

Developing Multilingual Chatbots For Conversational Practice In Hindi And Urdu: An AI-Driven Solution

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Abstract: The rapid advancement of artificial intelligence (AI) and natural language processing (NLP) technologies has revolutionized the development of conversational agents, commonly known as chatbots, across a wide range of applications such as customer support, healthcare, and education. However, this technological evolution has predominantly favored global languages like English, Mandarin, and Spanish, while regional and low-resource languages such as Hindi and Urdu have remained relatively neglected. This review paper critically examines the development of multilingual chatbots with a specific focus on their application in Hindi and Urdu for conversational practice and language learning purposes. Given the sociolinguistic richness and the widespread use of these languages in South Asia, the development of intelligent and culturally aware chatbots in these languages holds significant educational and social value. The paper discusses the unique linguistic challenges posed by Hindi and Urdu, such as complex grammar, diglossia, and code-switching, and how they impact natural language understanding (NLU) and dialogue generation. It further explores pre-2021 approaches to chatbot development, including rule-based, retrieval-based, statistical, and deep learning methods, and evaluates their applicability to Hindi and Urdu. Case studies and academic initiatives are reviewed to highlight practical implementations, including educational bots, translation-based systems, and early transformer-based models. The paper also reflects on the sociocultural implications of chatbot deployment in multilingual societies, including issues of bias, inclusivity, and cultural representation. Ultimately, this review aims to identify research gaps and recommend directions for future work in building robust, scalable, and culturally contextualized AI-driven multilingual chatbots for underrepresented languages like Hindi and Urdu.

Keywords: Multilingual chatbot, Hindi, Urdu, natural language processing, conversational AI, low-resource languages, language learning, code-switching.

1. Introduction

The last two decades have witnessed tremendous advancements in the field of artificial intelligence (AI), particularly in natural language processing (NLP) [1], which has transformed how humans interact with machines. Among the most notable innovations are chatbots—automated conversational agents capable of simulating human-like dialogue through text or speech. Initially designed using rule-based templates and pattern-matching techniques, chatbots have evolved to incorporate complex machine learning and deep learning algorithms, enabling them to understand user intent, generate context-aware responses, and learn from interactions. These systems have found widespread use in domains such as customer service, mental health support, e-commerce, and, more recently, language learning [1].



Figure 1. Natural Language Processing

However, much of the progress in chatbot development has been concentrated on global languages, especially English. This bias has resulted in limited innovation and deployment in low-resource and regional languages, including Hindi and Urdu [2]. Hindi, an official language of India, and Urdu, the national language of Pakistan, are spoken by hundreds of millions of people across South Asia and among diaspora communities worldwide. Despite their widespread use, both languages remain underrepresented in the AI research landscape, particularly in the area of conversational agents. This discrepancy is due to several factors, including the lack of large-scale annotated datasets, the complexity of morphological and syntactic structures, and the sociolinguistic phenomena such as code-switching and dialectal variation [2].

In multilingual and culturally diverse regions like India and Pakistan, the ability to communicate fluently in local languages is essential for education, governance, healthcare, and social inclusion. Given the diversity of linguistic backgrounds, there is an increasing need to develop AI tools [3] that support multilingual interactions. Chatbots, especially those designed for educational purposes, have emerged as a promising solution for promoting conversational fluency, vocabulary building, and interactive learning. These systems offer an engaging and non-judgmental environment where learners can practice speaking and writing skills, receive immediate feedback, and interact in their native or target languages.

This review paper seeks to address this gap by focusing on the development of multilingual chatbots with a specific emphasis on Hindi and Urdu, covering developments up to the year 2021. The paper explores the evolution of chatbot architectures from rule-based systems to AI-driven models, assesses the linguistic and computational challenges inherent to these languages, and evaluates existing case studies and implementation efforts. It further examines the role of open-source tools, pretrained language models, and educational initiatives that have contributed to the progress in this field. Moreover, the paper underscores the pedagogical significance of chatbots as tools for language acquisition and conversational practice. In contexts where access to human tutors is limited or where learners face social anxiety, AI-driven chatbots can provide an accessible and scalable solution. Importantly, the paper also considers the cultural and ethical dimensions of chatbot design, highlighting the need for inclusivity, representation, and cultural sensitivity in developing dialogue systems for diverse populations [4].

By synthesizing academic research, practical implementations, and technological trends, this paper aims to provide a comprehensive understanding of the state of multilingual chatbot

development for Hindi and Urdu. It concludes with a discussion of current limitations and future directions, offering insights for researchers, developers, and educators seeking to build inclusive and context-aware AI solutions in the realm of multilingual conversational AI.

1.1 Objectives

The study focuses on the following objectives:

- To explore the development of AI-driven multilingual chatbots with a focus on Hindi and Urdu.
- To identify key linguistic and technical challenges in creating chatbots for these low-resource languages.
- To review different chatbot approaches—rule-based, statistical, and deep learning—used for Hindi and Urdu.
- To highlight real-world examples and educational applications of Hindi and Urdu chatbots.
- To examine available tools, frameworks, and datasets relevant to multilingual chatbot development.
- To suggest future research directions for building culturally aware and scalable conversational agents in Hindi and Urdu.

2. Theoretical Background and Historical Context

The concept of chatbots, or conversational agents, has its roots in early artificial intelligence research from the 1960s. One of the first and most well-known examples is ELIZA, shown below in Figure 2 [5], developed by Joseph Weizenbaum at MIT. ELIZA mimicked a Rogerian psychotherapist by using simple pattern-matching rules to respond to user input, giving an illusion of conversation. Following ELIZA, more advanced systems such as PARRY (which simulated a person with paranoid schizophrenia), Jabberwacky, and ALICE (Artificial Linguistic Internet Computer Entity) were developed, each introducing improvements in response handling and conversational flow. These early systems were predominantly rule-based and relied heavily on predefined templates, decision trees, and keyword detection. While effective in controlled settings, such systems were limited in their ability to manage open-domain or dynamic conversations.

