

Opportunities and Challenges of Large Language Models for Low-Resource Languages in Humanities Research

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Abstract

Low-resource languages serve as invaluable repositories of human history, embodying cultural evolution and intellectual diversity. Despite their significance, these languages face critical challenges, including data scarcity and technological limitations, which hinder their comprehensive study and preservation. Recent advancements in large language models (LLMs) offer transformative opportunities for addressing these challenges, enabling innovative methodologies in linguistic, historical, and cultural research. This study systematically evaluates the applications of LLMs in low-resource language research, encompassing linguistic variation, historical documentation, cultural expressions, and literary analysis. By analyzing technical frameworks, current methodologies, and ethical considerations, this paper identifies key challenges such as data accessibility, model adaptability, and cultural sensitivity. Given the cultural, historical, and linguistic richness inherent in low-resource languages, this work emphasizes interdisciplinary collaboration and the development of customized models as promising avenues for advancing research in this domain. By underscoring the potential of integrating artificial intelligence with the humanities to preserve and study humanity's linguistic and cultural heritage, this study fosters global efforts towards safeguarding intellectual diversity.

1 Introduction

1.1 Research Background

1.1.1 Importance and Endangerment of Low-Resource Languages in the Global Linguistic Ecology

The linguistic landscape of the world constitutes a complex tapestry interwoven with a rich diversity of languages, each strand epitomizing a distinctive cultural, historical, and social identity. This global linguistic diversity forms a foundational pillar of human civilization, cultivating an array of perspectives and worldviews that enhance our collective intellectual legacy. Among these, low-resource languages occupy a particularly crucial position, not merely as modes of communication but as repositories of distinctive cultural knowledge, historical narratives, and worldviews. These languages, frequently spoken by smaller communities, are essential to the preservation of cultural heritage and the transmission of indigenous knowledge systems.

However, the global linguistic landscape is presently undergoing an extraordinary crisis, with low-resource languages among the most threatened. The swift vanishing of these languages is of serious concern, highlighted by concerning data and studies. It is estimated, for example, that around 40% of the world's 7,000 languages face extinction, with numerous low-resource languages having fewer than 1,000 speakers [94]. This decline is caused by several factors, such as the widespread effects

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of globalization, the challenges of urbanization, and the prevalence of dominant languages. These elements often marginalize low-resource languages, resulting in their gradual decline and eventual disappearance.

The importance of low-resource languages, both culturally and intellectually, is immense. These languages are not simply tools for conversation; they serve as vibrant repositories of human history, reflecting centuries of cultural and intellectual development. When a low-resource language disappears, it is as though an entire library fades away, taking with it distinctive stories, oral histories, and scientific insights. Such a cultural and intellectual loss deeply impacts humanity, stripping future generations of the diverse richness of human thought and experience these languages offer. Consequently, preserving and revitalizing low-resource languages are not only academic pursuits but also critical actions needed to protect our global cultural heritage.

1.1.2 Demand for Low-Resource Languages in Humanities Research and the Insufficiencies in Existing Studies

Languages with limited resources are crucial for advancing research in the humanities, especially in fields like anthropology, history, literature, and linguistics. These languages provide distinctive perspectives on cultures, societies, and intellectual traditions that are less frequently studied, thus broadening our appreciation of human diversity. For example, anthropologists frequently use indigenous languages to reveal hidden facets of cultural practices and social organizations not captured by dominant languages. Likewise, historians and literary scholars gain access to primary sources and oral histories maintained in low-resource languages, offering a more detailed and thorough understanding of historical events and literary traditions. In the field of linguistics, analyzing low-resource languages aids the creation of theories and models applicable to a wider variety of human languages, thereby deepening our knowledge of language universals and diversity [30].

The critical significance of low-resource languages notwithstanding, prevailing research methodologies encounter appreciable challenges when engaging with these languages. A principal limitation is the paucity of textual data. Numerous low-resource languages lack extensive written corpora, thereby complicating the execution of empirical studies and the development of computational models. Furthermore, the absence of specialized computational tools specifically adapted to these languages aggravates the issue [57]. Existing tools and resources are frequently designed for high-resource languages, thereby proving ineffective or inefficient for application to low-resource languages. This technological disparity is further heightened by the inadequate availability of essential linguistic resources such as dictionaries, grammars, and annotated corpora, which are imperative for both descriptive and computational linguistic research.

The literature concerning low-resource languages is marked by a significant disparity, with a disproportionate emphasis on high-resource languages. Such a bias constrains our comprehension of human culture and history, as it neglects the contributions of lesser-studied languages and cultures. The predominant focus on high-resource languages may lead to a skewed perspective, wherein certain cultural and historical narratives are accorded undue prominence over others. This imbalance not only compromises the integrity of humanities research but also perpetuates a form of cultural erasure. To rectify this gap, there exists an urgent requirement for the development of novel research methodologies and tools that can effectively integrate low-resource languages into scholarly discourse. Achieving this would facilitate a more inclusive and comprehensive understanding of human culture and history, ultimately allowing humanities research to realize its potential to illuminate the full spectrum of human experience.

1.2 Opportunities for Low-Resource Language Research Through Large Language Models

1.2.1 Breakthroughs in Language Processing with LLMs

The emergence of LLMs marks a new phase in natural language processing (NLP), significantly altering the field with their remarkable capabilities and adaptability. Examples of LLMs, such as GPT-4 [1] and LLaMA [20], are based on the transformer architecture. This architecture uses self-attention mechanisms to efficiently process and generate text with impressive fluency and contextual awareness. By supporting parallel processing of sequences, transformers overcome the challenges faced by earlier

architectures like Recurrent Neural Networks (RNNs) [11] and Long Short-Term Memory (LSTM) networks [28], which struggled with handling long-range dependencies and parallelization.

The advancements made by LLMs across several NLP tasks are remarkable. These models have set new benchmarks in areas such as machine translation, text generation, sentiment analysis, and language comprehension. For example, the BERT model [17], which originates from the transformer architecture, has greatly improved the effectiveness and scalability of NLP systems through self-supervised pretraining. In recent developments, generative models like the GPT series [9, 78] have demonstrated their zero-shot and few-shot in-context learning capabilities, allowing them to tackle various tasks without the need for task-specific fine-tuning. This flexibility highlights the extensive datasets used for pretraining these models, which incorporate a vast array of world knowledge and emerging skills.

