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Large Language Models: A technological approach for teaching Hindi

Abstract: Multiple large language models (LLMs) have been developed in recent years. In the research phase are GPT-3 and GPT-4 from OpenAI, LLaMA from Meta, and PaLM 2 from Google, among many others. From the inception of AI (artificial intelligence) technology, I have been experimenting with the use of AI instruments in the Hindi classroom. I contend for their value by providing three justifications for the use of LLMs in language instruction. The paper begins by investigating the potential use of LLMs in teaching Hindi. It emphasizes the role they can play in vocabulary development, grammar acquisition, and conversational practice. Next, it investigates how these models can help learners improve their proficiency by providing vocabulary-building definitions, synonyms, and example sentences. Thirdly, it shows how the models can provide correct sentence structures, grammatical constructions, and cultural insights, thereby facilitating students' comprehension of Hindi grammar and cultural nuances. Overall, the study highlights the value of combining language models with conventional learning techniques. It sets out a technological approach that can supplement traditional language teaching methodologies, and thus enhance the learning experience of Hindi language students.

Keywords: Hindi, large language models, artificial intelligence

1 Introduction

In recent years, the field of artificial intelligence (AI) has witnessed remarkable advancements, particularly in the development of Large Language Models (LLMs). Notable examples include GPT-3 and its successor, GPT-4, produced by OpenAI, the LLaMA series from Meta, and the PaLM series from Google, among others.[1] These LLMs represent a pivotal breakthrough in the realm of natural language understanding and text generation. With their capabilities continuing to evolve, they offer a tremendous potential for transforming many

1 In addition to the aforementioned popular LLMs up to December 2023, there are eight alternative AI models in experimental stages worth considering. These include BERT (developed by Google), T5 (developed by Google Research), XLNet (a collaborative effort between Google and Carnegie Mellon University), RoBERTa (created by Facebook AI), ERNIE (developed by Baidu), Turing-NLG (crafted by Microsoft), CTRL (engineered by Salesforce), and DistilBERT (formulated by Hugging Face).

aspects of education, including language instruction. A common method for working with LLMs is demonstrated in Figure 1.

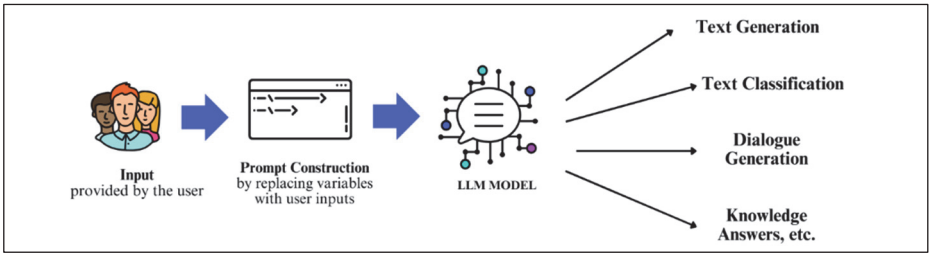

Figure 1: Procedural Setup of a typical LLM

This paper delves into the fascinating realm where cutting-edge technology intersects with the art of language teaching. It explores the possibilities for integrating LLMs, such as GPT-3, GPT-4, LLaMA, and PaLM 2, into the context of Hindi language education. This highly advanced software, commonly referred to either as LLMs or as Generative AI, develops cumulatively, and building on previously collected data (or the type/amount/size of user inputs), is able to generate new content, including writing, music, and images.

This rapidly evolving technology can automate jobs that were previously carried out by humans, and offers in particular a range of language-related skills and tools, as set out in the Table 1 below:

Table 1: Potential Applications of LLMs

Domain	Potential Applications of LLMs
Text Generation	Used for content creation, creative writing, or even generating the codes for software.
Translation	Used for translating text from one language to another, using text or image inputs.
Text Summarization	Used for producing summaries of long articles, documents, or web pages.
Sentiment Analysis	For determining the sentiment behind a statement, whether positive, negative, or neutral (mainly used in social media monitoring and customer feedback analysis; still in the learning phase in terms of the contextual sentiment of language).
Chatbots and Virtual Assistants	Powered by AI, and used for performing natural language conversation.

Domain	Potential Applications of LLMs
Text Generation	Used for content creation, creative writing, or even generating the codes for software.
Language Understanding	Used for extracting information from text, including named entity recognition (NER), or extracting key information from documents.
Text Classification	Used for assigning text to predefined categories or labels (helpful for tasks such as spam detection, content tagging, etc.).
Language Localization	Used for translating and adapting content to fit different regions and cultures, and thus ensuring that messages are culturally sensitive.
Content Recommendation	Analysing user preferences and behaviours in order to recommend relevant content, such as articles, products, or services (commonly used in e-commerce prompts and online searches).
Text-to-Speech (TTS)	For converting text into spoken words, to make it accessible for people with visual impairments, and to enhance the user experience in voice interfaces.
Speech Recognition	For transcribing spoken language into text, to enable applications such as voice assistants and automatic transcription services.
Grammar and Style Correction	For improving the user's writing by suggesting language-specific improvements to grammar and style.
Dialogue & Narratives	The creation of dialogues and narratives for video games, simulations, and virtual environments.
Language Preservation	For assisting in preserving endangered languages, through the provision of translation, transcription, and documentation services.
Language Tutoring	For providing language learning support, using explanations, examples, and practice exercises tailored to the language concerned.

My journey in experimenting with the deployment of these AI instruments in Hindi classrooms has been both pioneering and illuminating. I have used selected examples from the different LLMs as a way of supporting my teaching process. This paper examines the effectiveness and efficiency of LLMs in dealing with various different aspects of language, and seeks to promote the use of AI in the language learning classroom. All language instruction (LI) throughout the world focuses mainly on developing four skills: reading, writing, speaking and listening. Language trainers usually structure their courses into three different levels for the achievement of these four skills. The three levels most widely adopted are Basic,

Intermediate and Advanced. I regard this approach as being merely traditional, with no definite rationale behind the identification of the different levels.

I argue instead for using an Integrated Language Instruction (ILI) pedagogy (see Figure 2) in the current language teaching scenario, as a way of integrating the latest technological innovations with the CEFR hierarchy levels.

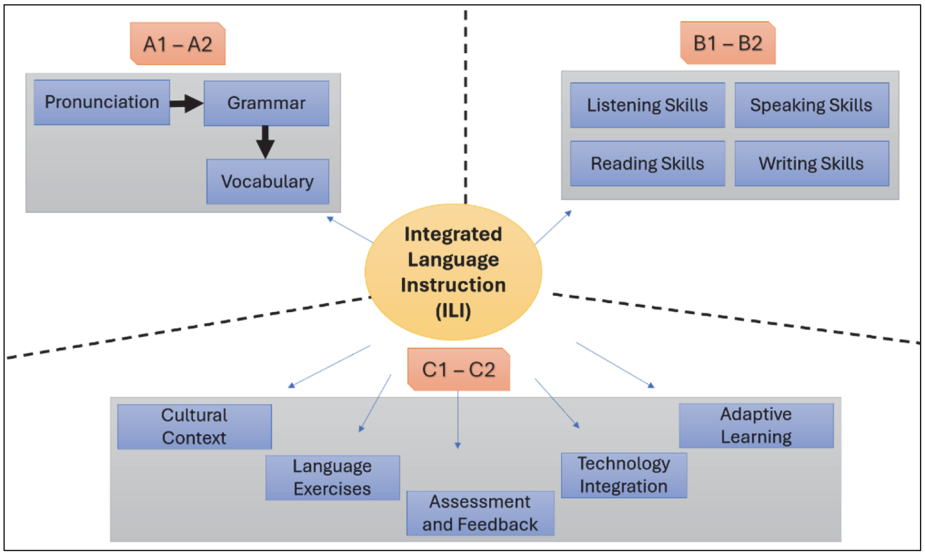

Figure 2: Pedagogy for Integrated Language Instruction (ILI)

CEFR stands for the Common European Framework of Reference for Languages. A specification for its "threshold level" was first formulated for the English language, with French following quickly after. CEFR offers a process for mastering a foreign language that is based on types of competence and subcompetence, each with its own descriptor. These descriptors were created without reference to any specific language, thus guaranteeing their general relevance and across-the-board applicability.

The specific choice of content and approach in ILI can vary depending on the language being taught, the goals of the learners, the resources available, and the instructional context. However, the ILI pedagogical approach provides the following focus points for the different levels of language instruction:

1.1 Focus Points for Levels A1–A2:

– **Pronunciation:** This may involve exercises in phonetics and speech patterns using AI tools. This helps learners improve their pronunciation of

words and accents through practice and feedback, usually via a process of looping the same sound and listening to this again and again.
- **Grammar:** AI can be used for instruction in the rules and structure of the language, including verb conjugation, sentence structure, tenses, and word order.
- **Vocabulary:** Vocabulary may be grouped using AI tools, by themes, topics, gender, or frequency of use. This helps in teaching the words and phrases that are essential for communication in a language, i.e. selected common keywords from the language concerned.

I have identified and propose a linear instructional approach at the current levels as optimal for achieving an elevated level of language proficiency in Hindi (refer to the 'User Experience from Hindi Classroom' section for further details). The suggested progression (shown through arrows in Figure 2) entails the trainee initially focusing on sound pronunciation, encompassing both vowels and consonants' positioning and articulation (developing basic writing and reading skills). Subsequently, the trainee progresses to the grammar level, where familiarity with the syntactical arrangements inherent in the language is developed (developing basic speaking and listening skills). Finally, the trainee advances to the vocabulary level, engaging in speech experimentation with less commonly used words in the native language. Nevertheless, this sequence can be tailored to meet the specific requirements of the learner and can be adjusted to align with different language goals.

1.2 Focus Points for Levels B1–B2:

- **Listening Skills:** Developing the ability to understand spoken language, including various accents and speaking speeds. AI can help by providing audio recordings, videos, or live conversations of the target language.
- **Speaking Skills:** Encouraging learners to practice speaking the language through dialogues, role-plays, and real-life conversations. AI can help provide dialogue exchange and natural expression tools.
- **Reading Skills:** Teaching learners to read written texts in the target language, starting with simple texts, and gradually progressing to more complex materials such as books, articles, and newspapers. AI can provide records from media services such as the BBC, publications, illustrations, news websites, magazines, and so on, to help develop the interpretation capacity usually required for intermediate learners.
- **Writing Skills:** Guiding learners in writing in the target language, including composing essays, emails, reports, and creative pieces. AI can provide

content that focuses on specific points, such as grammar, vocabulary, or coherence.

1.3 Focus Points for Levels C1–C2:

- **Cultural Context:** Providing insights into the culture, customs, and societal norms of the target language speakers. This helps learners understand the cultural context in which the language is used. In addition, AI tools can provide for cultural/collateral understanding of word nuances.
- **Language Exercises:** Incorporating drills, exercises, and related practice activities to reinforce vocabulary, grammar, and other language skills. These can also include interactive exercises, such as group discussions, debates, presentations, and games to promote active language use, whose prompts can be developed by AI.
- **Assessment and Feedback:** AI can evaluate learners' progress through tests, quizzes, assignments, and provide constructive feedback to help them improve.
- **Technology Integration:** Using sector-specific AI technology and customised language learning apps, software, or online resources can supplement instruction and provide additional practice opportunities. AI with Knowledge Representation (KR) tools can help develop creative abilities.
- **Adaptive Learning:** Drawing on user responses and inputs, AI can tailor instruction to fit the learner's individual needs and abilities, and this process can be further facilitated through technology-assisted personalized learning paths. These AI tools can thus promote the use of immersive environments for language instruction programmes in ideation and imitation.

The paper seeks to substantiate its claims with a tripartite exploration of the implementation of ILI pedagogy, consisting of three fundamental justifications of the indispensability of LLMs in augmenting the learning process for Hindi learners.

- To begin with, the paper examines in detail how LLMs can transform the way Hindi language structures are taught at levels A1–A2. It emphasizes the role of LLMs in developing vocabulary, strengthening grammar skills, and enhancing proficiency in pronunciation.
- Secondly, the study offers an examination of how LLMs can function as facilitators of proficiency enhancement for Hindi language students at levels B1–B2. It draws attention to the profound impact these models can have on the linguistic competence of learners, due to the multifaceted assistance they provide for honing skills in reading, writing, speaking and listening.

This assistance ranges from furnishing definitions and synonyms for vocabulary-building, to offering enlightening example sentences that aid in the practical application of acquired knowledge.

– Next, this research examines the role of LLMs in offering cultural insights and adaptive learning for C1-C2 learners of Hindi. These language models extend their utility beyond the realms of language structure and complex vocabulary by furnishing students with a nuanced understanding of cultural idiosyncrasies.