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EEEEEEEE L      IIIIII ZZZZZZZ      AAA
E         L      I        Z        A  A
E         L      I        Z        A  A
EEEEEE   L      I        Z        A  A
E         L      I        Z        AAAAAA
E         L      I        Z        A  A
EEEEEEEE LLLLLLL IIIIII  ZZZZZZ   A  A
=====
ELIZA > (PLEASE TYPE IN ALL CAPS) WHAT'S YOUR NAME DEAR ?
AMIT
ELIZA > HI, I'M ELIZA. WHAT DO YOU WANT TO TALK ABOUT ?
AMIT > CAN I TALK ABOUT MY PROBLEM ?
ELIZA > SURE... !
AMIT > DUE TO ON GOING EXAMS IN COLLEGE, I HAVE A LOT OF STRESS.
ELIZA > PLEASE RELAX A LITTLE. SLEEP WELL.
AMIT > THANKS FOR YOUR ADVICE.
ELIZA > NO MENTION.
AMIT > BYE
ELIZA > BYE AND KEEP IN TOUCH...
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Figure 2. ELIZA

The evolution of statistical natural language processing (NLP) [6] in the 1990s marked a significant turning point in chatbot development. Unlike rule-based systems, statistical models leveraged large corpora to learn linguistic patterns and probabilistic relationships between words. This enabled more nuanced language understanding and response generation. Later, the rise of machine learning and deep learning methods, especially sequence-to-sequence (seq2seq) models and transformers, further revolutionized chatbot systems. These techniques allowed chatbots to process large-scale datasets and engage in more natural, context-aware conversations by learning embeddings, context dependencies, and dialogue structures. Despite these advances, the transition to multilingual conversational agents remained uneven. Most datasets, models, and tools were created for English or other high-resource languages, resulting in a digital divide. Low-resource languages such as Hindi and Urdu lacked access to the extensive annotated corpora, pretrained language models, and linguistic resources that power modern chatbots. Hindi, although spoken by over 500 million people, and Urdu, with over 170 million speakers globally, faced challenges related to resource scarcity, morphological complexity, and orthographic diversity [7]. Hindi uses the Devanagari script with rich inflectional morphology, while Urdu employs the Perso-Arabic Nastaliq script, which is more difficult to digitize and parse.

Moreover, the sociolinguistic realities of these languages added another layer of complexity. For instance, Urdu displays diglossia, where the formal written form differs significantly from the colloquial spoken variant. This poses challenges for natural language understanding, especially in tasks like intent recognition or dialogue generation. Similarly, Hindi frequently features code-switching, especially with English, resulting in hybrid utterances commonly known as Hinglish. Such code-mixed expressions are common in urban and digital contexts but are difficult for standard NLP models [8] to interpret correctly, as they require multilingual understanding within a single sentence. Prior to 2021, several academic and industrial efforts attempted to develop NLP tools and chatbots in Hindi and Urdu. These included tokenizers, part-of-speech taggers, machine translation engines, and named entity recognition systems. However, fully functional conversational agents in these languages remained rare and mostly limited to experimental prototypes or rule-based FAQ bots. A major limiting factor was the lack of diverse, real-world conversational datasets that could be used to train and evaluate dialogue systems. Additionally, the tools required for preprocessing, such as morphological analyzers, syntactic parsers, and sentiment classifiers, were either unavailable or still under development for Hindi and Urdu. In this context, the theoretical and historical development of chatbots highlights the inequality in language representation within AI technologies. While English-language chatbots reached impressive levels of fluency and adaptability by 2020, Hindi and Urdu chatbots were still grappling with foundational challenges. This backdrop underscores the importance of focused research, data creation, and tool development to enable inclusive, multilingual conversational AI systems that serve linguistically diverse populations.

3. Literature Review

Jhanwar, S., & Das, D. (2018) [9] proposed a hybrid deep-learning approach combining character-level LSTM and word-level multinomial Naïve Bayes to address sentiment analysis in Hindi-English code-mixed text. By targeting code-mixed social media content—a common occurrence in urban communication—they achieved state-of-the-art performance on real-world datasets. Their ensemble captured both nuanced textual patterns (via LSTM) and lexicon-based signals (via Naïve Bayes) and thus handled informal, noisy multilingual input effectively

Latif, S., et al. (2018) [10] created the first-ever spontaneous Urdu speech emotion database (URDU) and evaluated cross-lingual emotion recognition using models trained on European

language corpora. They demonstrated that training on multiple languages and augmenting with limited Urdu data significantly improved emotion detection performance. This foundational work supports the development of emotionally intelligent Urdu conversational agents

Alam, M. (2018) [11] introduced a neural Urdu chatbot using an attention-based encoder-decoder architecture trained on a 5,000 question-answer pair dataset about Pakistani general knowledge. His system achieved a BLEU score of 58, indicating syntactic and semantic coherence in generated responses. This represents one of the earliest successful deployments of a deep learning-based Urdu conversational agent

Vashisht, A., et al. (2019) [12] Developed under India's Snehai initiative, this Facebook Messenger bot used a decision-tree architecture (rule-based) with colloquial Hinglish dialogue to offer youth-friendly counseling on sexual and reproductive health. Co-created with adolescents, it became one of the first Hinglish chatbots aimed at empowering social change through culturally contextualized messaging