An important advancement in the field of LLMs is their multilingual capability. These models can handle and produce text in a variety of languages, including those with limited resources. Unlike traditional approaches that rely heavily on large amounts of parallel text for accurate translation, LLMs utilize extensive pretraining across many languages, enabling them to create coherent outputs even for languages with limited training data. This feature is particularly crucial for low-resource languages, which often have limited text corpora and lack specialized computational tools. By using the multilingual pretraining of LLMs, researchers now have access to more powerful and versatile tools for processing and analyzing low-resource languages, helping to close the gap in current research practices.

The incorporation of LLMs into numerous practical applications is capturing growing interest, significantly affecting a variety of areas including education, healthcare, and robotics [13, 14, 36, 37, 51, 54, 56, 59–63, 65, 82, 92, 95, 103, 106, 108]. Their capacity for human-like comprehension and reasoning is a stepping stone toward Artificial General Intelligence (AGI), fostering societal progress across numerous disciplines [47, 50, 57, 96, 107–109]. As LLMs advance, they hold vast potential to enrich research in languages with limited resources, providing novel opportunities to preserve and comprehend the extensive cultural and intellectual treasures embedded in these languages.

1.2.2 Prospects and Challenges for Applications in Low-Resource Language Research

Integrating LLMs into research on low-resource languages presents numerous possibilities for enhancing understanding and conservation efforts associated with these languages. Models such as GPT-3, GPT-4, and LLaMA have demonstrated capabilities in areas like text generation, translation, sentiment analysis, and linguistic analysis. For instance, LLMs could generate coherent and contextually relevant narratives in low-resource languages, which might aid in documenting and sharing oral histories and cultural stories. In terms of translation, these models may help enable cross-linguistic communication by producing somewhat accurate and fluent translations, especially useful for languages with limited parallel corpora. Furthermore, sentiment and linguistic analyses could provide valuable insights into the emotional and structural nuances of these languages, supporting a more comprehensive understanding from linguistic and anthropological standpoints.

However, applying LLMs to low-resource languages presents certain challenges. A major hurdle is the scarcity of data. These languages often lack a substantial body of written material, which complicates the training and refinement of LLMs. This shortage may result in less than optimal performance, especially in languages with intricate linguistic aspects or minimal presence in the training datasets. Additionally, model bias is a notable concern. Although LLMs are pretrained on extensive and varied data collections, these might not adequately capture low-resource languages, culminating in skewed or incorrect results. Furthermore, the challenge of obtaining specialized training data persists. Although LLMs can undertake zero-shot or few-shot tasks via prompt engineering, their performance is notably improved with task-specific fine-tuning, necessitating extra data that might not be readily accessible for low-resource languages.

Current research endeavors are actively tackling these challenges through a range of techniques. Strategies like fine-tuning, transfer learning, and data augmentation are being investigated for adapting LLMs to low-resource languages. Fine-tuning entails training the model with a smaller, task-specific dataset, enhancing its performance on low-resource languages by customizing it to their unique features. Transfer learning utilizes the insights gained by LLMs during pretraining and applies them to novel, related tasks, thereby minimizing the requirement for a large amount of training data. Data augmentation approaches, including back-translation, have become prevalent in low-resource machine translation. Back-translation uses a model to convert monolingual target language data into the source

language, forming pseudo-parallel corpora that substantially increase the amount of training data for low-resource pairs. Unsupervised machine translation, which completely removes the need for parallel data, has emerged as a promising solution for low-resource languages by using monolingual corpora from both the source and target languages and developing the ability to align and translate between them via iterative back-translation and shared latent representations.

Notwithstanding these advancements, the implementation of LLMs in the context of low-resource languages persists as a subject of active scholarly investigation. The evolution of LLMs has unveiled novel opportunities for translation of low-resource languages, facilitating the generation of coherent textual outputs even in languages characterized by scarcity of training data. Nevertheless, the efficacy of these models in addressing the intricacies and unique linguistic attributes inherent to low-resource languages, particularly those with minimal representation in training datasets, remains a significant challenge. As research in this domain advances, it is imperative to persist in the exploration of innovative methodologies and tools that can effectively integrate low-resource languages into academic discourse, thereby augmenting our comprehension of human culture and history.

1.3 Research Objectives and Contributions

1.3.1 Investigation of Opportunities and Challenges of LLMs in Humanities Research on Low-Resource Languages

The main goal of this study is to thoroughly examine the potential benefits and obstacles associated with using LLMs for humanities research focused on low-resource languages. This goal is motivated by the pressing necessity to preserve and investigate these languages, as they hold distinctive cultural, historical, and social insights. By investigating how LLMs can advance research in this field, we aspire to make a valuable contribution to the wider spectrum of humanities research, thereby deepening our comprehension of human diversity and cultural legacy.

The main content of the article is summarized in the figure 1. This research aims to deliver substantial and diverse contributions. Primarily, it will offer an in-depth review of the current state of LLMs in the context of low-resource language research. This review will provide a detailed assessment of existing methodologies, tools, and datasets, and will spotlight both progress made and existing challenges in the field. Furthermore, we aim to pinpoint specific ways in which LLMs can substantially influence research in the humanities. These applications cover areas such as text generation, translation, sentiment analysis, and linguistic examination. Moreover, we'll delve into the potential for LLMs in areas like language variation and historical, cultural, and religious studies. For example, LLMs can aid in translating and interpreting ancient texts, analyzing linguistic changes and variations, and understanding cultural and religious subtleties in low-resource languages.

This research will critically examine the hurdles and constraints linked to utilizing LLMs for low-resource languages, marking a significant contribution to the field. Among these hurdles are limited data availability, model bias, the requirement for specialized datasets, and the ethical considerations of deploying LLMs in culturally delicate situations. By tackling these issues, the study aims to provide a balanced view of the potential and limitations of LLMs in this area. Additionally, it will propose recommendations for future research and practical applications, highlighting innovative methods and tools that can effectively integrate low-resource languages into academic discussions.

The importance of this research lies in its potential to aid in the preservation and study of low-resource languages, which serve as repositories of human history, capturing centuries of cultural evolution and intellectual progress. The disappearance of a low-resource language can be likened to losing an entire library, with its distinct stories, oral traditions, and scientific knowledge fading away. By harnessing the power of LLMs, we can improve our ability to document, study, and preserve these languages, protecting our global cultural heritage. This work is also crucial in the broader context of humanities research, as it opens up new possibilities for understanding the diverse tapestry of human thought and experience. In conclusion, this research aims to connect the advances in LLMs with the urgent necessity of preserving and studying low-resource languages. By exploring both the opportunities and hurdles presented by LLMs, we hope to advance the creation of innovative methods and tools that can effectively incorporate low-resource languages into academic discourse. This will, in turn, expand our comprehension of human culture and history, meeting the humanities' promise to shed light on the full range of human experience.