In sum, this study serves as a clarion call for the amalgamation of technological innovation, represented by LLMs, with established pedagogical approaches in the field of Hindi language instruction. It underscores not only the significance of this integration (in synchronous and asynchronous ways) but also the complementary role that active interaction with native speakers and authentic language practice continue to play in the holistic journey of Hindi language acquisition. By presenting a technology-enhanced paradigm for language teaching, this paper seeks to enrich the learning experiences of Hindi language enthusiasts, opening up new horizons of linguistic exploration and cultural understanding.

In this scholarly work, the term “interpretation” has been intentionally employed as a specialized term in various sections ahead. This preference persists even in instances where translation tests have been conducted. This choice is informed because of our preference for the evaluation of outcome with respect to the spoken form of the Hindi language (and less for the written or literature form of the Hindi language) – specifically, the linguistic choices a native speaker would make when cognitively opting to translate and articulate ideas orally.

2 Literature Review

2.1 The Development of LLMs for Language Study

AI-assisted language learning is a paradigm of learning in which interactive tools built to reflect the grammatical setup of the target language are used to help enhance foundational understanding of grammar and the cognitive capacity of the brain to retain linguistic structures within a social context. Research indicates that LLMs can effectively assist learners in grasping the fundamentals of the Hindi language. For instance, they can aid in vocabulary development by providing access to a wide range of words, idiomatic expressions, and

context-appropriate usage examples. They can also help learners acquire a solid grasp of Hindi grammar, including verb conjugations, sentence structures, and punctuation rules.

LLMs contribute to L2 instruction and language teaching by providing a versatile and adaptive platform for language learning, encompassing various aspects such as vocabulary, grammar, pronunciation, cultural context, and personalized learning experiences. Kramsch (1993) explicitly underscores the importance of culture in language learning. Consequently, numerous scholars are actively engaged in developing and refining LLMs by incorporating diverse facets of language learning into AI models. This literature review provides a comprehensive overview of the latest advancements in LLMs and their profound impact on various language teaching and research aspects.

Language modelling and understanding have been strikingly revolutionized by LLMs, exemplified by models such as GPT-3, which have attained state-of-the-art performance in tasks relating to natural language comprehension and generation (Brown et al. 2020). These models are distinguished by their remarkable ability to produce coherent and contextually relevant text, making them invaluable tools for exploring language structure and comprehension.

Multilingual capabilities have become a prominent feature in recent LLMs (Conneau et al. 2020), and are enabling them to comprehend and generate text in a multitude of languages. This capability facilitates cross-linguistic research, and opens doors for the exploration of linguistic commonalities and distinctions. I have tested the multi-lingual capacity of LLMs with regard to various dialectal variations of Hindi, and report on this in later sections.

Applications for LLMs are increasingly being found in text summarization and machine translation (Lewis et al. 2019). Their capacity to generate concise and high-quality summaries, as well as accurate translations, has contributed significantly to the advancement of language processing tasks. With these advancements, search engines can now use LLMs to provide improved cross-lingual search results. This means that users can search in one language, but receive relevant results from pages in multiple different languages. LLMs can also serve as a valuable resource for language learners. They can provide instant translations and explanations of idiomatic expressions, and help with grammar and vocabulary in context. In addition, the translation capacity of LLMs has been widely adopted commercially by companies and content creators, who use them to localize their content for different regions and cultures. LLMs can translate a text and adapt the cultural references, idioms, and other elements to make the content more relevant to a specific audience.

Equitable language generation refers to the use of natural language generation (NLG) techniques and technologies to produce text that is fair and unbiased, and that promotes equality. This concept is particularly relevant in the context of artificial intelligence and machine learning, where the language

generated by the algorithms can sometimes have the unintended consequence of perpetuating biases or stereotypes. Equitable language generation aims to address and rectify such issues. Bias and fairness in language models have gained considerable attention within the research community (Bolukbasi et al. 2016; Zhang et al. 2018). Researchers are actively addressing the challenges associated with mitigating biases within LLMs, to ensure that language generation and understanding are conducted in an unprejudiced and culturally sensitive manner.

Studies have demonstrated that LLMs can also synthesize speech in different languages (Chen et al. 2019) offering valuable learning support in acquiring decent naturalness in learning particular target language.

The creative potential of LLMs can be seen in the way they perform various creative tasks, such as poetry-writing and story generation. They helped in developing a creative assistant, allowing users to modify existing poems and create their own (Liu et al. 2017). This feature introduces new possibilities for exploring the creative dimensions of language. LLMs have also made a significant impact in the fields of computational linguistics and natural language processing (NLP), redefining the landscape by providing robust pre-trained models that can be fine-tuned for specific language-related tasks, thus reducing the dependence on extensive labelled data (Raffel et al. 2020).

As the capabilities of LLMs continue to grow, concerns regarding their ethical use and potential privacy violations have surfaced (Bender & Gebru 2021). Researchers are actively investigating methods to address these issues and foster the responsible development of language models. Studies exploring the limitations of LLMs in educational contexts have pointed to issues relating to biases in training data (Mehrabi et al. 2021). Concerns have been raised about the ability of LLMs to handle learner-specific needs. For example, Hao et al. (2023) reported that LLMs can struggle with problems that are easy for humans, such as generating action plans for executing tasks in a given environment, or in performing complex mathematical, logical, or common-sense reasoning.

In conclusion, the advancements in Large Language Models have had a profound and far-reaching impact on the development of language-related content, facilitating progress in language understanding, translation, creativity, and computational linguistics. Incorporating AI tools like LLMs into language training can create personalized plans for individual trainees, considering their past linguistic experiences. This diverges from the conventional practice of grouping learners based on established language learning levels. However, it is essential to remain vigilant in addressing the challenges relating to bias, ethics, and privacy, as these models continue to evolve.

2.2 Technology & AI Development in Hindi

Several researchers have published work on the syntactic analysis of Hindi, its compositional features, and the grammatical setup of the language. Yet although there has been a focus on the development of parsers, and intensive work to improve their efficiency and develop NLP tools, knowledge representation and machine learning models for developing efficient applications are currently still in an initial stage for the Hindi language. Hindi is, though, one of the Indian languages for which annotated corpora have been prepared, and this should aid in the development of an effective Syntactic Analyzer that can deal with the agglutinative and morphological features of the language.

In recent years, interest in the development of technology and AI for the Hindi language has been growing. The rise of artificial intelligence technology has also attracted the interest of educational technologists, and researchers have experimented with incorporating AI tools such as ChatGPT into domain-specific applications, as in the work reported by Sallam (2023). One area that has gained a lot of interest in academic writing is the development of AI-based tools for Hindi language processing. Research into technology development for Indian languages is on the rise, and there is a great interest in developing tools for computing in the various Indian languages. Academic works and investigations in both syntax and semantics of the Hindi language have also increased exponentially in the last few decades.

A few efforts at cross-language information retrieval (CLIR) have been reported in the literature, particularly for Hindi. These highlight the importance of leveraging technology and artificial intelligence to enhance the usability and accessibility of the Hindi language in different domains. Syntax and semantic analysis are crucial components in the development of Natural Language Processing tools for the Hindi language. While syntax deals with the arrangement of grammatical categories and elements within a language, semantics is concerned with understanding the meaning of words, phrases, and sentences within that arrangement.

In the context of NLP, syntactic analysis involves analysing the structure and order of the words in a sentence so as to determine its grammatical correctness. Semantic analysis, on the other hand, aims to understand the meaning of a sentence by analysing the relationships between the words and their context. Both syntax analysis and semantic analysis have a vital role to place in the development of effective NLP tools for Hindi language processing.

These techniques have enabled the development of tools that can accurately understand and process the Hindi language, leading in turn to a range of applications, such as machine translation, sentiment analysis, text summarization, and information retrieval. Some of the significant works identified with their significant contributions in this field are:

- Parser named as ‘Simple Parser’ for Indian language (Bharati et al. 2009)
- Development of constraint based Hindi dependency parser (Yeleti et al. 2009)
- Study of local morphosyntactic features in Hindi dependency parsing (Ambati et al. 2010)
- Study of Hindi dependency parsing using a combined model of MALT and MST (Kumari et al. 2012)
- Vishit: A visualizer for Hindi Text (Jain et al. 2014)
- Doctoral study of developing linguistic and computational approaches for Hindi complex Predicates (Vaidya 2015)

Researchers have tended to focus on texts in Hindi in relation to aspects of natural language processing, such as word identification, stemming, and summarization (Bafna et al. 2020). Such syntax-based approaches in Hindi NLP research have paved the way for advancements in semantic analysis (Krishnamurthi et al. 2015) and machine learning techniques.

One popular technique employed in NLP in relation to Hindi is the use of decision tree algorithms. A form of machine learning, these algorithms can read and analyse Hindi texts and language to extract meanings and discover interactions. This approach allows for the development of models and tools that can accurately interpret and analyse Hindi language data. By analysing the syntax and structure of sentences, decision tree algorithms can identify patterns and relationships between words, phrases, and clauses in the Hindi language.

3 The Challenges of using AI Instruments in the Hindi Classroom

While AI instruments offer substantial benefits, they also present certain challenges in terms of their integration into the Hindi classroom.

3.1 Colloquial Insensitivity

The source language (English, here) often contains idiomatic expressions and slang that may not have direct equivalents in the target language. Translating idioms is usually tricky because literal translations are unlikely to convey the intended meaning accurately. Colloquialisms are usually culture-specific, and translating them without a deep understanding of the cultural context can lead to misunderstandings, or even offense.

Both English and Hindi have a number of dialects and regional variations. A colloquial expression that is common in one region may not be understood in another. Accurate translation needs to account for these regional differences. Colloquial language often includes wordplay, humour, or puns that might not translate effectively. These linguistic elements rely on specific nuances of language and cultural references, making them difficult to convey accurately. I have experimented here with a number of colloquial sentences. Figure 3a shows the output from Google Translate, while Figure 3b shows the output from ChatGPT (which is based on Large Language Models).

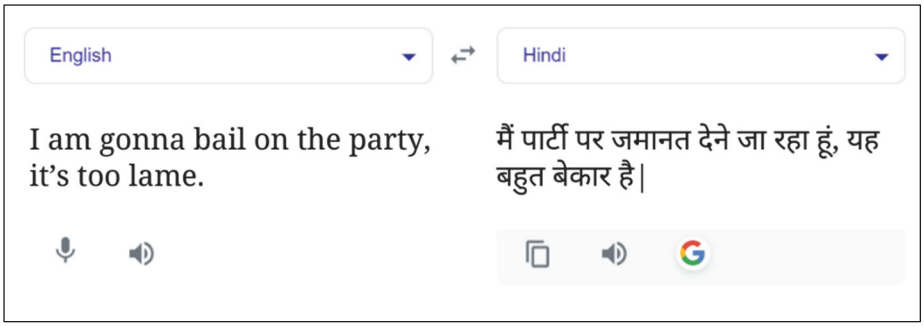

Figure 3a: English Example and its Hindi Equivalent in Google Translate (October 2023)

While the Hindi translation in Figure 3a is syntactically well formed, it lacks semantic sense. The sentence "I'm gonna bail on the party, it's too lame" is an informal and colloquial expression in English, used to express the intention of the speaker to leave the party because they find it uninteresting or not enjoyable. I experimented further with some other English colloquial sentences to understand the behaviour of LLMs (here, ChatGPT) with translated Hindi output.

1. "Wanna grab a bite?" - "कुछ खाना चाहते हो?"
2. "I'm gonna hit the sack." - "मैं सो जाऊंगा।"
3. "I ain't gonna do it." - "मैं यह नहीं करने वाला।"
4. "She's totally freaked out about the test." - "वह परीक्षा के बारे में पूरी तरह से घबराई हुई है।"
5. "He's a cool dude." - "वह एक कूल आदमी है।"
6. "Let's hang out some time, no pressure." - "कहीं बाहर घूमें, कोई दबाव नहीं।"
7. "This movie is a real tearjerker." - "यह फिल्म सच्ची आँसू बहाने वाली है।"
8. "I'm gonna bail on the party, it's too lame." - "मैं पार्टी से बाहर निकल जाऊंगा, यह बहुत ही बेकार है।"
9. "That burger joint is the bomb!" - "वह बर्गर जॉइंट बहुत बढ़िया है!"