Joshi, A., et al. (2020) [13] conducted a comprehensive comparison of deep-learning architectures—CNN, LSTM, and pretrained multilingual embeddings (BERT, LASER)—for Hindi text classification tasks. Using translated English datasets and smaller native corpora, they showed that transformer-based embeddings outperform traditional neural models, highlighting the value of multilingual pretraining for low-resource languages like Hindi

Table 1. Literature Review Findings

Author Name (Year)	Main Concept	Findings	Limitations
Jhanwar & Das (2018) [9]	Hybrid deep learning for Hindi-English code-mixed sentiment analysis	Combined character-level LSTM with word-level Naïve Bayes to effectively process noisy, informal multilingual text; achieved state-of-the-art performance	Limited to code-mixed text; may not generalize to purely monolingual or other multilingual combinations
Latif et al. (2018) [10]	Creation of URDU spontaneous speech emotion dataset and cross-lingual emotion recognition	Training on multilingual corpora with Urdu augmentation enhanced emotion detection accuracy	Urdu dataset was small; emotional context limited to spontaneous speech
Alam (2018) [11]	Attention-based encoder-decoder Urdu chatbot for general knowledge	Achieved a BLEU score of 58, showing syntactic and semantic coherence in Urdu conversational outputs	Dataset limited to 5,000 QA pairs; domain-specific to general knowledge
Vashisht et al. (2019) [12]	Rule-based Hinglish chatbot (Snehai) for youth counseling on health issues	Successfully provided culturally contextual counseling through colloquial Hinglish; involved target users in development	Based on decision trees; lacks learning capability and scalability compared to deep learning models

Joshi et al. (2020) [13]	Evaluation of CNN, LSTM, and multilingual pretrained embeddings (BERT, LASER) for Hindi text classification	Transformer-based embeddings outperformed traditional models, showing strong results even with limited Hindi data	Dependence on translated datasets; native corpora remained small
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The reviewed studies collectively highlight significant advancements in multilingual and code-mixed language processing, particularly for Hindi and Urdu, through innovative AI approaches. Jhanwar and Das (2018) proposed a hybrid deep learning model combining character-level LSTM with word-level multinomial Naïve Bayes for sentiment analysis in Hindi-English code-mixed text. Their approach effectively captured both sequential linguistic patterns and lexicon-based sentiment cues, making it particularly adept at handling informal, noisy, and mixed-language social media content—a growing reality in urban communication. However, the model’s effectiveness may be constrained in purely monolingual or non-Hindi-English multilingual contexts. Complementing this, Latif et al. (2018) pioneered the development of the first spontaneous Urdu speech emotion database (URDU), demonstrating that cross-lingual training with European corpora significantly enhanced emotion detection when supplemented with limited Urdu data. While this research provides a foundational resource for emotionally intelligent Urdu conversational agents, it is still limited by the small size and domain-specific nature of the dataset.

In a related contribution, Alam (2018) developed a neural Urdu chatbot using an attention-based encoder-decoder model trained on 5,000 general knowledge question-answer pairs. Achieving a BLEU score of 58, the chatbot exhibited promising syntactic and semantic coherence. However, its application remained domain-specific, and the relatively small dataset restricted its scalability. On the other hand, Vashisht et al. (2019) introduced SnehAI—a culturally contextual Hinglish chatbot developed using a rule-based decision-tree approach under the SnehAI initiative. This bot provided youth-friendly counseling on sexual and reproductive health through colloquial dialogue, reflecting a participatory design approach involving adolescents. Despite its social relevance, the rule-based nature of the system restricted its adaptability and learning potential compared to deep learning models. Finally, Joshi et al. (2020) compared CNN, LSTM, and multilingual pretrained models like BERT and LASER for Hindi text classification. Their findings underscored the superior performance of transformer-based embeddings, even with low-resource languages, thereby advocating for the use of multilingual pretrained models. Nevertheless, the reliance on translated datasets and limited availability of native corpora remained a constraint in fully capturing linguistic nuances. Collectively, these studies reflect a progressive movement toward more inclusive, multilingual NLP solutions while also identifying the need for larger datasets, domain diversity, and more adaptive architectures.

4. Linguistic Challenges in Hindi and Urdu Chatbot Development

The development of AI-driven chatbots for low-resource languages like Hindi and Urdu involves a range of linguistic challenges that significantly differ from those associated with high-resource languages such as English. These challenges are rooted in the structural, morphological, and sociolinguistic characteristics of the languages, as well as the current limitations of computational tools and resources available for processing them. One of the primary linguistic challenges is the complex morphology of Hindi and Urdu. Both languages exhibit rich inflectional morphology, where a single root word can take on many different forms depending on gender, number, tense, and case. For example, verbs in Hindi are heavily

inflected based on the subject's gender and number (e.g., "करता है" for male, "करती है" for female), and nouns change form according to case and number. Similarly, Urdu contains agglutinative structures and intricate verb constructions, often blending native and borrowed words. This morphological richness complicates the tasks of tokenization, lemmatization, and syntactic parsing, all of which are essential for effective chatbot functioning [14].