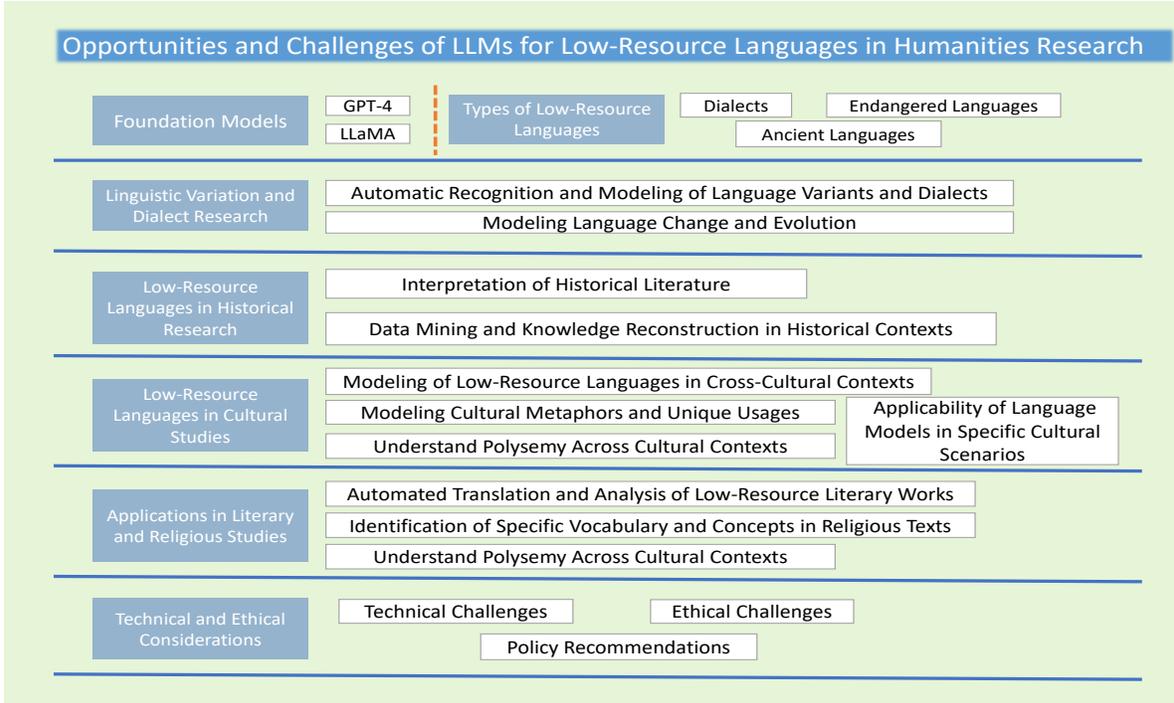


Figure 1: Overview of the structure outline of the article.

2 Foundational Framework for LLMs in Low-Resource Language Research

2.1 Definitions and Types of Low-Resource Languages

A **low-resource language** refers to a language that suffers from a significant scarcity of linguistic resources, such as corpora, dictionaries, and annotated datasets. These languages often lack large-scale digital support, posing challenges for NLP and computational linguistic research [32]. Despite their diversity and cultural significance, low-resource languages are underrepresented in modern technological and computational advancements. Below, we delve into the key classifications of low-resource languages, their unique challenges, and the role of LLMs in addressing these gaps.

2.1.1 Dialects

Dialects are regional or social varieties of languages that often lack standardized written forms. They are predominantly used in oral communication and are rich in linguistic diversity. For example, Chinese Cantonese, Hokkien, and Shanghainese are widely spoken but remain underrepresented in computational linguistics due to the absence of robust, large-scale corpora.

The challenges in processing dialects include:

- **Diversity:** Dialects often exhibit significant phonological, lexical, and syntactic differences, even within the same language family.
- **Resource scarcity:** Dialects are rarely documented comprehensively in written form, and existing data are typically fragmented.
- **Corpus complexity:** Capturing the linguistic rules and structures of dialects in a corpus requires extensive resources, including phonetic annotations and regional usage patterns.

Large language models, when augmented with transfer learning techniques or pre-trained on related high-resource languages, have the potential to bridge these gaps. However, dialects' inherent variability still presents a major obstacle to achieving high performance in NLP applications [101].

2.1.2 Ancient Languages

Ancient languages, such as Latin, Sanskrit, and Ancient Greek, hold immense historical and cultural significance but are no longer in widespread use for daily communication. These languages pose unique computational challenges:

- **Limited and fragmented corpora:** Ancient texts often exist in non-standardized formats or incomplete manuscripts.
- **Lack of alignment with modern linguistic paradigms:** Ancient languages frequently exhibit archaic grammatical structures and vocabulary, requiring specialized models for processing.
- **Preservation and digitization:** Many ancient scripts lack comprehensive digitization, hindering the availability of training data for machine learning models.

For instance, while Latin remains a cornerstone of religious and academic studies, its scarcity of annotated datasets and linguistic ambiguities complicate NLP tasks such as translation, semantic parsing, and automated analysis of ancient texts. Large language models designed with symbolic reasoning capabilities and fine-tuned on ancient text corpora may offer promising avenues for this domain.

2.1.3 Endangered Languages

Endangered languages are at risk of extinction, often spoken by small, isolated communities. Many indigenous languages in regions such as Australia, Africa, and the Americas face dwindling numbers of speakers, limited geographical reach, and minimal documentation.

The challenges in endangered language processing include:

- **Speaker scarcity:** Fewer native speakers mean fewer opportunities for collecting spoken and written data.
- **Minimal academic support:** Endangered languages often lack institutional resources for linguistic preservation.
- **Urgency:** The rapid decline of speakers demands accelerated efforts for documentation and computational support.

To address these challenges, large language models can leverage *transfer learning*, *zero-shot learning*, and *unsupervised methods* to process limited data effectively. Furthermore, community-driven initiatives can play a pivotal role in collecting and annotating linguistic data.