Figure 3b: English Examples with their Hindi Translations in ChatGPT

For the experimental sentences, the LLM versions show partial semantic plus native appropriateness in the target language (i.e., Hindi) in sentences 1-7, but sentences 8 and 9 lack commonality. In this experiment, the LLM was not able to use common/standard linguistic terms in Hindi to convey the colloquial expressions of the English. Sentences 4 and 7 are partially correct, but not observationally adequate expressions in Hindi. Google Translate performed proficient native translations for all sentences except the one illustrated in Figure 3a. In this particular test, wherein Google Translate, employing a neural machine translation (NMT) model with human input, generated an ungrammatical output, it is undoubtedly the case that the adaptability of the LLM tool (Figure 3b) was better than that of Google Translate (Figure 3a).

3.2 Regional Variation

Hindi is spoken in many regions of India, each of which has its own regional variations and dialects. AI models may find it difficult to adapt to these regional differences, and could thus potentially cause some confusion among learners. I tested the interpretation of a sentence from three major commonly called dialects of Hindi, as set out in Table 2.

Table 2: The Test Sentence in Three Major Regional Variations of Hindi. The English equivalent of each of the sentences is 'I don't know whose house he came from.'

Language	**Samples**
Khari Boli Hindi	मैं नहीं जानता... वह किसके घर से आया है।
Braj Hindi	हम नहिं जानत... बो कौनौ के घरै से आवौ है।
Awadhi Hindi	मय नाही जानिति.. हई केकरा घर सैने आवा हई।

The performance of all three of the LLMs tested (LLaMA 2, ChatGPT 3.5 and PaLM 2) was adequate in relation to the Khari Boli variant of Hindi, producing a satisfactory interpretation of the original, albeit with certain insignificant variations of aspect (Table 3a). For the other variants, Braj and Awadhi, the outputs are reported in Table 3b and Table 3c, respectively.

Table 3a: Responses generated by LLMs in interpreting the Khari Boli Sentence

Responses	**Samples**
Response from LLaMA 2	I don't know... he came from whose house.
Response from ChatGPT 3.5	I don't know... where he has come from.
Response from PaLM 2	I don't know... from whose home he has come

Despite the Khari Boli sentence being in the past tense and perfect aspect, both ChatGPT 3.5 and PaLM 2 demonstrated proficiency in capturing such linguistic information during English translation. However, LLaMA 2 consistently preferred rendering the output in simple past tense. It is noteworthy that ChatGPT 3.5 initially omitted the object "किसके घर" (i.e., whose house) in its final output. This omission is attributed to a lack of specific information rather than a grammatical error. Subsequently, after additional rounds of validation, ChatGPT 3.5 began incorporating the initially omitted object in its responses. In summary, all three Language Learning Models (LLMs), when evaluated for Khari Boli Hindi, have largely demonstrated the capability to produce outputs that closely resemble native language proficiency.

Table 3b: Responses generated by LLMs in interpreting Braj

Responses	**Samples**
Response from LLaMA 2	We do not know whose house this belongs to. (The phrase "कौनौ के" is a possessive phrase meaning "whose", "घरै" is the word for "house", and "है" is the copula meaning "is". However, the simple verb "आवौ" (āvau) is rendered as "belongs to" and marked with an inappropriate case marker.)
Response from ChatGPT 3.5	We don't know... from whose house they have come. (The interpretation can be considered adequate, regardless of the subjective issue of the choice of pronoun by the model.)
Response from PaLM 2	We do not know... from which house he comes. (This interpretation is the most accurate, and transmits the idea of the source language in English.)

Table 3c: Responses generated by LLMs in interpreting Awadhi

Responses	**Samples**
Response from LLaMA 2	I don't know... He has come from the house of the goddess (Kali). (Here, the LLM interpreted the word "केकरा" as the Goddess Kali; it gave the explanation "केकरा" is an adjective meaning "of the goddess".)
Response from ChatGPT 3.5	I don't know... Maybe the cake is at home. (This LLM interpreted the word "केकरा" as cake; this suggests a possible confusion in this interpretation with the Hindi word "केक".)
Response from PaLM 2	It seems that this language is unsupported. Please see documentation on supported languages. (Error code: 120)

3.3 Language Bias

AI models can inadvertently perpetuate biases present in their training data, and thus potentially reinforce stereotypes or misconceptions about Hindi culture. Educators must be vigilant in ensuring culturally unbiased content. However, any bias here tends to be due to the training data used for the LLMs; the more the machine learns, the more such biases can be improved.

Language bias based on accent or dialect can result in the stigmatization of individuals from specific regions, and have an impact on their self-esteem. For instance, when someone from a Hindi-speaking region with a distinct regional dialect, such as Bagheli or Bhojpuri, speaks in their native dialect, they usually prefer to use the word “Ham” for both genders of the singular and plural first-person pronoun. Since this form of language use is not part of the lingua franca of Hindi, these speakers often meet with an adverse reaction or mockery from individuals who speak the more standardized or urban form of Hindi. This is an example of language bias, where someone can be mistreated or subjected to ridicule based on the way they speak or their dialect, even though they are proficient in Hindi. The behaviour of the LLMs in avoiding language biases is subjective (they may or may not be able to identify bias any single-use case). Overall, though, it is a limitation of the current form of the LLM tools that they are not able to explicitly identify the possible biases surrounding a word like “Ham” in a spoken language scenario.

3.4 Phrasal Understanding

Hindi exhibits three significant complex verbal structures – compound verbs, conjunct verbs, and causal verbs – that are essential components of Hindi grammar. In addition, idioms are frequently employed to form verb phrases that effectively communicate thoughts, feelings, or concepts in a succinct and culturally distinctive manner in spoken language, indicating certain contextual subtleties. LLMs may have limited capacity to comprehend such contextual nuances of a discourse or informal language expressions. This can be a hurdle when teaching cultural references and nuances, which often reply on contextual information. As an example, I employed the LLM model (ChatGPT 3.5) to create a context related to “food desire/ feeling of hunger” with the LLM model (ChatGPT 3.5) in the following conversation, utilizing the Hindi sentence “मैंने कल से खाना नहीं खाया है”, which means that I have not consumed any food since yesterday. Subsequently, I conducted an experiment involving a metaphorical expression in Hindi, “पेट में चूहे कूदना” (with a present continuous structure in terms of tense and aspect) to convey the equivalent of the English expression ‘feeling very hungry’.

Default (GPT-3-5) Translate this sentence into English – मैं भारत में आया हूँ। मैंने कल से खाना नहीं खाया है। मेरे पेट में चूहे कूद रहे हैं। Here is the translation of the sentence into English: "I have come to India. I haven't eaten since yesterday. There are mice jumping in my stomach."	ChatGPT translated the given metaphor as 'There are mice jumping in my stomach', which shows the contextual insensitivity of this LLM at the current moment.
LLAMA - 2 Sure, here's the translation of the sentence मैं भारत में आया हूँ। मैंने कल से खाना नहीं खाया है मेरे पेट में चूहे कूद रहे हैं। into English: "I have come to India. I haven't eaten food since yesterday. Mice are crawling in my stomach." Note: This is a humorous way of saying that the person is feeling very hungry and has not eaten food for a long time. The phrase "मेरे पेट में चूहे कूद रहे हैं" is a metaphorical expression used to describe the person's hunger, where the mice is the stomach are symbolizing the person's growing stomach.	LLaMa translated the sentence incorrectly, but was able to show contextual sensitivity by providing some additional clarification.

Figure 4: Contextual Sensitivity of LLMs

3.5 Complex Grammar

Hindi grammar is intricate, and although AI models are proficient, they may not always handle complex grammatical rules accurately. This can lead to grammatical errors or awkward phrasing in learning materials. Hindi has predefined syntactical and morphological rules, so while the arrangement of objects in a Hindi sentence can vary at the utterance level, the syntactic arrangement is always fixed. I experimented with batches of verbal formations showing increasing complexity at every level, with case marker. For instance, here is a scenario of an inflated object (tested in ChatGPT 3.5) at various stages, with a common structure as the base:

1. to learn = सीखना
2. to learn Hindi = हिंदी सीखना
3. to learn better Hindi = बेहतर हिंदी सीखना
4. to learn better Hindi for speaking = बोलने के लिए बेहतर हिंदी सीखना
5. to learn better Hindi for speaking about India = भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना
6. to learn better Hindi for speaking about India in Taiwan = ताइवान में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना
7. to learn better Hindi for speaking about India in Taiwan's Group = ताइवान के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना

Figure 5: Object Formations in Hindi (Group A)

In the aforementioned test, it's not common to describe 'in the group from Taiwan' as 'Taiwan's group' in English. Despite the peculiarity of latter expression, I opted to retain the latter construction to assess the LLM's ability to comprehend such linguistic formations for Hindi speakers and its inclination toward utilizing such structures. In a formal linguistic framework for any language, when making inferences, the sentence is regarded as a set of functions. I endeavoured to conduct experiments involving clauses containing multiple arguments appended to the same verb function (see Figure 6 and Figure 7), in order to assess the capacity of an LLM to accommodate a varying number of arguments. Any descriptively adequate study of Hindi syntax and semantics would suggest that such object formation is unlikely to occur in a real-life situation. However, I performed and reported the following experiment to help understand the generative capacity of LLMs.

1. to learn better Hindi for speaking about India in Taiwan's Group of Yugandhar = युगांधर के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना
2. to learn better Hindi for speaking about India in Taiwan's Group of Yugandhar with Vivek = विवेक के साथ युगांधर के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना

Figure 6: Object Formations in Hindi (Group B)

1. to learn better Hindi for speaking about India in Taiwan's Group of Yugandhar with Vivek at the weekend = सप्ताहेंड पर विवेक के साथ युगांधर के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना
2. to learn better Hindi for speaking about India in Taiwan's Group of Yugandhar with Vivek at the weekend during Holi festival = होली त्योहार के दौरान सप्ताहेंड पर विवेक के साथ युगांधर के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना
3. to learn better Hindi for speaking about India in Taiwan's Group of Yugandhar with Vivek at the weekend during Holi festival in Hsinchu = ह्सींचु के होली त्योहार के दौरान सप्ताहेंड पर विवेक के साथ युगांधर के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीखना

Figure 7: Object Formations in Hindi (Group C)

Here, when exposed to sentences 1-7 (Group A), the LLM was able to identify the objects correctly, with native-like syntactic arrangements. For sentences 1-2 of group B and 1-3 of group C (added with two persons names viz. Yugandhar and Vivek, Holi is a festival and Hsinchu is a city in Taiwan), however, the information about 'Taiwan' goes completely missing. In a real-life situation, such object formation would unlikely occur in English or Hindi-speaking environments. Nevertheless, in a hypothetical scenario involving a Hindi-speaking context, an adept Hindi speaker possesses the capability to establish

relationships between objects, thereby forming complex objects in adherence to the syntactical rules inherent in Hindi grammar. The presented demonstration employs a complex object as a test sentence to assess the LLM's proficiency in comprehending the grammatical rules of Hindi and its ability to translate a hypothetical case-marked English sentence into its corresponding case-marked Hindi equivalents.

Also, in the Group C sentences, the LLM has produced a spurious word formation for weekend, सप्ताहेंड (saptāhenḍ). It may be an intuitive approach for the LLM to recognise a word and use its existing knowledge of Hindi grammar come up with a translation that fits the morphological rules of the language; unfortunately, any cross-validation with actual Hindi vocabulary seems to be lacking here. The word "सप्ताहेंड" is an ill-formed word from the LLM (ChatGPT in the current case), which has produced a compound word by morphing two separate elements together:

- "सप्ताह" (saptāh): This part of the word means "a week" in Hindi
- "एन्ड" (end): This word is not a word in the Hindi vocabulary. It is a common word in English, referring to "a final part of something".

AI, lacking a Hindi equivalent of the English word "weekend", has intuitively produced a morphed inter-language word. Such behaviour is part of the unique capacity of LLMs. Hindi does accept loan words from other languages into itself; however, it only allows intra-language morphing, and rejects inter-language morphing.

In the provided translations, the LLM is not actually deciding the word order or object arrangement by itself. It is providing translations based on the standard grammatical rules for Hindi, which typically follow a Subject-Object-Verb (SOV) word order. Thus, it is not explicitly rearranging the words in the sentences to arrive at a native-level arrangement. This is why it performed well for the less-inflated objects (the sentences in Group A), but could only provide inauthentic interpretations for the highly inflated objects (the sentences of Groups B and C).