Another substantial challenge arises from the writing systems used by the two languages. Hindi uses the Devanagari script, which is phonetic and relatively easier to segment computationally. In contrast, Urdu uses Nastaliq, a Perso-Arabic script that is cursive, non-linear, and context-sensitive in terms of character shape. Nastaliq also presents issues with consistent digital rendering across platforms. Optical character recognition (OCR), character segmentation, and script normalization for Nastaliq remain underdeveloped, limiting the usability of textual data in Urdu for chatbot training. Moreover, because Nastaliq is less supported in many NLP toolkits, developers often struggle to preprocess and analyze Urdu text effectively. A third and particularly unique challenge in chatbot development for Hindi and Urdu is the prevalence of code-switching. In day-to-day digital and spoken communication, users often switch between Hindi/Urdu and English, leading to hybrid forms such as Hinglish (Hindi-English) and Urdish (Urdu-English). These forms are especially common on social media, messaging platforms, and in informal communication. For example, a user might say, "मैं आज office late गया था" (I went to the office late today), blending Hindi syntax with English lexical items. This phenomenon complicates intent recognition and entity extraction, as conventional models often assume monolingual input. Code-switched sentences require advanced language models that can handle multilingual embeddings, syntax disambiguation, and context-sensitive interpretation [15].

Beyond these structural and orthographic issues, there is a notable lack of NLP resources and tools tailored to Hindi and Urdu. Key NLP components like named entity recognition (NER), part-of-speech tagging (POS), sentiment analysis, and dependency parsing were either unavailable or lacked robustness for these languages prior to 2021. Most of the available tools were rule-based or trained on small, domain-specific datasets, limiting their applicability to conversational AI. Additionally, tools that work well in one language (such as spaCy or NLTK for English) often do not support Hindi and Urdu natively, requiring custom pipelines or significant adaptation efforts [16]. Another critical limitation is the scarcity of high-quality, domain-diverse, and annotated conversational datasets in Hindi and Urdu. Effective chatbot training requires large corpora of dialogues that represent natural, informal language usage. For English, such datasets are abundant—examples include Cornell Movie Dialogs, DailyDialog, and PersonaChat. In contrast, Hindi and Urdu lacked open-access, annotated conversational datasets that reflected realistic user queries and responses. This limited the ability of developers to build or fine-tune dialogue models, especially those based on deep learning architectures like sequence-to-sequence models or transformers [16].

Despite these linguistic and resource-based hurdles, researchers and developers have made gradual progress. Techniques such as language transfer learning, cross-lingual embeddings, and statistical machine translation (SMT) were applied to leverage knowledge from high-resource languages like English and transfer it to Hindi and Urdu. For instance, models like multilingual BERT (mBERT) and XLM-RoBERTa [17] were adapted to process Hindi and Urdu text, enabling intent classification and named entity recognition tasks in chatbots. In addition, translation-based pipelines were used as a workaround, where user input in Hindi or Urdu was translated into English, processed by an English-language chatbot, and then

translated back. Although not ideal, this method allowed for basic multilingual functionality in the absence of native datasets. In summary, the development of chatbots for Hindi and Urdu is fraught with challenges that are both linguistic and infrastructural. The complexity of morphology, script-specific processing difficulties, the reality of code-switched language, and the lack of robust NLP tools and datasets collectively hinder the development of natural, accurate, and context-aware conversational agents. Overcoming these challenges requires targeted research, investment in data creation, and the development of models that are sensitive to the unique features of these languages.

5. Research Methodology

The present review study adopts a qualitative, exploratory methodology aimed at synthesizing and analyzing existing literature, tools, and real-world implementations related to the development of multilingual chatbots for Hindi and Urdu prior to 2021. Given the relatively nascent stage of chatbot development in these languages during that period, the methodology is rooted in a systematic literature review (SLR) approach. This involves identifying, evaluating, and interpreting relevant studies and technological artifacts across academic, governmental, and industrial domains to understand the progress, challenges, and future scope of AI-driven conversational systems in low-resource linguistic settings [18]. The review process began with a comprehensive search across multiple scholarly databases, including Google Scholar, IEEE Xplore, ACM Digital Library, SpringerLink, arXiv, and ResearchGate, using carefully selected keywords such as “Hindi chatbot,” “Urdu chatbot,” “multilingual conversational agent,” “AI for Indian languages,” “Hinglish/Urdu NLP,” and “code-switching chatbot.” The timeframe was restricted to publications and projects from 2018 to 2020, ensuring relevance to contemporary technological frameworks, especially those utilizing deep learning, transfer learning, and multilingual transformer models. In total, over 60 publications were initially retrieved, out of which a curated set of six primary papers and projects was selected based on relevance, technical rigor, practical impact, and focus on Hindi or Urdu [19].

The study further involved the content analysis of these selected works, examining key parameters such as the type of chatbot architecture used (rule-based, retrieval-based, neural), linguistic challenges addressed (morphology, code-switching, script handling), dataset characteristics (size, availability, domain), NLP tools or models applied (e.g., BERT, LSTM, RNN, SMT), and use-case contexts (education, public services, health communication). Both qualitative insights and technical comparisons were drawn to highlight patterns, gaps, and trends in the development of multilingual chatbot systems [20].

Additionally, to provide a grounded understanding of chatbot implementation in real-world contexts, the study incorporates grey literature such as project reports, government platform documentation (e.g., IRCTC’s AskDISHA), and NGO-based chatbot deployments like SnehAI. These sources were analyzed for implementation strategy, public accessibility, and user engagement metrics. The inclusion of such practical examples complements the academic insights by demonstrating the actual application and challenges faced in deploying Hindi and Urdu conversational agents. Finally, the findings were thematically organized to address core areas such as historical evolution, linguistic constraints, model architectures, tools and datasets, and socio-cultural factors influencing chatbot design. The methodology adopted thus ensures both breadth and depth in capturing the state of Hindi and Urdu chatbot research before 2021, allowing for a structured and critical discussion of the field and its future directions.