2.2 Scarcity and Complexity of Corpora in Low-Resource Languages

Low-resource languages are characterized by the scarcity of corpora, which significantly hinders their integration into modern NLP systems [101]. Unlike high-resource languages such as English and French, which have benefited from decades of extensive corpus development, these languages often lack sufficient datasets. The challenges in data collection are multifaceted, involving logistical difficulties, financial constraints, and cultural sensitivities. Assembling even basic corpora for such languages can be a significant undertaking, and the lack of resources limits the development of NLP models tailored to these linguistic contexts.

The available datasets for low-resource languages often suffer from poor quality and limited scope, making them suboptimal for robust model training [80]. Inconsistencies within the datasets and the absence of comprehensive linguistic coverage further restrict their utility. The problem is exacerbated by the underrepresentation of these languages in AI research, as commercial interests have historically focused on high-resource languages. This imbalance has resulted in technological advancements that predominantly benefit languages with larger speaker bases and more substantial economic influence.

The linguistic complexity of low-resource languages further amplifies these challenges. Many of these languages possess unique grammatical structures, such as the lack of clear distinctions between grammatical categories or the use of non-linear syntax [80]. These features make it difficult to adapt existing NLP techniques designed for high-resource languages. Moreover, orthographic diversity adds

another layer of difficulty. Some languages lack standardized writing systems, while others use scripts that are challenging to digitize or process with current computational tools.

Additionally, regional variations within low-resource languages pose a significant obstacle to corpus development. Differences in pronunciation, vocabulary, and syntax across geographical areas require highly localized datasets to capture the full linguistic diversity of these languages [101]. Such regional variations demand substantial effort to develop representative and contextually accurate corpora. These factors collectively underscore the pressing need for innovative strategies to overcome the intertwined issues of scarcity and complexity in low-resource language processing.

2.3 Role of Large Language Models in Addressing Challenges

Large language models offer a transformative approach to addressing the challenges posed by low-resource languages. By leveraging advanced techniques such as *few-shot learning*, *meta-learning*, and *unsupervised pre-training*, these models can mitigate the effects of data scarcity and complexity. Some promising strategies include:

- **Transfer learning:** Pre-training on high-resource languages and fine-tuning on related low-resource languages.
- **Synthetic data generation:** Using generative models to create artificial corpora that replicate linguistic features of low-resource languages.
- **Collaborative annotation:** Engaging native speakers and local communities in the creation of datasets to ensure linguistic authenticity.

While the road ahead is challenging, the integration of community efforts, advanced computational methods, and interdisciplinary research holds the potential to unlock the linguistic treasures embedded within low-resource languages. These advancements will not only benefit NLP but also contribute to the preservation of linguistic and cultural diversity.

2.4 Techniques Supporting Low-Resource Languages

To improve the performance of LLMs in processing low-resource languages, researchers have proposed a range of technical approaches. These methods aim to enhance the adaptability of LLMs by improving training data quality, leveraging cross-language transfer, and incorporating multi-modal information. Together, these techniques contribute to significant advancements in processing low-resource languages, despite their inherent challenges.

2.4.1 Transfer Learning

Transfer learning is a widely adopted technique to address the challenges posed by low-resource languages [110]. By pre-training a model on high-resource languages and fine-tuning it on low-resource languages, the model can acquire foundational linguistic knowledge from the former and adapt to the unique characteristics of the latter.

Key benefits of transfer learning include:

- **Knowledge reuse:** High-resource languages serve as a knowledge base, enabling the model to understand basic linguistic structures, syntax, and semantics of low-resource languages.
- **Resource efficiency:** Reduces the amount of data required to train the models specifically for low-resource languages.
- **Improved generalization:** Enhances model robustness in handling sparse or noisy data.

For example, pre-trained language models such as BERT, GPT, and RoBERTa have been shown to adapt effectively to new languages and domains through fine-tuning, improving their performance in low-resource settings. However, the effectiveness of transfer learning often depends on the degree of linguistic similarity between high-resource languages and low-resource languages.

2.4.2 Cross-Language Pretraining

Cross-language pretraining is another powerful method, exemplified by multilingual models like mBERT, XLM, and XLM-R [27]. These models are trained on multilingual corpora, enabling them to learn shared representations across languages.

Advantages of cross-language pretraining include:

- **Shared representations:** Multilingual models encode universal linguistic features, facilitating cross-linguistic knowledge transfer.
- **Scalability:** These models can support a wide range of languages without the need for extensive language-specific fine-tuning.
- **Support for zero-shot and few-shot learning:** Cross-language pretraining enables models to perform well on unseen low-resource languages by leveraging knowledge from related languages.

For instance, mBERT has demonstrated effectiveness in tasks like cross-language question answering and translation, where shared multilingual embeddings provide a robust foundation for low-resource language processing.

2.4.3 Multi-Task Learning

Multi-task learning involves training models on multiple related tasks simultaneously, allowing them to share knowledge across tasks [105]. This approach is particularly beneficial for low-resource languages as it enables the model to leverage auxiliary tasks to improve performance.

Applications of multi-task learning for low-resource languages include:

- **Shared knowledge:** Tasks such as translation, sentiment analysis, and text classification provide complementary information, enhancing model generalizability.
- **Regularization:** Multi-task learning acts as a form of regularization, preventing overfitting on small datasets.
- **Efficient resource usage:** Combines multiple objectives into a unified training framework, reducing the need for extensive single-task datasets.

By exposing the model to diverse tasks, multi-task learning helps the model generalize better to low-resource language challenges, including those with limited linguistic features.

2.4.4 Data Augmentation

Data augmentation addresses the problem of insufficient training data by generating additional examples [79]. This technique enriches the dataset, providing the model with more diverse and representative samples for training.

Common data augmentation methods include:

- **Synthetic data generation:** Machine translation can create parallel corpora by translating high-resource language datasets into low-resource languages.
- **Paraphrasing:** Generating alternative expressions for existing sentences to increase linguistic diversity.
- **Noise injection:** Adding controlled noise to data to simulate real-world variability and improve robustness.

For example, back-translation has proven effective in tasks like machine translation and text classification, where augmenting datasets with machine-generated examples significantly boosts model performance.

2.4.5 Multi-Modal Integration

Incorporating **multi-modal information**, such as audio, video, and images, has emerged as a promising approach to enhance low-resource language processing. By leveraging non-textual data, models can better understand and represent the contextual nuances of languages.