The LLM provided translations that were grammatically correct in Hindi while maintaining the intended meaning of the English phrases. These were based on the general rules of Hindi grammar and sentence structure. Since the LLMs were able to perform well in this scenario, for the less-inflated objects, I undertook some syntactic re-designs to perform further tests on the LLMs, as shown in Figure 8:

1. to learn = सीखना
2. learning Hindi = हिंदी सीख रहा है
3. learning Hindi in a better way = बेहतर तरीके से हिंदी सीख रहा है
4. learning better Hindi for speaking = बोलने के लिए बेहतर हिंदी सीख रहा है
5. to learn Hindi in a better way to speak about India = भारत के बारे में बेहतर तरीके से बोलने के लिए हिंदी सीख रहा है
6. to learn better Hindi in Taiwan for speaking about India = ताइवान में भारत के बारे में बोलने के लिए बेहतर हिंदी सीख रहा है
7. to learn better Hindi in Taiwan's Group for speaking about India = ताइवान के समूह में भारत के बारे में बोलने के लिए बेहतर हिंदी सीख रहा है

Figure 8: Mixed Object Formations in Hindi

When I rearranged the objects and modified the sentence structures in the above examples, the LLM was able to understand the changes and provide accurate translations, because it analysed the context and the linguistic patterns to generate a meaningful response. This ability to adapt to different structures and orders is a fundamental aspect of natural language processing models, and can be used intuitively by language trainers in teaching Hindi.

In conclusion, while AI instruments such as LLMs offer significant advantages for the teaching Hindi, educators must be aware of the challenges they pose. To maximize their benefits and provide a comprehensive Hindi language education, a balanced approach that combines AI tools with traditional teaching methods, and emphasizes cultural sensitivity, context awareness, and interactive learning, is crucial.

4 Aspects of Hindi Language Teaching with AI

4.1 Pronunciation Practice

The conversational practice of any language involves using and practising daily conversational sentences of normal life routines. However, syllable practice is a more formal requirement, involving traditional methods of practicing the articulation and mannerisms of the sound system of a language. Syllable practice helps learners develop phonetic awareness, which is the ability to distinguish and reproduce the distinct sounds of a language. This awareness is crucial for recognizing and pronouncing words correctly. The recursive methodology I have devised for establishing a strong foundation in pronunciation is set out in Figure 9a. By mastering individual syllables, learners gain the ability to correctly articulate consonants, vowels, and combinations of

sounds. This foundation is essential for clear and accurate speech in any language.

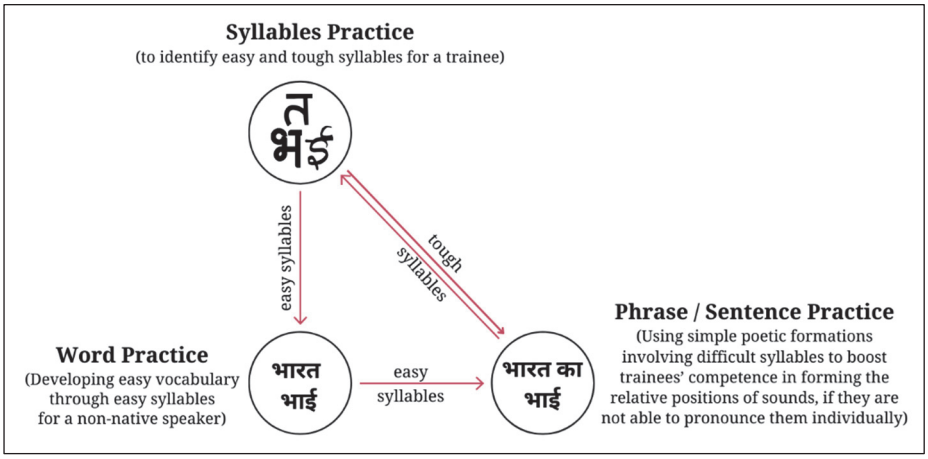

Figure 9a: Recursive Method of Pronunciation Practice

The recursive method of pronunciation practice includes the following steps, as described in sections 4.1.1 through 4.1.3:

4.1.1 Syllable Practice

Syllabic practice allows for the identification of specific phonological patterns (e.g., patterns of aspiration and non-aspiration), and rules governing the arrangement of sounds (e.g., palatals, cerebrals, etc.) in syllables. Learning these patterns through syllable practice can make it easier for learners to apply them in real-life conversations. A trainee learns the exact manner and position for the articulation of the vowels, consonants, etc. of Hindi. Starting out with syllable practice allows learners to gradually build up confidence in their pronunciation skills. As they become more proficient in producing individual syllables accurately, they can proceed on to word practice.

4.1.2 Word Practice

The Word Practice level entails developing easy vocabulary using easy syllables. For instance, the standard Hindi alphabet, as agreed by the Government of India, has 11 vowels and 35 consonants. In this setup, the trainees can

usually give the correct pronunciation of thirty-three of the consonants and ten vowels, owing to what they have learned in the previous step about the process and the positions for articulation.

Consider a scenario within a specific Hindi language class where a trainee, encountering a total of 46 Hindi characters, encounters difficulty in pronouncing or struggles with three characters while demonstrating proficiency with the remaining forty-three. For illustrative purposes, let us designate the challenging-to-pronounce characters (for the given trainee) as our reference syllables: भ (bha), त (ta), and ई (ī). In such instances, it becomes imperative for the instructor to furnish the trainee with a curated list of words incorporating these three specific syllables.

At this juncture, artificial intelligence (AI) can prove instrumental in assisting both the trainer and trainee by generating a compilation of commonplace words featuring the targeted syllables. For instance, ChatGPT 3.5 generates words like भाषा (Language), भविष्य (Future), भूत (Ghost), तारीख (Date), ईमानदारी (Honesty), भगवान (God), among others using our reference syllables. Consistent practice with these words facilitates trainees in acclimating themselves to the pronunciation nuances of challenging syllables, cultivating an intuitive grasp of articulating them within the context of complete words.

4.1.3 Phrase/Sentence Practice

At this level, the trainees come up with poetic sentences formed using the difficult syllables (भ (bha), त (ta) and ई (ī) in the current case). This helps boost their competence in forming the relative positions of the sounds, if they are not able to pronounce these syllables individually. The AI can be asked to provide sentences using these syllables and words. An illustration of this would be the following examples of poetry that were generated by ChatGPT utilizing the target syllables. These poems are presented in English (Figure 9b) and Hindi (Figure 9c).

In the realm of time, where भविष्य lies, A world of mystery, where the soul flies. With भूत and spirits unseen, In the night's shroud they convene.	A tapestry of diverse भाषा we weave, In this world of languages, we believe. Each word, a treasure, a precious gem, Uniting hearts, making us a team.

Figure 9b: Sample caption Poetic rendition in English of target syllables using ChatGPT

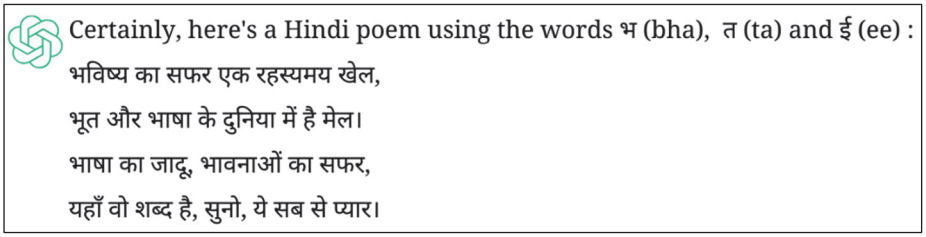

Figure 9c: Poetic rendition in Hindi of target syllables using ChatGPT

Once a trainee achieves native-level fluency with the syllables in the third stage, they may be able to pronounce भ (bha) and ई (ī) adequately, but not त (ta). In such a case, the above recursive loop will be re-iterated to optimise their ability to pronounce त in the next round, which will focus on the त syllable.

At the start of the stage of learning the native script for Hindi, however, I recommend the use of a transliteration schema, that is, using the diacritic marks with Roman characters. This allows for the development of a dyadic understanding of the sound system among non-native trainees, through recognition of the Devanāgrī script alongside the Roman script with the diacritical marks. However, it is essential for a Hindi language trainer to focus on the key components.

My hypothesis is that student learning of pronunciation can be improved more through awareness, and less by imitation. Hindi (Devanāgrī script) has a different set of sounds compared to English. Teaching learners the Hindi alphabet and its corresponding sounds through the specific ideas of manner and the positions for articulation helps them develop a sense of accurate pronunciation from the very beginning.

To reinforce correct pronunciation, a trainee must be taught the distinctions between voiced and unvoiced sounds. Hopefully, AI tools can help by providing samples from internet resources to explain the structure of Hindi syllables, including examples of the standard pronunciation of Hindi consonants and vowels.

Here is a snapshot of AI-generated responses from PaLM 2 hosted over the Vertex AI platform from Google. In its first response, using syllabic pronunciation (see Figure 10), PaLM 2 provided me with a transliteration of each Hindi consonant and vowel; when I did another query using online links to fine-tune my pronunciation of the Hindi alphabet, it provided me with the web-hosted link, regardless of the page's SEO (search engine optimisation) ability. I do not have a quantitative study of the data to support my claims, due to the small student cohort size; but based on my decade of teaching experience from 2013 to 2023, I have identified the retroflex sounds (ट, ठ, ड, ढ, ण) and nasal sounds (ङ, ञ, ण, न) that are difficult for American and European speakers (but not

Asian speakers). Hence, I recommend training should be adapted to the trainee's background and cultural experience. In such cases, a trainer can use and create minimal pairs exercises, where learners can practice distinguishing between similar sounds that might be challenging for them.

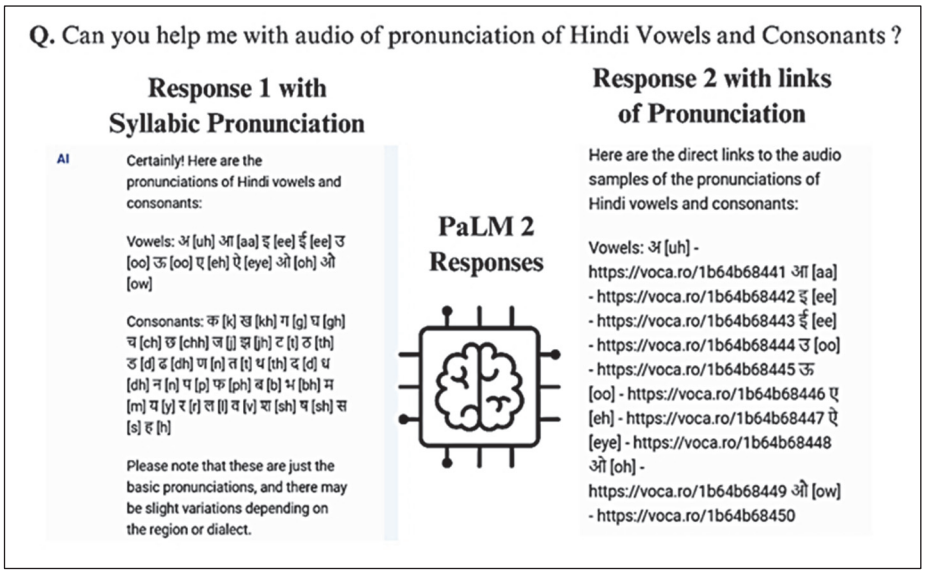

Figure 10: LLM Response over Hindi Syllable Pronunciation (by PaLM 2)

It is a worth mentioning point that, in the above response, PaLM 2 was not able to recognise the transliteration distinction between उ and ऊ, which are distinct sounds and usually transliterated as 'u' and 'ū' respectively. While उ (u) is used in words where the vowel sound is short and centralized, ऊ (ū) is used in words where the vowel sound is long and open-to-mid. Similarly, in transliterating the consonant group, the LLM was not able to distinguish between cerebral and dental sounds. These are some identified limitations of AI usage in syllabic pronunciation practice.

Hindi is a syllable-timed language, which means that every syllable carries equal weight. However, stress can vary depending on context and emphasis. Thus, Hindi has developed rhythm and word stress patterns within itself for correct lexeme identification, and understanding these patterns can improve not only fluency and natural-sounding speech but also the vocabulary ability of trainees. I have developed a variety of practice materials, including audio recordings, tongue twisters, and exercises, that target specific pronunciation challenges. I use multimedia resources and online links provided by AI tools here to enhance the learning process.

As a language trainer, I ensure that I highlight the cultural aspects of pronunciation, such as politeness levels, and words where the correct pronunciation is a must, or they should be totally avoided. This can enhance learners' understanding of the language and its social nuances. For example, as shown in Figure 11, one can identify the difference in first and second-word intonations and the social nuance this can create in usage. So here, the first word means devotion and the second word refers to a type of funeral activity. This means that the pronunciation must not be incorrect in either case, without fail. In such situations, understanding the Devanāgrī script and the alternative script of 'Roman with diacritic marks' helps to boost the trainee's confidence in correct word pronunciation.