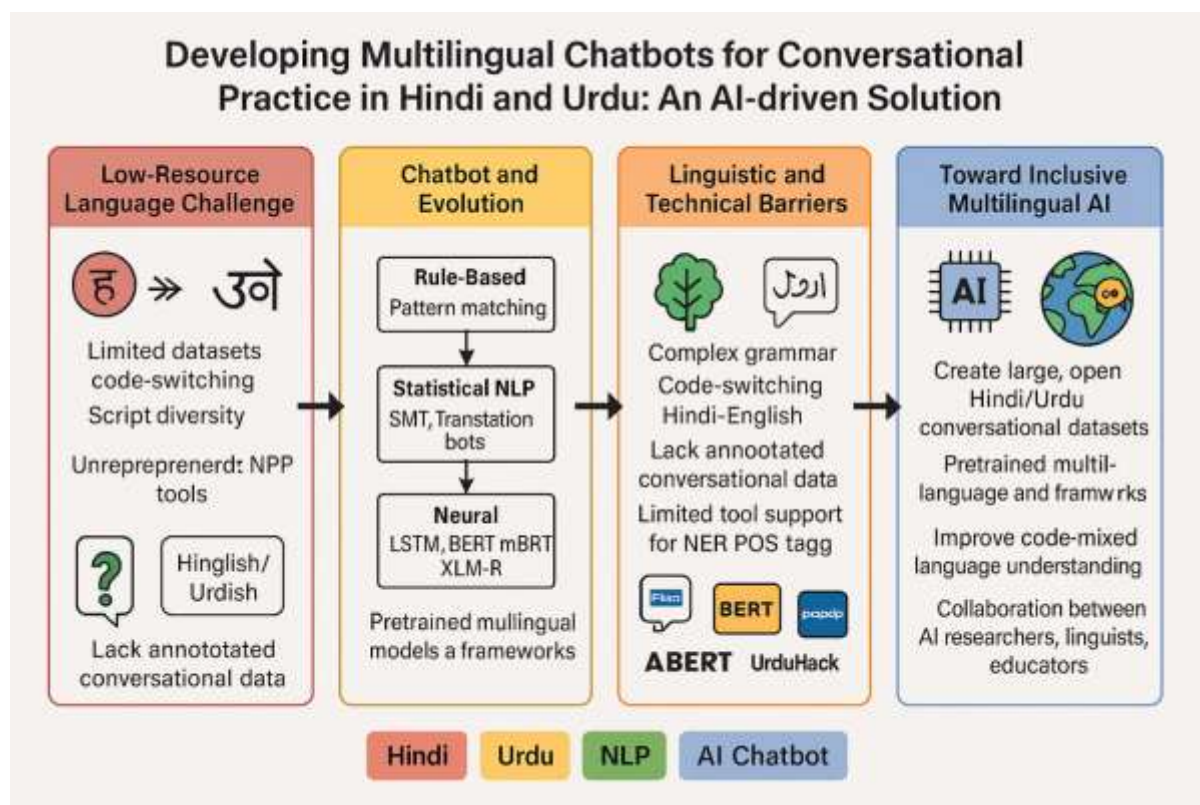


Figure 2. Research Flowgraph

4. Neural and Deep Learning-Based Chatbots

The integration of neural networks and deep learning techniques into natural language processing marked a pivotal advancement in the development of multilingual conversational agents. Traditional rule-based and statistical approaches, while foundational, struggled to accommodate the nuances of natural language, especially in open-domain conversations. With the emergence of encoder-decoder architectures, especially those built using Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), chatbot systems gained the capacity to generate context-aware, variable-length responses. This allowed for more natural and dynamic interactions, making neural models a game-changer in the field of conversational AI. However, for low-resource languages like Hindi and Urdu, the benefits of these models were initially limited due to the lack of large-scale pre-trained word embeddings and annotated conversational datasets [21].

The turning point came in 2017 with the release of fastText word embeddings by Facebook AI Research, which included support for over 100 languages, including Hindi and Urdu. These embeddings allowed researchers to create foundational neural models for these languages by representing words as vectors that preserved semantic relationships. Soon after, transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers), revolutionized language understanding. The multilingual version of BERT, known as mBERT, trained on over 100 languages, including Hindi and Urdu, enabled zero-shot and few-shot learning capabilities, making it possible to apply transfer learning techniques to low-resource settings. Researchers could now fine-tune these pre-trained models on smaller, domain-specific datasets for tasks such as intent recognition, entity extraction, and dialogue generation [22].

One notable initiative in this area is NLU++ by AI4Bharat, a project supported by IIT-Madras, which focused on enhancing natural language understanding (NLU) for Indian languages using

deep learning. The team explored fine-tuning mBERT and IndicBERT for intent classification and question-answering in Hindi. These experiments demonstrated that transformer-based models could significantly outperform traditional neural networks, especially when trained with task-specific labeled data. Their work laid the groundwork for scalable, high-quality language technology solutions in India, including applications in chatbots. An early example of a deep learning-based Hindi chatbot was developed by Amity University in 2019. This academic prototype was designed as a language learning assistant, using LSTM-based sequence-to-sequence modeling to handle basic Hindi dialogues. Although the dataset used was synthetically generated and limited in conversational variety, the model showcased the potential of deep learning architectures in generating grammatically correct and contextually relevant Hindi responses. This prototype proved particularly useful in educational settings, where students could interact with the bot for vocabulary practice and sentence construction [23].