Advantages of multi-modal integration include:

- **Complementary information:** Audio and visual data provide cues that are absent in textual data, such as pronunciation and gestures.
- **Improved accessibility:** Enables the processing of languages with oral traditions or limited written records.
- **Enhanced semantic understanding:** Multi-modal models can capture richer, context-aware representations.

For instance, speech-to-text and text-to-speech models trained on multi-modal data have shown significant improvements in processing spoken languages with limited textual resources.

2.5 Adaptation and Gaps Between LLMs and Low-Resource Languages

In recent years, LLMs have made significant progress and demonstrated immense potential in the field of humanities research. These models can process vast amounts of text, uncover hidden information, and provide new perspectives and methods for tasks such as ancient text interpretation and cultural analysis. This capability is particularly beneficial for humanities research, especially for low-resource languages, where LLMs can serve as a critical tool to break research bottlenecks, enhancing the understanding, analysis, and preservation of these languages. However, there are still limitations in the adaptation of current LLMs to low-resource languages that need to be thoroughly examined.

2.5.1 Gaps Between Available Corpora, Model Capabilities, and Research Needs

Availability of Corpora The available corpora for low-resource languages are diverse but fraught with issues. On one hand, the sources include digitization projects of historical documents, language archives from specific regions, and limited academic research collections. However, these sources are scattered and significantly smaller in scale compared to high-resource languages. On the other hand, the quality of low-resource language corpora is often poor. The lack of standardized curation processes leads to numerous annotation errors and irregular records, which severely impact the accuracy of LLMs in understanding and processing these languages.

Model Capabilities Existing large language models have inherent limitations when dealing with low-resource languages. The model architectures are primarily designed based on extensive data from high-resource languages, making them less effective in handling the unique grammatical, lexical, and semantic features of low-resource languages. Additionally, the generalization capabilities of these models are insufficient. When encountering new vocabulary, expressions, or culturally specific semantics in low-resource languages, the models struggle to effectively utilize their training patterns for accurate understanding and generation.

Research Needs In humanities research, there are specific demands for processing low-resource languages. For instance, in ancient text translation and interpretation, models need to precisely understand the semantics and cultural connotations of ancient low-resource languages. In the preservation and study of minority cultures, models must comprehensively handle various texts involving minority languages. In the analysis of language evolution, models need deep insights into historical language changes. These demands require models to possess high precision and a deep understanding of linguistic nuances. However, there is a significant gap between current model capabilities and these research needs, particularly in handling complex metaphors, symbols, and other culturally loaded content in low-resource languages.

2.5.2 Special Requirements for Low-Resource Language Data and Limitations in Generative Technology

Special Requirements for Low-Resource Language Data From a data perspective, the scarcity of corpus data for low-resource languages is a critical factor limiting the further training of LLMs and

their effective application in low-resource language research. The existing corpora, both in quantity and quality, are insufficient to meet the needs to improve LLM performance. To better utilize LLMs for low-resource language research, it is urgent to establish a specialized corpus for low-resource languages. This corpus should cover various aspects of low-resource languages, including different historical periods, regional variants, and text types. Additionally, high-quality data annotation is essential, with annotations including grammatical structures, semantic information, and cultural contexts, to improve data usability and value, providing better training materials for LLMs.

Limitations in Generative Technology Current LLM technology has some inherent limitations when dealing with low-resource languages. The pre-training data primarily consists of large-scale text collections dominated by high-resource languages, causing the models to overlook low-resource languages during initial learning. Consequently, when processing related tasks, the models lack prior knowledge, such as the ability to capture unique vocabulary usage, grammatical rules, and semantic networks in low-resource languages.

3 Linguistic Variation and Dialect Research in Low-Resource Languages

In the field of sociolinguistics, research on under-described languages has traditionally been constrained to specific tasks such as part-of-speech tagging, text classification, and machine translation[66]. However, the emergence of LLMs, as outlined in the foundational framework, has transformed this landscape. By leveraging their computational power, reasoning capabilities, and advanced methodologies, LLMs confront the challenges posed by limited documented linguistic resources, enabling more comprehensive research on linguistic variation and dialects in low-resource languages.

Unlike widely used corpus-based approaches in linguistics, which struggle to handle low-resource languages due to data scarcity, LLMs-based methods utilize advanced techniques to effectively process diverse language variants. Through these innovations, LLMs play a crucial role in bridging the gaps left by conventional methods, opening new possibilities for understanding and preserving linguistic diversity in under-described languages. These innovations open new pathways for understanding and preserving the linguistic diversity of under-described languages while addressing critical gaps in research methodologies.

3.1 Automatic Recognition and Modeling of Language Variants and Dialects

Recognizing and modeling language variants and dialects in low-resource contexts is a complex but crucial task in NLP. LLMs address these challenges by leveraging multilingual datasets and employing techniques such as prompt engineering, retrieved-augmented generation (RAG), and meta-learning that allow the linguistic system to adapt to specific dialects and generalize across diverse linguistic contexts, even with small training data size.

3.1.1 Existing Methods of Handling Diverse Variants in LLMs

Several structured methods have been developed to enhance LLMs pipelines for processing various language variants and dialects. These approaches focus on building efficient systems for identifying, modeling, and leveraging linguistic diversity:

Transfer Learning and Fine-Tuning LLMs utilize transfer learning to adapt knowledge from high-resource languages to low-resource languages[3], effectively bridging linguistic gaps. Fine-tuning on small, domain-specific datasets helps capture regional and dialectal nuances. Techniques such as Low-Rank Adaptation (LoRA) and QLoRA further enhance fine-tuning efficiency, making this approach computationally accessible for low-resource settings.

Prompt Engineering and In-Context Learning Prompt engineering is crucial for tailoring LLMs outputs to specific dialectal contexts. Minor modifications to the prompts, such as the adjustment of word order or structure, can significantly influence the model output[75]. In-context learning further supports low-resource scenarios by enabling LLMs to adapt without requiring extensive re-training, leveraging contextual examples to generate more accurate responses.

Retrieval-Augmented Generation RAG enhances the performance of LLMs by integrating retrieval mechanisms that fetch relevant contextual data, which is especially valuable for underrepresented languages. It is particularly valuable for underrepresented languages, where contextual augmentation can compensate for limited data availability[89]. In addition to leveraging retrieval data to enhance training datasets, there are advanced RAG approaches that dynamically select the appropriate dialect context from external knowledge bases or corpora to enhance generation accuracy.