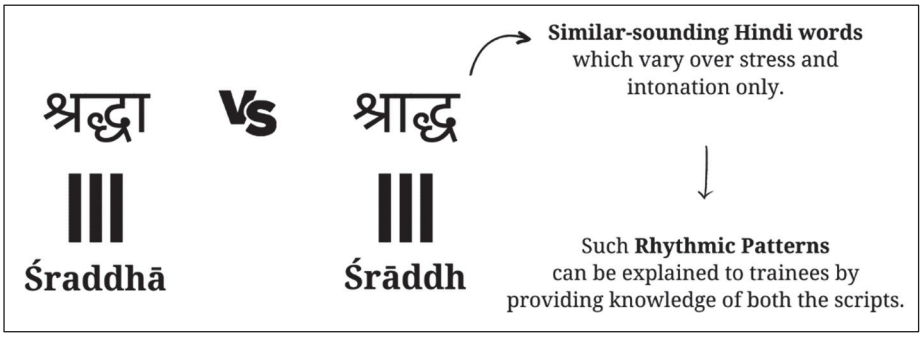

Figure 11: Example of a Hindi word and its socio-cultural nuances

Hindi, like many languages, has a variety of words that may sound similar but have different meanings. These similarities can sometimes lead to confusion, so it is important for learners to understand the context in which these words are used. Furthermore, there are generally no silent letters, unlike in English. Typically, each letter in Hindi has a direct impact on the sound of the word. A common technique employed by native Hindi speakers is to place the greatest emphasis on the initial syllable of a word, with the pitch progressively decreasing towards the end of the word. In Hindi, tonalities are applied to consonants based on the vowel applied. Nevertheless, there are specific instances in which a written vowel may not be spoken in some spoken varieties of Hindi.

The provided Table 4 displays an AI-generated compilation of Hindi word pairs with similar pronunciations. This resource is intended for synchronous study and can be utilized for revising Hindi vocabulary. During conversation, mispronunciation can lead to two complications: unidentified semantics and cultural subtle-ties related to placement.

Table. 4: Contextual Placement for similar-sounding pairs, as explained by ChatGPT

Word 1	**Word 2**	**Context of Words (as explained by ChatGPT)**
कल (kala)	**काल** (kāla)	**Meaning:** "कल" means "tomorrow" in Hindi. **Context:** This word is used when referring to the day that follows the current day. **Meaning:** "काल" generally means "time" or "era" in Hindi. It can also be used to describe "black" colour. **Context:** This word is used in broader contexts and can refer to time in a more general sense or even to the concept of "blackness" when describing colour.
माँ (mā̃)	**मान** (māna)	**Meaning:** "माँ" is a term of endearment and respect used to refer to one's mother. It is a common word used to address or talk about one's own mother or mothers in general. **Context:** This word is used when discussing or addressing one's mother or referring to motherhood in general. **Meaning:** "मान" generally means "respect" or "honour" in Hindi. It refers to the esteem or regard given to someone or something. **Context:** This word is used when discussing respect, honour, or the value attributed to a person, idea, or concept.
चिंता (cintā)	**चिता** (citā)	**Meaning:** "चिंता" translates to "worry" or "anxiety" in Hindi. It refers to a state of mental distress or concern about a problem or an uncertain future event. **Context:** This word is used when discussing concerns, fears, or anxieties about a situation or an issue. **Meaning:** "चिता" refers to a "funeral pyre" or the place where a deceased person's body is cremated as per Hindu funeral customs. **Context:** This word is used when discussing funeral rituals, cremation, or related matters.
छूट (chūṭa)	**झूठ** (jhūṭha)	**Meaning:** "छूट" generally means "discount" or "concession" in Hindi. It refers to a reduction in the price or value of something, often in the context of a sale or an offer. **Context:** This word is used when discussing discounts, price reductions, or special offers. **Meaning:** "झूठ" means "lie" or "falsehood." It refers to a statement or information that is intentionally untrue or deceptive. **Context:** This word is used when discussing lies, dishonesty, or false statements.

4.2 Foundational Grammar

4.2.1 Understanding Compositionality

LLMs can understand the compositionality of Hindi sentences by leveraging their knowledge of word meanings, syntactic rules, and semantic relationships. They excel at contextual understanding, enabling them to interpret the complex meanings that arise from the combination of words and phrases in Hindi sentences.

With regard to syntactic compositionality, LLMs make use of word embeddings, which are numerical representations of words. These embeddings capture the semantic relationships between words. For example, the LLMs learn that "रंग" (colour) and "दिन" (day) are different concepts, but can be combined to mean "रंगीन दिन" (colourful day).

LLMs have been trained using a vast corpus of Hindi texts, which has exposed them to a wide range of idiomatic expressions and linguistic structures, including grammatically correct and incorrect sentences. This has helped them to learn the rules of Hindi grammar, and to understand the composition of sentences, and whether or not a sentence is well-formed. LLMs are also proving their ability in semantic compositionality, and can put together words and phrases in such a way as to fit in with the overall meaning of a sentence. For example, they can understand that "मेरी प्यारी गाड़ी" (my beloved car) refers to the speaker's affection for their car.

Recently, I have argued that there are two types of syntactic compositionality in Hindi, linear and non-linear (Tripathi 2024). In this connection, I tested an AI tool (ChatGPT 3.5) using a range of examples of linear compositionality, to see how it performed. The idea of compositionality in objects can be represented as a hierarchical structure in which parts are combined to form larger parts, with the process continuing until the entire object is constructed. This hierarchy allows for a more flexible and scalable representation. For instance, in the linear composition illustrated below (see Figure 12), we see a sequential linear pattern where the X object is modified by the Y object, and then the (X + Y) object is modified with Z, resulting in a complete object construction.

Linear composition involves an organization or arrangement that follows a linear or sequential pattern. In this kind of object formation, a native speaker usually prefers an economic formation in which their innate knowledge does not allow them to repeat the same case marker, so as to avoid word repetition. Hence, they modify the object with a different case marker during the composition, e.g., the use of के लिए (ke liye) and के बारे में (ke bāre mẽ) helps a native speaker to avoid repetition and simultaneously come up with a creative object

formation. Figure 12 shows one example of linear composition in which an AI tool can understand syntactic and semantic compositionality. The bracketing system employed in the first column is intended to aid identification of the distinct lexical categories (which are put together in linear fashion), and should not be mistaken for the conventional bracketing system utilized in generative grammar.

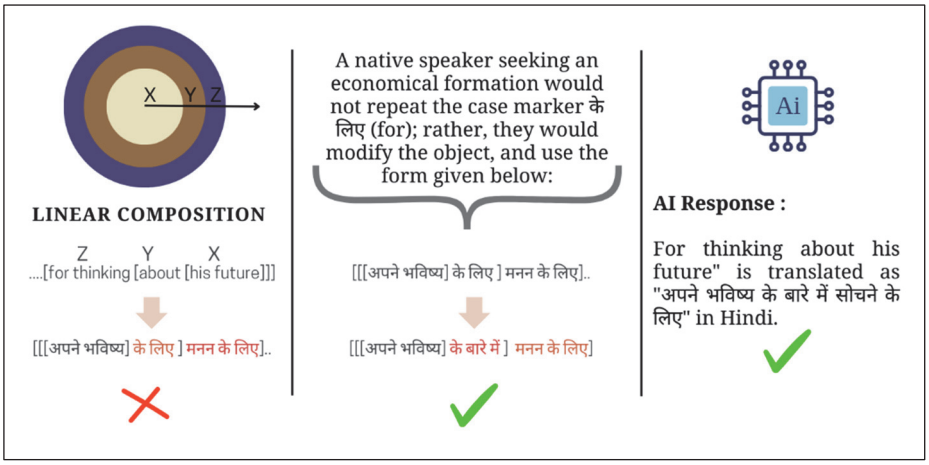

Figure 12: Syntactic and Semantic Compositionality of the ChatGPT LLM

The AI further explained the breakdown of the sentence, as follows:

- "अपने" means "his" or "one's own".
- "भविष्य" means "future".
- "के" is a possessive marker that connects "भविष्य" with "बारे में".
- "बारे में" means "about".
- "सोचने" is the gerundive form of "सोचना", which means "thinking".
- "के लिए" means "for".

LLMs implicitly learn to recognise the hierarchical structure of sentences. They understand how words combine to form phrases, clauses, and sentences, following the grammatical rules of Hindi. LLMs can deal with sentence ambiguity by considering multiple possible interpretations, and they often generate contextually appropriate responses. In addition, LLMs excel at contextual understanding. They consider all the surrounding words and phrases when interpreting the meaning of a word or phrase within a sentence, and this allows them to disambiguate homonyms and understand idiomatic expressions.

4.2.2 Understanding Direct and Oblique Forms

LLMs can understand both direct and oblique forms of Hindi sentences by leveraging their extensive training data and contextual understanding. To analyse the response patterns of LLMs with respect to these linguistic constructs, I employed ChatGPT to generate English translations of some sample Hindi sentences (in both the direct and the oblique case). The selection of LLM as ChatGPT 3.5 was based on its superior performance in the aforementioned test when compared to other LLMs. The translations were produced in both the direct and oblique case structures for comprehensive evaluation, which are discussed ahead. Below is an illustration of how the LLMs handle these forms.

4.2.2.1 Direct case structure

In the direct form of a Hindi sentence, the subject (कर्ता – kartā) performs the action on the object (कर्म – karma). In direct form, the gender of the subject modifies the inflection of the verb. If the subject is masculine, then the verbal inflection will be masculine, whereas for feminine subjects, the verbal inflection will become feminine. LLMs can recognize the subject, verb, and object in a sentence, and understand the action being performed.

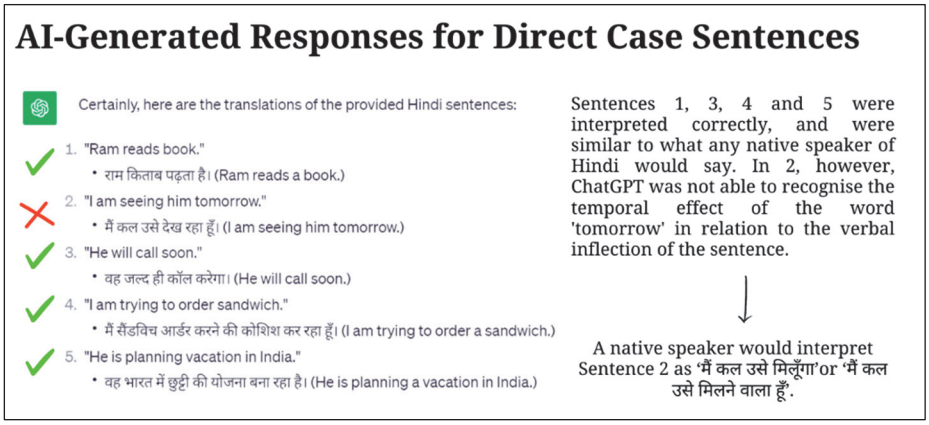

Figure 13: AI-generated responses for Direct Cases in Hindi (ChatGPT)

For instance, in sentence 2 in Figure 13, "मैं" (I) is the subject, "कल" (tomorrow) indicates the time, "उसे" (him) is the object, and "मिल रहा हूँ" (am seeing) conveys the action of seeing or meeting. Using the direct translation approach, ChatGPT has correctly translated the second sentence by interpreting the verb as देखना (seeing). However, the use of 'seeing' in this context does not constitute a phrasal structure; rather, it involves the addition of a temporal aspect to the

English verb, resulting in a modification of the verb's meaning. The temporal aspect represents a modification of the original verb dynamics, because it conveys a temporal dimension, such as duration, frequency, regularity, or continuity. Based on this, I wish to emphasize that a more correct interpretation in Hindi would be "मिलना" for "seeing" here.

4.2.2.2 Indirect case structure

In the oblique form of a Hindi sentence, the subject is usually modified by case markers. In oblique form, the gender of the subject modifies the inflection of the verb. When a subject is modified by a case marker, it is referred to as an oblique subject. Similarly, adjectives, nouns, and possessives can also be modified by case markers, to form their oblique case. I tested the LLMs against these parameters, to identify the adaptability of the AI tools to the oblique form of sentences.