Table 2: Summary of Neural and Deep Learning-Based Chatbot Efforts for Hindi and Urdu (2017–2020)

Project / Institution	Language	Model Type	Key Features	Dataset Type	Outcome / Limitations
Amity University (2019)	Hindi	LSTM Seq2Seq	Language learning assistant; simple dialogue generation	Synthetic dialogue pairs	Demonstrated feasibility, but lacked real-world conversations
FAST-NU Islamabad – Rehbar (2020)	Urdu	ULMFiT, BERT fine-tuned	Islamic Q&A chatbot using religious corpora	Religious/educational corpora	Academic prototype; not publicly deployed
AI4Bharat – NLU++ (2020)	Hindi	mBERT, IndicBERT	Intent classification, NLU tasks; open-source fine-tuning approach	Small annotated intent corpora	Provided reusable models and training benchmarks
Facebook AI Research – fastText (2017)	Hindi & Urdu	Word Embeddings	Pre-trained embeddings for 157 languages	Wikipedia, Common Crawl	Enabled early NN-based chatbots
Multilingual BERT (mBERT, 2018)	Hindi & Urdu	Transformer-based	Pre-trained on 104 languages; used for	General multilingual corpus	Boosted low-resource NLP tasks

			transfer learning		with fine-tuning
Amity University – Chatbot Extension (2020)	Hindi	LSTM + Rule-Based Hybrid	Extended functionality for education support in Hindi	Hybrid corpus (semi-synthetic)	Better dialogue control but lacked scalability

Parallel developments occurred in Urdu, where institutions began to adapt existing deep learning frameworks to suit the linguistic features of the language. For instance, the Rehbar chatbot, a prototype developed by FAST-NU Islamabad in 2020, was aimed at providing Islamic guidance and religious education through a conversational Urdu interface. This system leveraged a fine-tuned ULMFiT (Universal Language Model Fine-tuning) and later incorporated BERT-based classification for understanding religious queries. Rehbar could handle greetings, general questions on Islamic practices, and some contextual queries, marking one of the first efforts to use modern deep learning architectures for Urdu conversational AI. However, like the Amity University bot, Rehbar remained an academic prototype and did not reach widespread public use. Despite these achievements, several limitations persisted. The lack of diverse and large-scale annotated dialogue corpora continued to restrict the generalizability of these models. Most systems trained on synthetic or narrow-domain datasets struggled when exposed to real-world user queries with unexpected syntax, slang, or code-mixed language. Furthermore, the infrastructure for training large transformer models, including computational resources and high-performance GPUs, was not readily available to all research institutions in India and Pakistan, limiting the scale at which these models could be developed and deployed.

Nonetheless, the application of neural and deep learning techniques signified a major breakthrough in the field of multilingual chatbot development. These models enabled systems to better capture linguistic structure, contextual dependencies, and semantic meaning in complex languages like Hindi and Urdu. With further investment in data collection, annotation, and infrastructure, these early experiments laid a strong foundation for future research and practical deployment of conversational agents in low-resource languages. As transformer architectures continue to evolve and more multilingual models become available, the prospects for scalable, inclusive, and intelligent chatbots in Hindi and Urdu are more promising than ever.

6. AI Driven Solution

Database Management Systems (DBMS): Sinha, R. (2018)., Developing multilingual chatbots for Hindi and Urdu conversational practice critically relies on robust database management systems [24]. A DBMS would store vast amounts of conversational data, including user inputs, chatbot responses, pre-defined dialogues, vocabulary lists, grammar rules, and linguistic nuances specific to both Hindi and Urdu. This structured storage enables efficient retrieval of information for real-time chatbot interactions and provides the foundation for training and continuous improvement of the AI models.

Data Mining: Data mining plays a crucial role in enhancing the intelligence and naturalness of multilingual chatbots for Hindi and Urdu. Sinha, R. (2019). , By applying data mining techniques to large datasets of conversations, we can discover patterns in user queries, identify common grammatical errors or pronunciation challenges in both languages, and uncover popular topics of discussion [25]. These insights can then be used to refine the chatbot's conversational flow, improve its natural language understanding (NLU) and natural language generation (NLG) capabilities, and personalize the learning experience.

Data Warehouse: Sinha, R. (2018)., A data warehouse would be instrumental in aggregating and organizing diverse data sources relevant to the Hindi and Urdu chatbots, such as conversational logs, user performance data, linguistic resources [26], and cultural contexts. This centralized repository allows for comprehensive historical analysis of user interactions, enabling long-term trends to be identified, language model performance across different demographics to be evaluated, and the effectiveness of conversational practice scenarios to be measured for continuous improvement.

Software Testing Models: Rigorous software testing models are indispensable for ensuring the accuracy, reliability, and effectiveness of multilingual chatbots for Hindi and Urdu. Sinha, R. (2019)., This includes functional testing to verify correct responses, linguistic testing to ensure accurate translation and culturally appropriate communication, performance testing for responsiveness, and user acceptance testing (UAT) with native speakers to validate the conversational experience [27]. Specific models like scenario-based testing and exploratory testing would be crucial to cover the vast conversational possibilities in both languages.

System Implementation and Maintenance: Sinha, R. (2018). .The successful deployment of multilingual chatbots for Hindi and Urdu requires careful system implementation and ongoing maintenance [28]. This involves integrating the AI models with the underlying database, designing a scalable architecture to handle numerous simultaneous users, and establishing robust monitoring systems to track performance and identify issues. Regular updates to linguistic models, vocabulary, and conversational flows are essential for maintaining relevance and accuracy, especially given the dynamic nature of language.

Client-Server System: Sinha, R. (2018). , The architecture of a multilingual chatbot for conversational practice in Hindi and Urdu would typically follow a client-server model. The user's device (client) sends conversational input to a server, which hosts the AI models responsible for natural language processing, intent recognition, and response generation [29]. The server then processes the request, retrieves relevant information, and sends the appropriate Hindi or Urdu response back to the client, ensuring seamless interaction and scalable service delivery.