Meta-Learning Meta-learning improves the adaptability of LLMs, allowing them to generalize across multiple tasks and linguistic variations. By training on a variety of tasks, meta-learning empowers LLMs to recognize unseen dialects and adapt to new linguistic contexts with minimal labeled data. This capability is invaluable for under-described languages, where conventional training often fails to achieve desired accuracy[102].

3.1.2 Dialect Speech Recognition in Low-Resource Contexts

Speech recognition systems are indispensable for addressing dialect recognition in low-resource settings, where annotated datasets are scarce. Advanced methods such as the state-of-the-art Conformer Transducer (ConfT) model, combined with Model-Agnostic Meta-Learning (MAML), have demonstrated substantial improvements in dialect-specific tasks. These methods optimize parameters for rapid fine-tuning with minimal data, reducing word error rates by up to 12% for low-resource accents, as evidenced in recent studies[83] [22]. Building on advancements in speech-to-text and text-to-speech models, LLMs can further enhance dialect recognition by integrating phonetic and acoustic features into language understanding pipelines. By leveraging dialect-specific lexicons and fine-tuned language models, these systems achieve improved transcription accuracy, making them vital tools for the preservation and accessibility of linguistic diversity.

3.1.3 Challenges in Dialect Recognition and Modeling

Despite technological developments, significant challenges persist in the recognition and modeling of dialects, particularly in low-resource contexts based on dialect processing:

- **Annotation Gaps:** Limited or poorly annotated datasets restrict the model’s performance and generalization to diverse linguistic contexts.
- **Inconsistencies in Spoken and Written Forms:** Variations in grammar, orthography, and style complicate model training and evaluation, often leading to misinterpretations and reduced accuracy.
- **Biases and Sampling Limitations:** Over-representation[34] of high-resource languages in training data skews model output, undermining efforts to build inclusive systems capable of capturing the full spectrum of linguistic variation.
- **Complex Acoustic Features in Dialects:** The unique phonological and prosodic features require specialized modeling techniques for dialects. Speech recognition systems must account for these variations, which often necessitate additional training resources and strategies.

Addressing these challenges requires a multifaceted approach that includes community-driven data collection, advanced annotation tools, and multi-modal integration. Beyond computational methods, interdisciplinary collaboration remains essential to develop robust and inclusive dialect recognition systems.

3.2 Modeling Language Change and Evolution

The evolution of low-resource languages is a dynamic and complex process. It is shaped by factors such as the shrinking or migration of communities that use the language over time, which leads to the simplification of grammatical rules or the integration of vocabulary from other languages. As a result, low-resource languages often develop unique dialects or variants. These languages typically face challenges in language technology applications due to limited corpora and insufficient technological support. However, with the rapid advancements in NLP, particularly with the advent of LLMs, new possibilities have emerged for tracking and analyzing the evolution of low-resource languages. These

models not only facilitate the digital construction of language resources but also offer unprecedented tools to understand the dynamic changes of languages across time and space.

3.2.1 The potential and limitations of LLMs in tracking the evolution of low-resource languages

As one of the most advanced tools in the field of Natural Language Processing, large language models have demonstrated immense potential and advantages in tracking low-resource languages. However, this tracking process also faces several limitations due to factors such as data scarcity and unique grammatical structures.

Potential

First, LLMs possess remarkable generalization abilities; after extensive training on large-scale multilingual data, they can adapt to low-resource languages through few-shot learning or fine-tuning on limited language samples. This adaptability makes them capable of recognizing and responding to the gradual changes within these languages. Moreover, self-supervised training methods endow LLMs with the ability to predict and generate language contextually, allowing them to infer emerging vocabulary and new expressions from minimal data samples. Additionally, LLMs can stay aligned with language evolution through regular parameter updates or periodic fine-tuning, ensuring their continued relevance to the latest linguistic trends in low-resource languages.

Limitations

The primary issue stems from the scarcity of available data, which limits the model’s exposure to comprehensive language patterns such as spoken versus written distinctions or context-specific expressions. Small sample sizes can lead to sampling bias, where the model may capture expressions specific to certain regions or communities, while overlooking broader linguistic diversity. Furthermore, the slow accumulation of low-resource language data delays the update process, hindering the model’s ability to reflect recent linguistic shifts accurately.

3.2.2 Spatiotemporal variant processing in low-resource languages

Low-resource languages often exhibit strong spatiotemporal variability, displaying significant linguistic differences across time periods, regions, and social groups. When applying LLMs to low-resource languages, it is crucial to consider this variability in model design and optimization. To address the spatiotemporal variations inherent in low-resource languages, several methods are commonly employed in the optimization and improvement of LLMs, including but not limited to the following approaches:

Cross-lingual Transfer Learning Cross-lingual transfer learning, as referenced in [10], is a widely used approach that leverages shared features from high-resource languages to aid in the processing of low-resource languages. This method helps capture fundamental linguistic features and can be generalized to accommodate different spatiotemporal variations.

Removal of Explicit Language Tag Embeddings By removing explicit language classification encodings for words, this approach allows different languages to share feature representations[12]. It enables the model to benefit from data across multiple languages, thereby enhancing its broader linguistic understanding.

Multimodal Architectures and Representation Learning Enhancing LLMs’ ability to process low-resource languages through multimodal learning is an effective strategy[68]. For example, combining visual and textual features can improve the model’s understanding ability of spatiotemporal variations and cultural context differences.

Sentence Augmentation Techniques Some studies focus on sentence augmentation techniques to handle low-resource languages, such as Kazakh[7]. By generating more diverse sentences and expressions using LLMs, these methods address regional language variations. They enable the generation of more natural low-resource language sentences, expanding the data coverage and improving the model’s generalization capabilities for new language inputs.

3.3 Opportunities and Challenges

Automated modeling provide linguistic scholar transformational opportunities with advancing research on low-resource languages like Quechua by enabling in-depth analysis of unique linguistic features and dialectal variability. For instance, it provides tools for interpreting sociolinguistic contexts, such as

the placeholder "na," which functions both as a hesitation marker and as a substitute for omitted words, offering insights into bilingual code-switching and linguistic structure. Automated approaches also support the exploration of dialectal variability and linguistic borrowing[64]. These contributions not only facilitate the preservation of linguistic diversity, but also enhance understanding of bilingual interactions and address the complexities inherent in dialectal variation.

However, significant challenges persist in achieving reliable and accurate modeling of dialects, with model errors often stemming from data shortages and standardization issues. The lack of high-quality annotated datasets remains a critical limitation, particularly for low-resource languages and under-represented dialects. This scarcity is exacerbated by inconsistencies between spoken and written forms, where variations in orthography, grammar, and writing style introduce additional complexities for model training and evaluation.