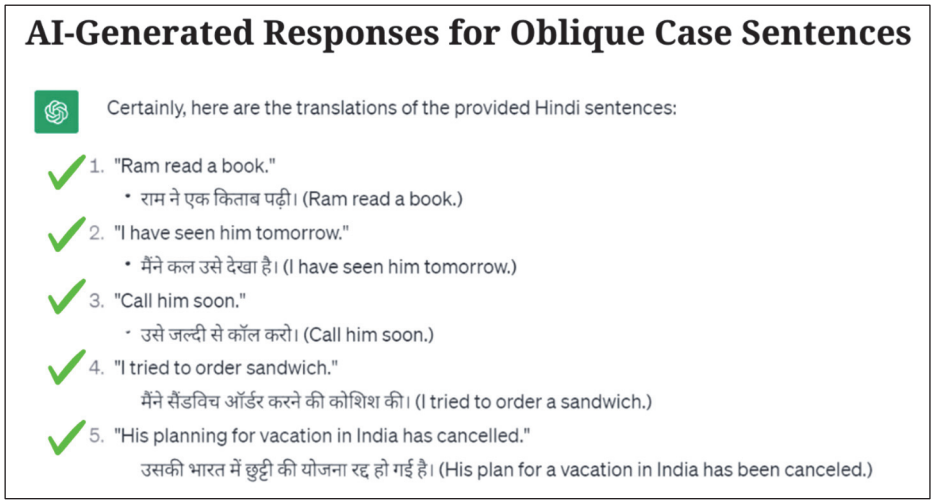

Figure 14: AI-generated responses for Oblique Cases in Hindi (ChatGPT)

On a minor note, it is noteworthy that the English sentences generated by ChatGPT exhibit certain grammatical shortcomings. For instance, sentence two presents a grammatical inconsistency, featuring a past tense coupled with a future action – a construction divergent from the conventions of English native-speaking contexts. Additionally, in the final sentence, an identification was made wherein ChatGPT 3.5 outputs the UK spelling "cancelled" while concurrently referencing the US spelling "canceled" alongside the corresponding Hindi sentence.

The Hindi language is nuanced, and context-specific interpretations can vary in the case of oblique formations. But the performance of ChatGPT in oblique sentences was equivalent to native expression. For translating oblique case sentences, LLMs rely on an understanding of the context, word relationships, and sentence structure. They analyse the provided sentences, break them down into their constituent parts, and apply the appropriate grammatical rules to produce an accurate translation. This ability to handle different sentence structures and grammatical cases is a result of their training process, and the extensive linguistic knowledge embedded in the model.

4.2.3 Understanding Gender Agreement

Hindi, like many Indo-Aryan languages, features grammatical gender, where the nouns have their pre-defined gender, and associated adjectives, verbs, and pronouns are modified to agree with the gender of the noun. In Hindi, there are two primary genders: masculine and feminine. Gender agreement is a fundamental aspect of Hindi grammar, and understanding it is crucial for constructing grammatically correct sentences in the language. While there are certain general rules for gender agreement, there can also be exceptions and irregularities to be aware of. In the following investigation, I tested the LLMs on gender agreement in relation to different syntactic categories.

- **Agreement with Adjectives:** For masculine singular nouns, adjectives typically end in "◌ा" (ā), while for feminine singular nouns, adjectives often end in "◌ी" (ī).
- **Agreement with Verbs:** Verbs change their form based on the gender and number of the subject, as per the different tense conditions. The tense-representing lexemes end in "◌ी" (ī) for feminine nouns, and t◌ा" (ā) for masculine nouns.
- **Agreement with Possessives:** Possessive adjectives in Hindi agree in gender with the noun that is being possessed. Possessive adjectives are modified using "◌ा" (ā) or "◌ी" (ī), depending, respectively, on whether the noun being possessed is feminine or masculine.

The evaluation of ChatGPT's proficiency in comprehending the nuances of gender within the Hindi language has been conducted accurately. While a limited subset of sentences is showcased in this research, it is contended that the Language Learning Models (LLMs), including other AI tools, have demonstrated commendable proficiency in identifying gender across diverse sentential structures. This proficiency is particularly evident in scenarios encompassing varying predicate lengths and linguistic structures. Consequently, using LLMs to

elucidate syntactical understanding of gender operations is advocated for effectively learning Hindi as a gendered language.

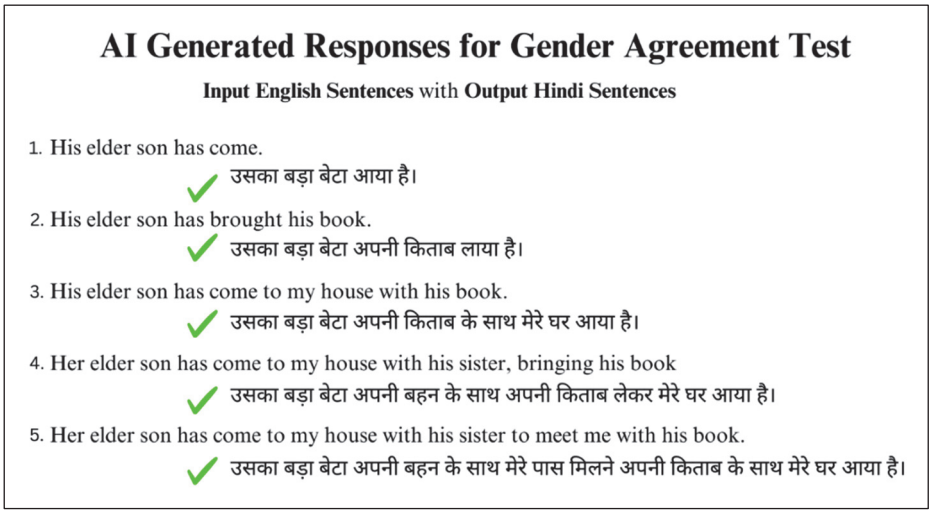

Figure 15: AI-generated responses for Gender Agreement (ChatGPT)

4.2.4 Understanding Aspect and Tense Conjugations

Aspect and tense are two distinct but related grammatical features in Hindi, and understanding their use is essential for grasping the temporal and situational characteristics of the verbs in Hindi sentences. Native speakers of the language make use of the lexemes tā/tī/te for the present tense, yā/yī/ye for the past tense, and ũgā/ũgī/egā/egī/ẽge/oge for the future tense. These lexemes are added to the primary verb to portray the time at which an action or state takes place. However, the secondary verbs hũ/hai/haĩ and thā/thī/the are also added in the present and past tense, respectively. For aspects, which deal with the way an action is viewed or the nature of its completion, Hindi native speakers use rahā/rahī/rahe to denote the progressive aspect, and cukā/cukī/cuke to denote the perfective aspect. Moreover, native speakers can also creatively mix lexemes to generate other ideas relating to aspect.

Both tense and aspect play a crucial role in constructing sentences with accurate temporal and situational meanings in Hindi. In Hindi, aspect and tense can be combined to create various nuanced expressions which do not allow symmetric mapping to an equivalent English expression. I argue that the interpretation of Hindi's aspect- and tense-based sentences does not always

lead to an exact equivalent in the English language, and thus, that there exists an information gap between the cross-cultural languages in terms of aspect- and tense-based phenomena.

To reflect this, I have experimented with these combinations, and performed both 'English to Hindi' interpretations and 'Hindi to English' interpretations of selected sentences, using all possible combinations of tense and aspect. These interpretations demonstrate how verbs are conjugated in the different tenses in Hindi to indicate various the temporal aspects of an action or event.

4.2.4.1 English to Hindi Interpretation using AI

For requests regarding the aspect and tense combinations in the first group of sentences below (Group A), the LLM (in this case, ChatGPT) used its knowledge of Hindi grammar and verb conjugation rules to accurately translate the sentences into the appropriate tenses. With access to a wide range of linguistic patterns and examples from training data, the LLM was able to generate contextually appropriate translations.

Present Simple	The monkey eats peanuts. - बंदर मूंगफली खाता है.	✓
Present Progressive	The monkey is eating peanuts. - बंदर मूंगफली खा रहा है.	
Present Perfect	The monkey has eaten peanuts. - बंदर मूंगफली खा चुका है.	
Past Simple	The monkey ate peanuts. - बंदर ने मूंगफली खा ली.	✓
Past Progressive	The monkey was eating peanuts. - बंदर मूंगफली खा रहा था.	
Past Perfect	The monkey had eaten peanuts. - बंदर मूंगफली खा चुका था.	
Future Simple	The monkey will eat peanuts. - बंदर मूँगफली खाएगा।	✓
Future Progressive	The monkey will be eating peanuts. - बंदर मूंगफली खा रहा होगा.	
Future Perfect	The monkey will have eaten peanuts. - बंदर मूंगफली खा चुका होगा.	

Figure 16: Group A Sentences of English to Hindi Translations (ChatGPT)

It is evident that the AI-generated present, past, and future perfect forms are semantically accurate. However, the AI has introduced an extra nuance of "already" in these translations, as can be seen in Figure 16. Such an attempt by the AI can be its intuitive capacity to ensure that the overall composition reflects the intended meaning of the Hindi sentence. It also entails that AI can add linguistic items to avoid ambiguity, vagueness, or misinterpretation in communication.

As for the requests regarding the next group of sentences below (Group B), the LLM was not able, at the current time, to deliver contextually appropriate native readings for these expressions.

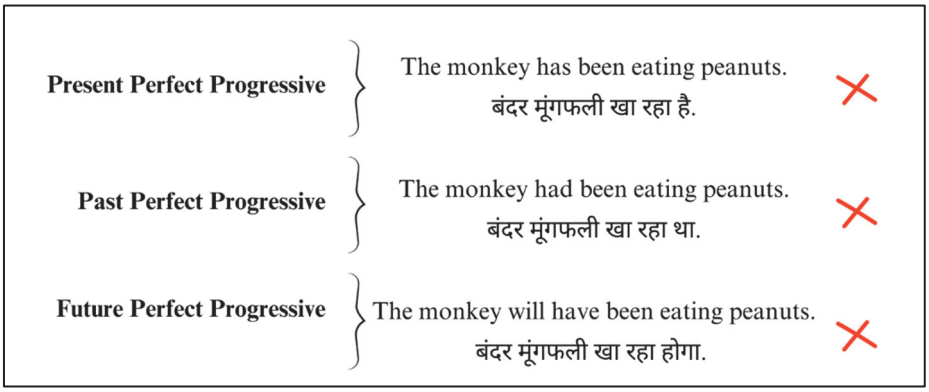

Figure 17: Group B Sentences of English to Hindi Translations (ChatGPT)

Looking at the Group B sentences from the perspective of a combining semantic logic of tense and aspect of Hindi suggests that the translations for these sentences should have been: बंदर मूंगफली खा रहा चुका है, बंदर मूंगफली खा रहा चुका था and बंदर मूंगफली खा रहा चुका होगा. All the Hindi sentences in Figure 17 are grammatically ill-formed, owing to the limitations in the lexemes चुका and रहा. While Hindi natives use चुका strictly to denote the completion of an action (i.e. the perfect aspect) and रहा to denote ongoing action (i.e. the continuous aspect), the perfect progressive aspects are verb tenses that combine elements of both the perfect aspect and the progressive aspect. Each of these tenses emphasizes the duration and continuity of an action, but they are used in different temporal contexts. Here, a native Hindi speaker will usually divide up the semanticity of the sentence, conveying the perfect progressive aspect by rendering the progressive aspect using the रहा lexeme (as adopted by the LLM here), and the idea of completion at a specific point in time using temporal keywords. For instance:

- Present Perfect Progressive (ongoing actions that started in the past and are continuing into the present) – a more valid interpretation of 'The monkey has been eating peanuts' would be बंदर अभी तक मूंगफली खा रहा है.
- Past Perfect Progressive (ongoing actions that were happening before a specific point in the past) – a more valid interpretation of 'The monkey had been eating peanuts' would be बंदर तब तक मूंगफली खा रहा था.

– Future Perfect Progressive (ongoing actions that will be happening up to a specific point in the future) - a more valid interpretation of 'The monkey will have been eating peanuts' would be बंदर तब तक मूंगफली खा रहा होगा.

Thus, we can say, that Hindi verb tenses and aspects do not always have a direct one-to-one correspondence with English sentences. However, a detailed study of Hindi aspects reveals that the intended meanings are generated by the Hindi speaker by identifying the semantic senses of the lexemes and carefully crafting the verb-final element of the Hindi sentence.

4.2.4.2 Hindi to English Interpretation using AI

Since I have been striving for accuracy in all my experiments with tenses and aspects, it is important to observe that the sentence examples I used for my 'Hindi to English' translations are expressions commonly encountered from native speakers of Hindi. I tried to do interpretations of such sentences using LLMs knowledge about aspects.