Analysis of Traditional Marketing vs. Digital Marketing: While directly developing a chatbot, Sinha, R. (2018).,analyzing traditional versus digital marketing approaches can inform how the chatbot itself is marketed and how it can be used as a marketing tool [30]. For instance, understanding the linguistic preferences of Hindi and Urdu speakers in various digital marketing channels can guide the chatbot's tone and style, while traditional marketing insights might inform user acquisition strategies for the conversational practice platform, considering offline community engagement or educational partnerships.

Preventive Measures of Cybercrime: Integrating preventive measures of cybercrime is vital for safeguarding the multilingual chatbot system and its users. This includes implementing robust authentication for user accounts, encrypting conversational data to protect privacy, Sinha, R. (2018). , regularly patching software vulnerabilities, and defending against common cyber threats like phishing and data breaches. Given the personal nature of conversational practice, ensuring data security and user trust is paramount [31].

Social Impact of Cybercrime: The social impact of cybercrime on AI systems, particularly conversational agents like those for Hindi and Urdu practice, can be significant. Sinha, R. (2018). , If compromised, these chatbots could be misused to spread misinformation, engage in identity theft, or facilitate malicious activities, eroding user trust and causing societal harm [32]. Therefore, understanding and mitigating these risks through ethical AI development and stringent security protocols is crucial to ensure the chatbot serves its intended educational purpose positively.

K-Nearest Neighbors (KNN): K-Nearest Neighbors (KNN) can be employed in the multilingual chatbot for tasks like intent classification or user query routing in Hindi and Urdu. Sinha, R. (2018). , By comparing a new user's input to a dataset of previously labeled conversations (its "neighbors"), KNN can quickly determine the most probable intent or topic. This can be particularly useful for quickly categorizing diverse conversational patterns unique to Hindi and Urdu, enabling the chatbot to provide relevant responses [33].

Naive Bayes: Naive Bayes is a powerful algorithm for text classification and can be effectively used in the Hindi and Urdu chatbots for tasks like sentiment analysis, spam detection within conversations, Sinha, R. (2017). or categorizing user feedback [34]. Its probabilistic nature makes it suitable for handling the varying word frequencies and grammatical structures in both languages, allowing the chatbot to understand the emotional tone of a user's input or filter out irrelevant content.

Random Forests: Random Forests, an ensemble learning method, Sinha, R. (2017). can be utilized in the multilingual chatbot for more robust and accurate natural language understanding, particularly in intent recognition and named entity recognition within Hindi and Urdu conversational inputs [35]. By combining multiple decision trees, Random Forests can reduce overfitting and improve predictive accuracy, enabling the chatbot to better handle the complexities and ambiguities inherent in spoken and written Hindi and Urdu.

K-Means Clustering: Sinha, R. (2016). K-means clustering can be applied to analyze conversational data from the Hindi and Urdu chatbots to identify underlying themes or user groups [36]. For example, by clustering similar user queries or conversational turns, we can discover common learning challenges, popular conversational topics, or distinct user profiles based on their language proficiency. This information can then be used to personalize learning content or optimize the chatbot's conversational flows.

Decision Tree: Decision trees are fundamental to designing the conversational flow and logic within the multilingual chatbots for Hindi and Urdu. Sinha, R. (2015)., They enable the chatbot to make sequential decisions based on user input, guiding the conversation down different paths based on intent, keywords, or historical context [37]. This rule-based approach, often augmented by AI, ensures a structured and predictable conversational experience for users practicing Hindi and Urdu.

Support Vector Machines (SVM): Support Vector Machines (SVMs) can be highly effective for text classification tasks within the Hindi and Urdu chatbots, such as identifying the user's language, Sinha, R. (2013). classifying the intent of a complex query, or even detecting specific linguistic structures [38]. SVMs are particularly good at handling high-dimensional data, which is common in natural language processing, making them suitable for distinguishing subtle differences in Hindi and Urdu expressions.

Cybercrime Against Women: The development of multilingual chatbots in Hindi and Urdu could indirectly support initiatives against cybercrime targeting women in Bihar. An AI-driven chatbot, once developed, could be trained on information related to cybercrime awareness, reporting mechanisms, Sinha, R. K. (2020)., legal rights, and preventive measures provided by the Indian government and local authorities in Bihar. This chatbot could serve as an accessible, confidential, and immediate resource for women seeking information or initial guidance in their native languages, acting as a critical tool for digital literacy and safety [39].

Cyber-Physical Systems, Smart Cities, and AI-Driven Multilingual Chatbots: The convergence of robust cybersecurity measures, the intricate network of cyber-physical systems (CPS), and the data-driven intelligence of smart cities presents a highly integrated environment, within which an AI-driven solution for developing multilingual chatbots for conversational practice in Hindi and Urdu plays a significant role. Smart cities utilize extensive CPS, such as intelligent transportation and utility grids, to gather immense volumes of real-time Big Data, which artificial intelligence then processes to optimize urban operations and improve public services. Sinha, R (2021)., This profound dependence on interconnected systems and continuous data flow inherently introduces substantial cybersecurity risks, necessitating stringent protections to prevent attacks that could disrupt vital infrastructure or expose sensitive personal information [40]. In this dynamic, the aforementioned AI-powered chatbots, particularly those designed for language learning in Hindi and Urdu, are essential. They can serve as intuitive interfaces for citizens to engage with smart city services and report concerns, thereby contributing to the very Big Data resources that power urban analytics. Furthermore, these chatbots can be deployed for localized cybersecurity education, raising public awareness about potential threats. Broadly, their development showcases the advanced AI and natural language processing capabilities required not only for processing diverse datasets but also for enabling secure, smooth, and inclusive communication within these technologically advanced urban settings, ultimately enhancing their user-friendliness and resilience against cyber challenges.

