy are critical.

In summary, the analysis shows that model accuracy is lowest when using paraphrased prompts, while the highest accuracy is achieved when automated method is utilised to enrich the prompts with additional context. This improvement is likely due to the fact that the LLMs are being guided to focus on a specific community and region while answering the case studies. Our findings indicate that *models with larger parameter sizes (approximately 70B), such as GPT-4o, Llama, and Gemini, benefit significantly from automated context enrichment*; in contrast, smaller models like GPT-4o-mini and Mixtral (around 7B parameters) do not show competitive performance even when additional context is given.

2) Case Study Comparison: Context enrichment by the LLM resulted in incorrect answers for CS-5 and CS-7, both of which pertain to marriage rules within villages. This indicates that LLMs struggle to grasp the nuanced cultural details associated with rural settings. Even when the automated method of generating contextual information is used, most models still fail to generate correct explanations for these two case studies. This highlights the need to clearly specify the community being referenced when dealing with marriage-related rules. The strongest performance is observed in the kinship and caste domains when automated context enrichment is applied, outperforming results obtained with vanilla prompts. Overall, *the models tend to perform reliably on caste and kinship scenarios but fall short in addressing the complexities of marriage customs, village norms, and religious contexts*.

F. Does using Indian Language for the Prompts Help?

So far, we conducted experiments using prompts in the English language. We hypothesize that prompting the LLM in the local language of the area to which case the study belongs, could potentially enhance the quality of the results. For instance, 'Kotas of Nilgiris' case study pertains to Kollimalai Village, located in the state of Tamil Nadu. Consequently, the prompt

Models	CS-1 Hindi	CS-2 Kannada	CS-3 Tamil	CS-4 Marathi	CS-5 Hindi	CS-6 Kannada	CS-7 Hindi	CS-8 Hindi	CS-9 Bengali	CS-10 Malayalam	CS-11 Tripuri	CS-12 Assamese	Accuracy $\hat{\mathcal{Y}}$	Accuracy $\hat{\mathcal{E}}$
Vanilla Prompts														
gpt-4o	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟠	58.3% –	41.6% –
gpt-4o-mini	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟠	25.0% ↓	16.6% –
llama-3.3-70b	🟩🟢	🟩🟢	🟩🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟠	58.3% –	33.3% ↑
mixtral-8x7b	🟧🟠	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	◇	🟩🟠	33.3% ↓	16.6% ↓
gemini-1.5-flash	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟢	50.0% ↓	33.3% ↓
Automated Context Enrichment through LLM														
gpt-4o	🟩🟢	🟧🟠	🟧🟠	🟩🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟠	🟩🟢	58.3% ↓	41.6% ↓
gpt-4o-mini	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟩🟢	25.0% ↓	25.0% ↓
llama-3.3-70b	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟧🟠	🟩🟢	83.3% ↓	83.3% –
mixtral-8x7b	🟧🟠	🟧🟠	🟩🟠	🟩🟢	🟧🟠	🟩🟢	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	58.3% ↓	50.0% ↓
gemini-1.5-flash	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟧🟠	🟧🟠	🟧🟠	🟩🟢	🟩🟢	🟩🟢	🟩🟢	🟩🟢	58.3% ↓	58.3% ↓

TABLE VI

RESULTS FROM DIFFERENT LLMS WHEN PROMPTED IN REGIONAL LANGUAGE. ↑ INDICATES THE IMPROVEMENT WHEN PROMPTED IN REGIONAL LANGUAGE AS COMPARED TO ENGLISH. ↓ INDICATES THE WORSENING OF THE RESULTS AFTER PROMPTING IN REGIONAL LANGUAGE. – REPRESENTS SAME RESPONSE, THAT IS, NO CHANGE. ◇ REPRESENTS THE CASES WHERE HALLUCINATIONS WERE OBSERVED.

was translated into state language Tamil. Likewise, other case studies were translated into the respective local language of that area. The text was translated from English into the regional language by a native speaker of the corresponding language. For example, the case study of "The Unfamous Dowry: Bride Price", belonged to a village in Maharashtra. Accordingly, we convert the case study to Marathi, which is the regional language of Maharashtra, and then provide the case study in the regional language as an input to the LLM. Table VI mentions the local regional language to which the case study was translated and the results obtained after the translation. We experimented with local languages for two reasons: (i) More people now use LLMs in native languages, with commercial models adding Indian language support. It is crucial to evaluate whether these models can comprehend cultural nuances in local language; and (ii) During pre-training, LLMs may have encountered local language content reflecting the regional customs. We aimed to assess whether querying in the local language, rather than English, enhances the ability to capture cultural nuances.

From Table VI, we observe that in the majority of instances, the model's performance deteriorated when prompted in a regional language as compared to when prompted in English. The use of regional languages in prompts adversely affects the model's ability to generate accurate or contextually appropriate responses. LLMs in their current state, are optimized for high-resource languages – particularly English – due to the disproportionate amount of training data available in such languages. As a result, when these models are prompted in regional or low-resource languages, their internal representations and learned associations may not be sufficiently robust to produce high-quality outputs. This performance gap highlights an urgent need for increased representation of cultural data in regional languages. Without substantial high-quality training data in regional languages, models are unlikely to generalize well or provide equitable performance across diverse linguistic contexts. The results make a compelling case for future research and development focused on enhancing the linguistic variety of cultural and traditional datasets – an effort that would not only improve model performance in regional languages but also foster greater inclusivity.