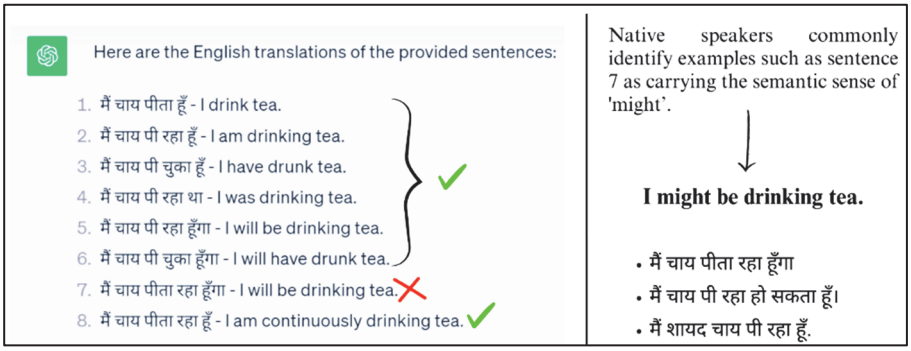

Figure 18: Group C Sentences of Hindi to English Translations (ChatGPT)

In sentences 5 and 6, the verb पी with the added aspect lexemes रहा or चुका denotes continuity or completion of the verb action, respectively. However, with the future tense-based verbal inflection of हूँगा, the potentiality of the verb पी to perform its action is reduced, and becomes uncertain. Because such combinations suggest a lower level of certainty, a sense of possibility but with no guarantee, they can be treated as equivalent to the presumptive mood of the English language (i.e. "might be"). The same can be said for Sentence 7, where the addition of the inflection ता to the verb पी, indicating that the action is habitual for the subject, also reflects the idea of "might be". Although formations such as 5, 6 and 7 suggest that the event has a lower degree of likelihood, so that it possible but not guaranteed, native speakers prefer to use

keywords such as the lexeme शायद or the auxiliary हो सकता है to convey the sense of 'might be' in Hindi.

It is important to note, however, that LLMs are capable of learning extensively from their training data. Hence, it is absolutely vital that the training data is correct, because if errors exist in the training data or if the model is fine-tuned using incorrect examples, those errors are likely to be propagated.

Thus, the errors seen above could be due to issues with the training data or to the lack of contextual information. LLMs process text in chunks, and may not always consider the broader context, especially when translating isolated sentences. A more extensive context can sometimes clarify the intended meaning. So here, the LLMs have given me some examples of correct interpretations, but also a few instances of poor interpretations.

4.3 Vocabulary Development

LLMs can significantly contribute to vocabulary development among language learners, as they are trained on a vast amount of text data. I have used AI extensively in developing narratives around a particular word, usually termed a 'Communication Chain'. Figure 19 demonstrates a variety of use-cases of a given target word.

Communication chains are a great way to learn new words. They refer to the chain of common dialogue placed around the target word, and show how a word is used in real-life situations. Another highly important method of vocabulary development is 'Word Use Cases'. Word use cases refer to the various ways in which the target word is applied in different linguistic contexts and real-time situations.

For example, for the target word 'सेब' (apple), a learner can ask any LLM to produce a variety of sentences using this word. On finding these sentence examples, the trainer and their student can work in unison to develop a communication chain and word use cases. Such an activity will boost the confidence of the Hindi trainees and further develop their visualisation and cognitive capacity to help them use the target word in different actual situations.

Vocabulary is a cornerstone of language learning because it enables effective communication, enhances comprehension, and provides a deeper understanding of both culture and context. It plays a vital role in all aspects of language acquisition, from listening and speaking through to reading and writing, and it is essential for personal, academic, and professional growth. Particularly, in the case of the Hindi language, I am inclined to develop vocabulary among non-native speakers by applying a cognitive process of morphology recognition method.

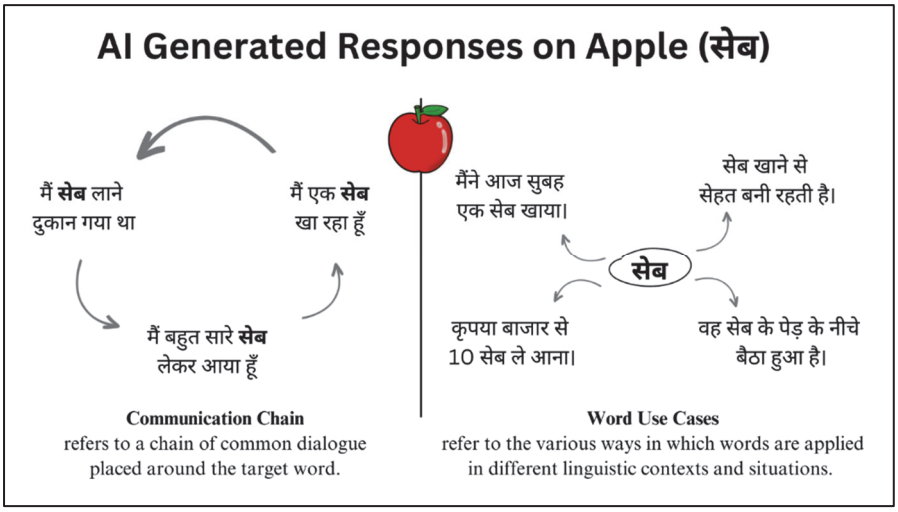

Figure 19: Demonstration of Communication Chain and Word Use case Methods (ChatGPT)

One of the best ways to learn a new word is to see it used in context. LLMs can help provide us with use cases, that is, example sentences that can help learners to understand the meaning of a word, and how it is used in different situations. For example, if one wants to learn the Hindi word for "apple", a trainee can discover the lexical meaning through a dictionary (or an LLM) and find example sentences from online resources, including online dictionaries, textbooks, and news articles.

The importance of vocabulary to language learning cannot be overstated. Here are several focus points for learning vocabulary through AI, that apply to any language:

4.3.1 Communication keywords using AI

Vocabulary is the building block of effective communication. Without a sufficient vocabulary, it is difficult to express ideas, thoughts, and emotions in a coherent and meaningful way. A rich vocabulary enables a person to convey their message accurately and comprehensively. AI provides models that can suggest synonyms for Hindi words, enabling learners to diversify their vocabulary. However, a problem with AI-based synonym recommendation is the ability to identify commonality among the people. To overcome this issue, I developed a beta version of an android app, called Hindi TED (see Figure 20), for learning Hindi through an AI-based popularity algorithm. This app has a primary goal of using an "algorithm which decides the popularity level of Hindi

words" using social media; in other words, it finds the most popular, day-to-day spoken word in Hindi through sites such as Facebook, X (formerly Twitter) and Wikipedia. When the user searches for a word (English or Hindi), the app shows the synonyms labelled according to popularity. The innovative features of the app are set out below:

- It shows the Hierarchy of each and every word (A1–A2; B1–B2; C1–C2).
- It enables Hindi/English Language Learning based on the international CEF (Common European Framework for Languages) Levels.
- It helps in Dictionary Usage by creating a Word Family (consisting of meaning, idioms, proverbs and contextual meaning).
- It also provides Translation Support through Sentence examples, with Hindi and English Word Search Functionality.

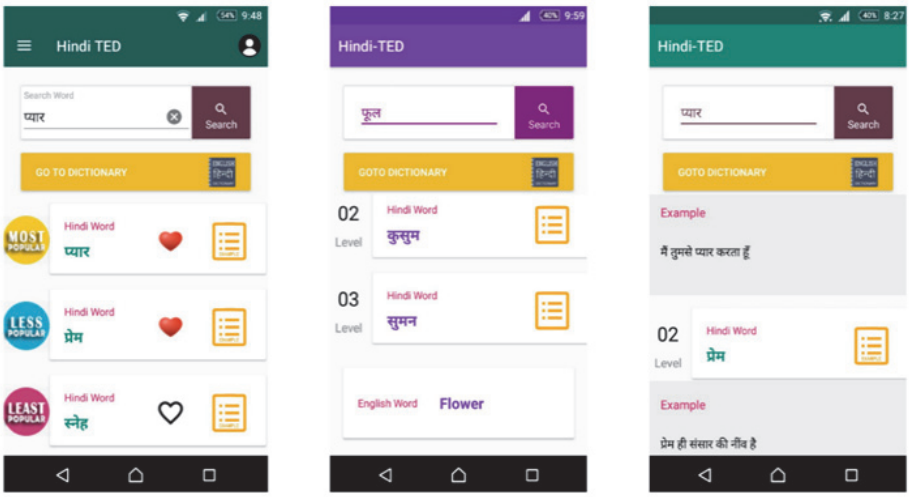

Figure 20: UI of Hindi-TED app (Beta Testing) feeding data through word popularity

In this app, the most popular words as words among the Hindi community are recommended to students at levels A1–A2; less-popular words are recommended to students at levels B1–B2 level; and students at levels C1–C2 are shown the least common synonyms for the target word. Vocabulary is an essential component of language fluency. The more words a student knows, the more fluent they become in understanding, speaking, and writing in the language. Here, we observed a positive improvement among Hindi trainees while using this app.

4.3.2 Comprehension through AI

To understand spoken or written language in any context, a trainee must have the capacity to recognize and understand the words being used. I use a method of 'fill in the blanks' in multiple situations to help Hindi learners develop robust vocabulary, understand a situation, and determine the applicability of words within the grammatical setup of the Hindi language. In this process, learners are required to apply their creativity and fill in words to substitute for some of the existing words in a sentence. A robust vocabulary helps them comprehend texts, conversations, and instructions more easily. An advanced learner is not one who knows all the complicated words of a language, but one who can understand a situation well enough to choose an easy word, and use it according to the requirements of the grammatical setup of the language.

AI can help with such word finding; however, AI is limited when it comes to suggesting alternative formations of sentences over common semantics. When learners can perform their own word substitutions (and thus sentence substitutions), they develop an innate capacity for situation observation and native-level confidence in explanations. This substitution is generally a many-to-one substitution (one-to-one substitution is not recommended). Here is a suggestive idea of alternate semantic formations which can be used in substitution (Figure 21).

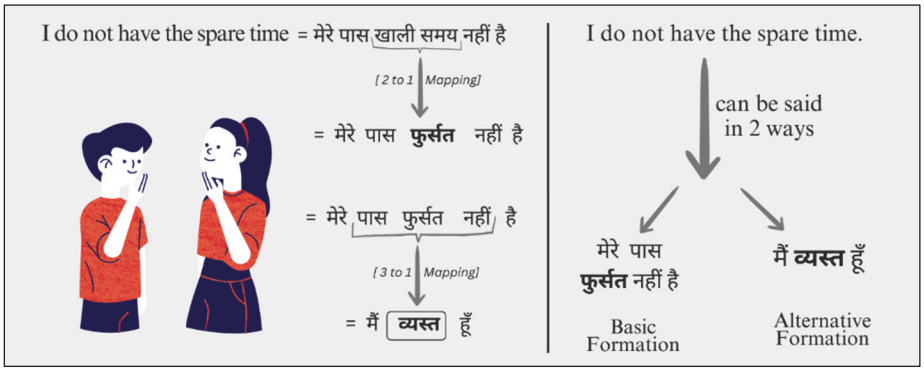

Figure 21: Idea of alternative semantic formation in a Language

4.3.3 AI for Cultural Understanding

Learning the vocabulary of a language often involves gaining insights into the culture and values of its speakers. Understanding cultural nuances through

vocabulary helps students to navigate social situations and avoid misunderstandings.

AI-driven translation tools can help to translate phrases or sentences from Hindi into the trainees' native language, or vice versa. Some advanced LLMs (such as LLaMA) also provide contextual translations, helping students understand the cultural implications of specific phrases. This AI system can integrate language and culture seamlessly. For example, when learning a new word or phrase in Hindi, LLaMA can supply cultural context, usage scenarios, and even related cultural notes (see Figure 22).

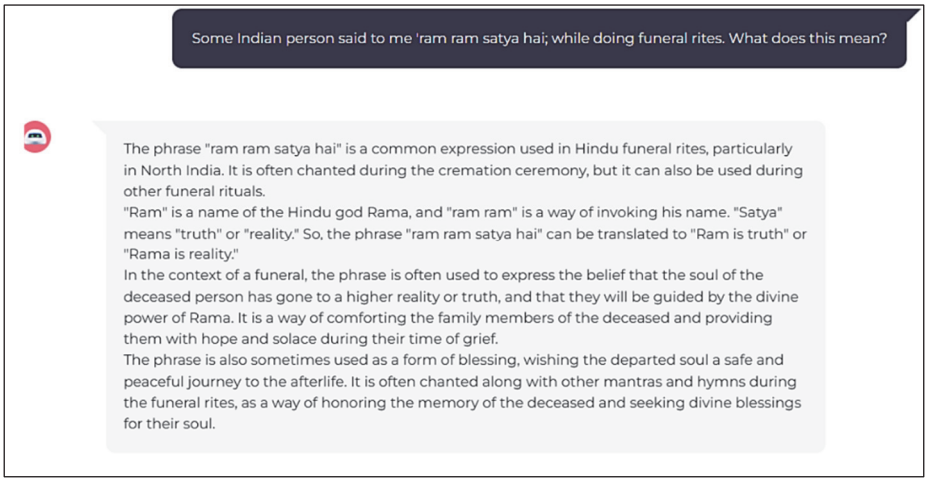

Figure 22: Snapshot of response given by LLaMA 2 when asked about a cultural expression

4.3.4 AI used for Cognitive Benefit in Hindi

Learning new words and their meanings stimulates cognitive development. It develops memory, analytical thinking, and problem-solving skills, leading to overall mental growth. As a person acquires more vocabulary, they become more adaptable in various linguistic situations. They can switch between formal and informal language, understand different dialects, and adapt their language use to fit the moment. I used AI to develop comical stories for different situations. Friedlander (2018) studied the use of comics and advocated using comic narratives, as these allow learners to understand the relationship between speakers, speech forms and context in a way that is more accessible than dialogues thar are only in text or audio format.