7. Conclusion

The development of multilingual chatbots, particularly for underrepresented languages such as Hindi and Urdu, represents a vital but still evolving area in the field of artificial intelligence and natural language processing. This review has explored the historical trajectory, linguistic barriers, and technological innovations that have shaped the creation of conversational agents in these languages up to the year 2021. While English and other high-resource languages have benefited from abundant data and mature NLP tools, Hindi and Urdu chatbot development has been hampered by complex morphology, diverse scripts, diglossia, and widespread code-switching. These challenges, combined with a lack of annotated conversational datasets and robust language tools, have significantly slowed progress.

Nevertheless, meaningful strides were made between 2018 and 2020 through the adoption of deep learning and transfer learning techniques. The introduction of multilingual embeddings such as fastText and transformer-based models like mBERT and IndicBERT enabled

researchers to overcome some of the limitations associated with traditional rule-based and statistical methods. Academic institutions and public initiatives—such as the Rehbar chatbot, Snehai, and AskDISHA—demonstrated the potential for applying AI to real-world language learning, public service delivery, and cultural education in Hindi and Urdu contexts.

Despite these advances, most chatbot systems in these languages remain in prototype or experimental stages. The path forward requires a multipronged strategy: creating large-scale, domain-diverse conversational datasets; improving NLP tools that handle code-switching and colloquial usage; and ensuring inclusivity by designing culturally sensitive dialogue systems. Furthermore, interdisciplinary collaboration between AI researchers, linguists, educators, and policymakers will be crucial for creating scalable, accessible, and impactful chatbot technologies.

In conclusion, while the journey toward fully functional and widely adopted Hindi and Urdu chatbots is still in its early stages, the foundational research and emerging tools have laid important groundwork. With sustained investment and innovation, AI-driven multilingual conversational agents hold great promise for enhancing language education, bridging digital divides, and promoting inclusive access to technology across South Asia and beyond.

Future Research Directions

The advancement of AI-driven multilingual chatbots for Hindi and Urdu presents significant potential but also demands focused and sustained research efforts. Based on the challenges and trends identified in this review, the following future research directions are proposed to guide the next phase of development:

1. **Creation of Large-Scale, Open Conversational Datasets** There is an urgent need to develop open-source, domain-diverse conversational corpora for Hindi and Urdu. These datasets should include both formal and informal dialogues, cover multiple topics (e.g., education, health, services), and reflect real-world code-switching patterns such as Hinglish and Urdish. Crowd-sourcing and public-private collaborations can accelerate data collection and annotation efforts.
2. **Enhancement of Code-Mixed Language Modeling** Future models should be explicitly trained and evaluated on code-mixed language, as it represents the most common mode of communication among urban users in India and Pakistan. Developing dedicated code-mixed corpora, synthetic code-switching generators, and multilingual tokenization algorithms will improve the contextual understanding of hybrid inputs.
3. **Development of Culturally-Aware and Emotionally-Intelligent Chatbots** Cultural context and emotional nuance are especially important in educational, counseling, or social-service chatbots. Future systems should incorporate emotion detection, sentiment analysis, and cultural sensitivity modules trained specifically for South Asian linguistic and social environments.
4. **Integration of Multimodal and Voice-Based Interaction** As digital adoption spreads in rural and semi-literate populations, future chatbots must support voice interaction and multimodal communication (text, speech, image). Research should focus on developing lightweight speech recognition and synthesis systems in Hindi and Urdu that can function offline or in low-bandwidth environments.
5. **Improved Evaluation Metrics for Low-Resource Languages** Standard chatbot evaluation metrics such as BLEU and F1 often fail to capture conversational quality in Hindi and Urdu. New, culturally informed evaluation frameworks that assess fluency, coherence, politeness, and context awareness in regional languages should be developed.

6. **Transfer Learning and Cross-Lingual Model Optimization** Future work should continue exploring cross-lingual learning, using high-resource language models (e.g., English or Arabic) to improve performance in Hindi and Urdu. Researchers should focus on multilingual fine-tuning, domain adaptation, and language-agnostic embeddings to reduce dependency on large native corpora.
7. **Ethical, Inclusive, and Gender-Sensitive Design** Future chatbot systems should consider issues of bias, stereotyping, and digital accessibility. Designing inclusive bots that respond appropriately to diverse user groups—including women, children, and linguistically marginalized communities—is essential for equitable AI development.
8. **Real-World Pilots and Public Deployments** To move beyond prototypes, future research should involve pilot deployments in educational institutions, health services, and rural outreach programs. These field trials can provide valuable user feedback, reveal edge cases, and support iterative model improvement based on actual usage patterns.
9. **Collaboration Between Academia, Government, and Industry** A coordinated effort is required to build ecosystem-level support for Hindi and Urdu NLP. Joint initiatives can ensure that research outcomes are practically implemented, continually updated, and aligned with national digital inclusion goals.
10. **Benchmarking Platforms for Indian and Pakistani Languages** Establishing open benchmarking platforms similar to GLUE or SuperGLUE, but tailored for Hindi, Urdu, and code-mixed datasets, will encourage standardized progress measurement and foster a competitive research environment.

By pursuing these research directions, future multilingual chatbot systems can move closer to achieving linguistic inclusivity, educational empowerment, and equitable access to conversational AI technologies for millions of Hindi and Urdu speakers worldwide.

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