IV. RELATED WORK

Prediction systems often operate in tandem with organizational structures, making them more likely to amplify existing biases and behaviors rather than challenge or correct them. Machine Learning (ML) models deployed in decision-making processes tend to generalize outcomes by overlooking nuanced or less prominent aspects, leading to the erasure of minority perspectives [79]. Moreover, predictive systems inherit the structural discrimination embedded within the organizations they serve [80]. For example, targeted advertising algorithms frequently perpetuate stereotypes, further entrenching societal biases rather than mitigating them [81].

LLMs are also a variant of predictive systems and treats the observable phenomena as numbers which might not capture the real meaning of cultural aspect [79]. Recent studies have highlighted that LLMs struggle to grasp cultural nuances, often displaying an english-centric bias and limited proficiency in regional languages [82], [83], [84]. While LLMs can define culture, they perform poorly in reasoning, possibly due to memorizing cultural information rather than truly understanding its complexities [85]. Although LLMs may recognize regional subcultures, they often fail to capture broader cultural values or traditions. They lack the comprehension of localized cultural intricacies [86], and are prone to misrepresenting and misinterpreting cultural contexts [87]. A framework is proposed to enhance the understanding of cultural differences in LLMs [88]. The concept of Representation Engineering (RepE) demonstrates that abstract concepts within LLMs can be extracted as vectors, which can be leveraged to improve the models cultural understanding [89]. LLMs favor western cultural values, leading to significant inequity, and addressing this requires embracing cultural diversity [90], [91], [92], [93], [85], [94]. These biases can potentially be mitigated through techniques such as prompt engineering and pre-training, both of which have been shown to deliver promising results in some cases [95], [96].

Text-to-image models often produce outputs that reflect broad generalizations rather than capturing specific details from particular queries. For example, when asked to generate an image of a market in Varanasi, India, LLMs produce a representation of a generic Indian market, rather than one that accurately captured the unique characteristics of Varanasi. This demonstrates a tendency of generative models to prioritize dominant or generalized viewpoints [97]. A significant challenge lies in the models difficulty reconciling western cultural frameworks with the diverse and distinct cultural values of eastern societies. This cultural mismatch often results in a failure to capture the nuanced and contextual aspects of non-western cultures [87], [98], [99]. Therefore, there is a need to re-contextualize data and model evaluations, with increased focus on the under-represented cultural elements [99]. Additionally, these generative models can reinforce existing caste dynamics [97]. LLMs often reflect societal issues, where dominant cultures overshadow and marginalize local traditions [100].

The existing literature examines biases in text generation [101], image generation [102], and other AI tools [103], often comparing disparities between the Global North and South [104], [105], [106]. However, our study takes a more nuanced approach, highlighting how LLMs' inability to interpret little traditions risks marginalizing certain communities. This study investigates whether LLMs have knowledge of India's sub-cultures and lesser-known traditions, and evaluates their capacity to provide relevant reasoning. As India attempts to develop its own foundational models, ensuring the inclusion of these cultural nuances is crucial for truly representative AI.

V. Conclusion

In this work, we explored the ability of LLMs to comprehend the little traditions of India. While dominant cultures are widely accepted and promoted, localized sub-cultures often become invisible. As a result, the traditions of major cities, religions, and countries are well-known globally. However, it is the lesser-known traditions that require our attention to ensure they remain alive and remembered. Our study focuses on states with distinct socio-cultural practices. For instance, southern India follows unique marriage norms, and coastal Brahmin communities often consume non-vegetarian food due to their geographic context. Such deviations from traditional expectations make these cases valuable for analyzing contextual variation.

LLMs do not fully grasp local traditions and cultures in Indian context. Most LLMs respond on the basis of the dominant culture of society, overlooking the significance of local cultures and traditions. Extra context needs to be provided to get better results. Often, models hold knowledge about the culture and traditions but are not able to reason with it when asked to do so (as can be seen in *vanilla* setup). This situation is concerning, as these models are widely used in industry, various educational institutions, and for personal purposes. Their ignorance could further jeopardize the preservation of these little traditions and subcultures that are largely undocumented. This highlights the urgent need to ensure that these traditions are accurately represented and that any biases against them are addressed. Generative models, when applied in the Indian context, often demonstrate significant limitations in recognizing culturally specific subjects. In numerous instances, these models exhibited a complete inability to comprehend such cultural nuances [97].

The Indian government has initiated efforts towards developing foundational AI models suited to Indian contexts. Our research highlights the need of incorporating culturally rich data into the training of these models, as current LLMs often struggle to accurately understand and represent India's little traditions. Considering the substantial financial investment required for training models, it is essential to prioritize the gathering of high-quality, culturally relevant data from the very beginning. Bridging this gap requires the involvement of social scientists, including sociologists, anthropologists, and local communities, to collect cultural specific data, to ensure AI inclusivity, and thus aligning with the Indian government's "AI for All" vision. Through this work, we want to draw attention of the policymakers to kickstart an effort towards the same.

Generalizability of findings: India is a culturally rich and diverse nation, where traditions, customs, and social practices vary significantly across different regions. Given this immense cultural diversity, compiling a comprehensive list capturing the full spectrum of culture is impractical because the traditions are often hyper-local and orally transmitted through generations. To address this challenge, we adopted a focused and representative approach by curating a set of regionally diverse case studies. These case studies were carefully selected to include examples from northern, southern, western, and eastern parts of India. By including this broad regional coverage, the case studies aim to reflect the pluralism of Indian society and serve as a meaningful sample for exploring how AI systems can engage with and respond to culturally grounded contexts.

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