In conclusion, while LLMs provide promising solutions for handling diverse language variants, continued innovation in integrating dialect resources and addressing structural challenges is essential to achieve reliable and equitable linguistic modeling in low-resource settings.

4 Applications of Low-Resource Languages in Historical Research

Low-resource languages often carry rich historical and cultural information but are now at risk of gradual extinction. Protecting low-resource languages is not only a critical topic in linguistic research but also an essential aspect of historical studies. These languages have become "low-resource" due to a combination of factors. Over thousands of years, wars, colonialism, and political upheaval have forced certain language communities into displacement, leading to interruptions in language transmission [84–88]. Industrialization and modernization have transformed traditional agricultural societies, sparking intense social change [100]. Many people have migrated from rural areas to cities, abandoning their original languages in favor of more widely spoken ones. Under the influence of globalization, dominant cultures and languages often overshadow and displace weaker ones.

The importance of protecting low-resource languages within historical research cannot be underestimated. By preserving and studying these languages, we gain a deeper understanding of humanity's past, enrich historical scholarship, and promote cultural diversity and social inclusivity. With the advancement of artificial intelligence and natural language processing technologies, efforts to protect low-resource languages have gained new momentum [54, 55, 58, 95]. Large language models and computer vision technologies can be used to identify, translate, and interpret low-resource language literature, providing powerful tools for historical research [90]. The application of these technologies not only improves research efficiency but also expands the depth and scope of studies, allowing a broader range of low-resource language literature to be fully utilized. This section will delve into the application of LLMs in the interpretation of historical literature in low-resource languages.

4.1 Interpretation of Historical Literature

Literature in low-resource languages often carries rich historical and cultural information. Ancient texts, especially those written in low-resource languages, are important resources for studying specific cultures and historical periods. However, translating and interpreting these ancient texts currently face numerous challenges.

Specifically, these challenges include:

Scarcity of Literature: The quantity of ancient documents in low-resource languages is often limited and scattered across different locations such as archaeological sites, libraries, and private collections. Many of these texts are severely damaged due to their age, making portions of the content difficult to recognize.

Linguistic Complexity: The grammatical structures and vocabulary of low-resource languages differ significantly from modern languages, increasing the difficulty of translation. Even within the same language, there can be substantial differences in writing styles across different regions and historical periods.

Scarcity of Language Experts: The number of experts proficient in low-resource languages is limited. Many minority groups have integrated into modern civilized life and do not have mastery over their own ethnic languages.

There has already been some work using AI to translate and decode low-resource languages, such as the deciphering and restoration of the Dead Sea Scrolls [18, 19, 45, 77], the recognition of ancient Egyptian hieroglyphs [6], text restoration of ancient Greek inscriptions [4], the decoding of oracle bone script [29], and the unified Visual-Linguistic understanding of oracle bone scripts[40]. These early efforts, however, did not yet make use of LLMs. LLMs can play a pivotal role in addressing these challenges. Firstly, to combat the scarcity of literature, LLMs coupled with advanced computer vision techniques can assist in digitizing and reconstructing fragmented or damaged ancient texts. This not only preserves existing documents but also consolidates them into accessible digital archives for researchers worldwide. Secondly, regarding linguistic complexity, LLMs can be fine-tuned on available data, even if limited, to learn the unique grammatical structures and vocabulary of low-resource languages. Lastly, to mitigate the scarcity of language experts, LLMs can serve as virtual assistants, providing preliminary translations and analyses. This empowers a broader range of scholars and enthusiasts to engage with these languages, thereby expanding the pool of individuals who can contribute to their study and preservation.

4.2 Data Mining and Knowledge Reconstruction in Historical Contexts

LLMs have demonstrated remarkable potential in the mining of historical data and the restoration of knowledge, particularly concerning low-resource languages [90]. These advanced models can learn the unique grammatical structures and vocabularies of these languages from limited datasets. By doing so, they can fill information gaps in historical documents and unearth unsystematized historical knowledge and informal records that have long been inaccessible to researchers.

Historical documents written in low-resource languages often suffer from significant information loss due to their age, poor preservation conditions, and the fragility of the materials used. These issues result in fragmented texts with substantial gaps, making it challenging to comprehend the complete historical context. LLMs can analyze the known portions of these texts, learning from their syntax and semantics to generate plausible reconstructions of the missing content. This process helps restore the integrity of historical documents, providing a more holistic view of the past.

Historical research has traditionally focused on formal documents like official records, treaties, and academic works. However, a wealth of historical information resides in informal records such as personal diaries, letters, folklore, and oral traditions. These sources offer invaluable insights into the daily lives, cultures, and social dynamics of historical communities but are often scattered across various archives and personal collections without systematic organization.

LLMs can process and analyze these informal records, extracting historical information that might otherwise remain hidden. By identifying patterns and drawing connections across disparate documents, LLMs provide new research perspectives and enable historians to construct more nuanced narratives [54]. This capability is particularly crucial for low-resource languages, where such informal records may be the primary sources of historical data.

In addition, LLMs can help to unify fragmented data from diverse sources, recognizing patterns that might otherwise be missed and aiding historians in constructing a more holistic view of historical events and cultural narratives. With advancements in technology, the application of LLMs in this field is expected to become more widespread and profound, enhancing historical analysis by making underutilized sources and scattered information accessible and meaningful. This trajectory points toward a future where LLMs enable deeper exploration of lost languages, unearth hidden knowledge, and enrich the field of historical studies in unprecedented ways.

4.3 Challenges and Opportunities

The application of LLMs to the historical study of low-resource languages has shown great potential, but still faces many technical difficulties in practice. Among them, the limitations of optical character recognition (OCR) technology, a key technology for digitizing ancient documents, are particularly prominent. The standard processing flow of OCR includes image preprocessing, text region localization, feature extraction, character recognition, and post-processing [5]. In these links, the accurate positioning of text region is crucial, which mainly involves two tasks of text detection and character segmentation.

The special characteristics of ancient documents make these two tasks more difficult to accomplish. Many documents are presented in handwritten or non-standardized fonts, and are often difficult to

recognize due to blurring, fading, or physical damage [71]. Such conditions place high demands on OCR systems, making it difficult to effectively recognize areas containing text during text detection [72]. Similarly, some ancient documents (e.g., cursive scripts) have continuous writing and characters stacked on top of each other, which poses a challenge for character segmentation. These scenarios require the system to have higher resolution capability and accurate segmentation algorithms to avoid character misjudgment or character concatenation phenomenon.