A Query made to ChatGPT: Can you create a basic comic of dialogue for having a shopping conversation with a friend in Hindi? Figure 23 displays the output produced by ChatGPT:

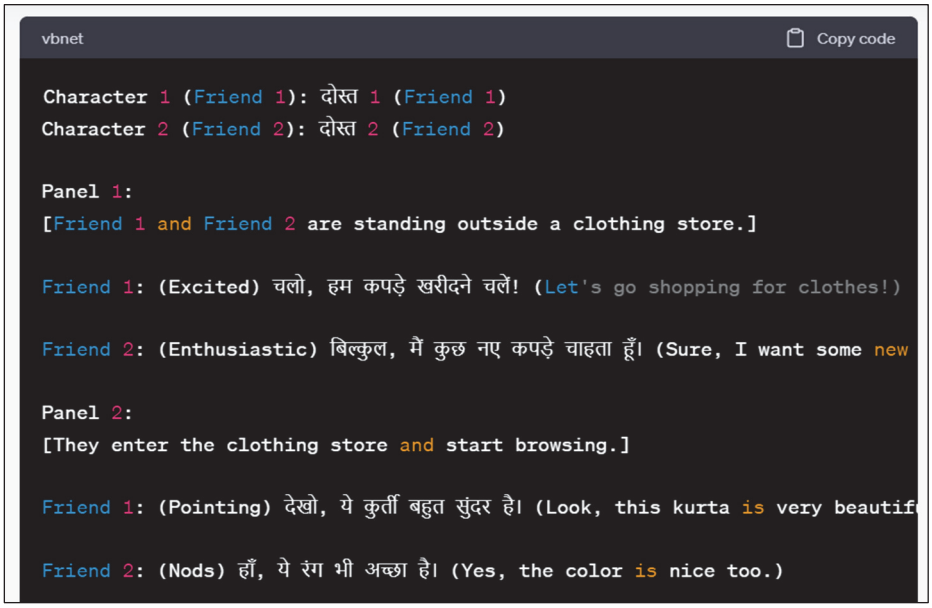

Figure 23: ChatGPT generated comic panel for 2 friends doing shopping in Hindi

I further experimented with this AI-generated content, and developed a series of panels using an image-generating platform (https://www.comicsmaker.ai/) relating to the idea of shopping in an Indian market. The characters I chose were Lionardo De Caprio and Tom Cruise (famous Hollywood actors).

The first prompt I gave to the AI platform was: 'male leonardo de caprio, in a shopping market, wearing an Indian dress, full shot, comic book illustration by jack kirby'; and the second prompt given was: 'male tom cruise, in a market, wearing an Indian dress, portrait, comic book illustration by Gustave Doré, doing shopping'. As a result, the following comic scenes were generated (see Figure 24). It is fascinating to see illustration that was developed, and I would argue that comic generation through AI for language learning has the merits of creativity of situation, viability of context, and understanding of the language. I would argue for using AI-generated comics as part of a repertoire of resources in Hindi language teaching.

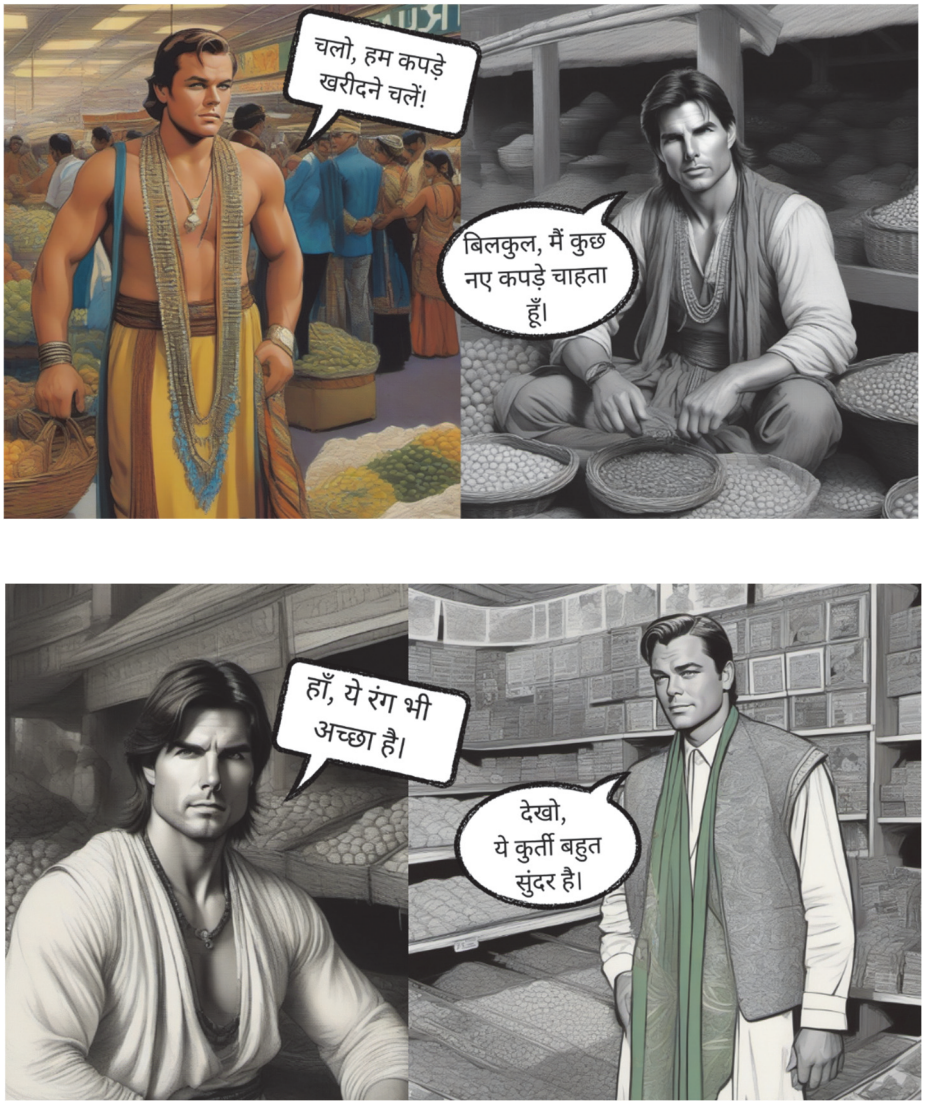

Figure 24: AI generated comic characters (ChatGPT & Comicsmaker)

5 User Experience from the Hindi Classroom

Many students from my classroom who have engaged with Large Language Models (LLMs) for language learning have reported numerous benefits from

using AI tools. These students often highlight the LLMs' versatility in providing instant access to a vast array of language resources, including vocabulary, grammar explanations, and contextual language use. They appreciate the personalized learning experience, the way in which the LLMs adapt to their specific needs by offering them tailored language lessons and feedback.

Moreover, LLMs enable immersive language practice by providing conversation simulations, which boost speaking and comprehension skills. Students value the convenience of learning at their own pace and the 24/7 availability of AI-driven assistance. Ultimately, these positive feedback responses underscore the valuable role that LLMs play in making language learning more accessible, more engaging, and more effective for students around the world.

The Hindi language proficiency of my student cohort (43 students) ranged from beginner to intermediate level, and none of the students were from an Indian background or had advanced knowledge of Hindi language and literature. I, along with my team, performed a survey of these non-native students on our college campus. It is important to emphasize that this study was performed with a small student cohort from a diverse range of backgrounds, who had all been exposed to ILI pedagogy. The user responses were collected anonymously, both to preserve date privacy, and to allow an unbiased understanding of the impact of AI-based language learning on their Hindi language learning journey. The survey consisted of tests, rating scales, performance metrics, a checklist and some inventories, leading to clear conclusions in relation to the following aspects:

- We checked on their general experience of using LLM for learning Hindi, asking the students to rate this on a scale of 1 to 5. A total of 97% of the students voted in favour of using LLMs for understanding the complex structure of grammar rules, while approximately 51% favoured its use in pronunciation practice. A small group of students (27%) also favoured using AI tools for understanding the morphology of Hindi words.
- Students were asked about usage patterns for LLMs in Hindi language learning, with a primary focus on the tools they used for learning Hindi. This provided us with an idea of the adaptability of LLMs to the Hindi language. We found that, in the current time and place, ChatGPT stood out as a better AI platform compared to the LLaMA and PaLM tools.
- In terms of the effectiveness of LLM, we focused primarily on the identification of aspects of the language learnt by the students. However, students uniformly voted that AI had given them improved vocabulary, enhanced grammar understanding, better conversational skills, improved cultural insight, and so on. Further, the challenges they encountered while using LLMs for the Hindi language were addressed, and this revealed

misinterpretation of cultural nuances and lack of contextual understanding, along with the regional variations in Hindi, as major problems with the AI.

– The students exposed to ILI pedagogy provided the final outcomes of this study. ILI pedagogy came out much more strongly than LI pedagogy in the efficient/effective development of language skills among the students. However, the AI provided too much information content for certain language aspects in this pedagogy; hence curation of content to maintain its suitability is crucial on the trainer's side.

6 Conclusion

My conclusions about the use of AI in teaching Hindi highlight the promising potential of integrating Large Language Models (LLMs) such as GPT-3, GPT-4, LLaMA, and PaLM 2 into the classroom. These advanced AI instruments offer a multiplicity of advantages, encompassing structural guidance, vocabulary enhancement, and cultural insights, which will ultimately enrich the learning experience for Hindi students. Nevertheless, my research acknowledges the necessity of addressing their limitations in semantic expression modes. LLMs have a huge information gap when it comes to Hindi morphology. However, in terms of syntactic issues relating to object formation and conjugation, it performed unexpectedly well, which merits its long-term consideration for use in language teaching scenarios.

First of all, this study encourages a harmonious blend of technological innovation with established teaching methodologies, reaffirming the importance of active engagement with AI tools for native-like authentic language practice and foundational grammar.

Second, LLMs enhance Hindi language learning by offering a comprehensive resource for vocabulary, grammar, and pronunciation improvement. LLMs can help in the learning of Hindi vocabulary by providing definitions, synonyms, and sentence examples. For grammar, they can offer explanations, practice exercises, and correct usage examples. In terms of pronunciation, LLMs can provide audio pronunciation guides and practice, aiding learners in mastering accurate pronunciation skills.

Third, LLMs can facilitate adaptive learning by assessing a language learner's skill level and tailoring content accordingly. They can provide progressively challenging exercises, quizzes, and reading materials to match the learner's proficiency. Additionally, LLMs can analyse conversational patterns and provide feedback, helping learners improve their speaking and listening skills. They can assist in developing conversational ideas through the use of

comics and narratives, by generating dialogues, stories, and scenarios that learners can engage with, thereby promoting practical language use and enhancing conversational skills.

Fourth, it is a valid hypothesis that the syllable pronunciation of students can be improved more by awareness than by imitating native speakers. This awareness can be generated through techniques for identification, such as scripting and ideas about the manner and positions for the articulation of syllables. In these awareness techniques, AI can play a pivotal role by collecting online resources relating to the target syllables and the continuous playing of pre-recorded auto-looping sounds of individual syllables.

My conclusion, after having employed AI tools in the Hindi classroom since 2017, is that these tools should be explored in the teaching of any language. I believe that they can significantly aid in learning Hindi in terms of vocabulary, grammar, conversational practice, and providing cultural insights, all of which promote a deeper understanding of the language. These tools can also assess a learner's skill level, for adaptive learning.

However, AI needs to improve in relation to more natural and realistic conversational interactions, including handling slang, colloquialisms, and non-standard language. There is a gap in real-time evaluations for trainees using LLMs, and more detailed and accurate feedback on pronunciation, including voice recognition technology to enhance the speaking skills of trainees, is a much-awaited development for the use of LLMs in language teaching.

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