Last but not least, there are many limitations in automatically converting ancient characters to modern languages. Low-resource languages often lack sufficient text corpora to provide high-quality training data for LLMs [66], which results in lower accuracy rates for translation or transcription of ancient characters. To further complicate matters, these languages tend to be morphologically variable and complex, and lack standardized writing rules. The morphology of a word may be varied and diverse depending on the context, tense, or syntactic roles, which poses a great problem for models to recognize and translate ancient texts. Finally, most of the current LLMs are primarily trained on large-scale datasets of modern languages, so researchers need to develop new approaches or adapt existing technical frameworks to address the particular challenges of low-resource scripts.

5 Applications of Low-Resource Languages in Cultural Studies

5.1 Diversity of Cultural Corpora and Model Adaptation

5.1.1 Modeling of Low-Resource Languages in Cross-Cultural Contexts

Low-resource languages in cross-cultural contexts carry unique cultural values, often transmitting rich historical and social meanings through oral traditions, religious rituals, local ecologies, and artistic forms. Some oral traditions not only preserve the cultural semantics of ancestor worship but also shape intricate narrative rhythms. At the same time, the fusion of festive language with religious ritual language imbues regional languages with sacred elements in everyday usage. The integration of performing arts and architecture showcases the complex forms of language expression within cross-cultural settings[24]. Low-resource languages are often deeply influenced by these cultural factors, leading to complex and diverse modes of expression. Therefore, cross-cultural language modeling demands more than technical precision; it also requires integrating cultural understanding to develop models that reflect the cultural depth.

The corpora of low-resource languages, especially those carrying cultural histories such as oral traditions and folk narratives[91], are often insufficiently digitized or standardized, posing significant challenges for model adaptation. Some researchers have successfully incorporated these cultural differences into large models, yielding promising results[48]. In the processing of low-resource languages, studies have shown that domain-adaptive pretraining (DAPT) can significantly enhance the performance of language models on culturally specific corpora[69].

5.1.2 Challenges in Modeling Cultural Metaphors and Unique Usages

Cultural metaphors and special usages pose unique challenges for LLMs. These linguistic phenomena are deeply embedded in specific cultural contexts, carrying rich historical, social, and emotional connotations. For instance, cultural metaphors often convey profound meanings through symbolic expressions, while special usages include slang, regional dialects, and cross-disciplinary terminology. Such linguistic features not only require models to understand context and surface meanings but also demand the ability to capture the complex cultural contexts and knowledge underlying the language.

To address this challenge, LLMs need more robust contextual modeling and knowledge integration capabilities. On the one hand, building a more diverse and culturally representative training corpus helps models encounter more instances of cultural metaphors and special usages. On the other hand, incorporating external knowledge bases or knowledge graphs can provide the model with richer background information and reasoning abilities. Additionally, techniques such as contrastive learning and few-shot learning can enhance the model’s generalization capabilities in low-resource domains, enabling it to understand and generate these linguistic features even with limited examples. Ultimately, achieving culturally sensitive language modeling will open up new possibilities for cross-cultural communication and intelligent language interactions.

5.2 Interaction Between Cultural Customs and Language Expression

5.2.1 How Language Models Understand Polysemy Across Cultural Contexts

LLMs demonstrate a remarkable sensitivity and adaptability to cultural contexts when handling linguistic ambiguity. This is because the meaning of language is not only constrained by literal interpretation but is also deeply influenced by the cultural background and social norms in which it is used. Within the same language, specific words or expressions may exhibit different semantic layers due to cultural differences. By learning from vast, multilingual, and multicultural corpora, LLMs are capable of dynamically capturing contextual cues when analyzing text, enabling them to appropriately adapt to ambiguous words based on cultural context. This ability is particularly crucial in tasks such as language translation and cross-cultural dialogue generation, as it directly impacts the accuracy and cultural relevance of the generated language[70].

However, Polysemy - the existence of multiple but related meanings for a single form - has always been problematic for purely structural accounts of meaning[15]. LLMs face significant challenges when processing specific linguistic ambiguity - polysemy across different cultural contexts. The model's performance largely depends on the breadth and diversity of its training data. If certain cultural corpora are underrepresented, or if the semantic characteristics of a particular culture are overrepresented, the model may provide overly simplified interpretations of ambiguous words, overlooking the subtle cultural differences underlying the language. The proposed computational framework for quantifying polysemy, as outlined in recent research, introduces a novel approach to tackling this challenge. By combining graph-based methods with syntactic structures, such as dependency parsing and Ollivier Ricci curvature, this framework enhances the model's capacity to estimate polysemy scores and map linguistic ambiguity with precision[26]. Furthermore, linguistic ambiguity is often intertwined with metaphors, idioms, and other deep forms of expression, which poses even higher demands on the model. To enhance LLMs' generalization ability in multicultural contexts, it is essential to incorporate balanced and multi-layered corpus resources, along with cultural context annotations and domain-specific knowledge to guide the model's learning. These improvements can significantly enhance the model's adaptability in multicultural environments, making it more accurate and comprehensive in language generation and understanding tasks.

5.2.2 Research on the Applicability of Language Models in Specific Cultural Scenarios

LLMs have been applied globally, but their effectiveness in specific cultural contexts faces several challenges. These models are typically trained on vast datasets that encompass multiple languages and cultures. However, data biases and cultural specificities can lead to misunderstandings or misinterpretations in certain cultural settings. For instance, slang, proverbs, or traditional expressions that carry deep cultural significance in some languages may lose their original meaning or even be misunderstood in the content generated by the model. Additionally, metaphors, humor, and polite expressions unique to certain cultures might not align well with the model's general algorithms, limiting its interaction capabilities in complex cultural contexts.

To enhance the applicability of LLMs in specific cultural environments, researchers can approach the issue from three key areas: data, architecture, and evaluation. First, integrating more localized and high-quality datasets into model training can help cover a wider range of cultural backgrounds and expressions[81]. Second, model architectures can include targeted modules, such as cultural context embeddings or bias correction mechanisms, to better accommodate diverse cultural needs. Lastly, by collaborating with local users and cultural experts, a cultural sensitivity evaluation system can be established to thoroughly test the model's performance in specific cultural contexts. These efforts would contribute to promoting the fair and efficient use of LLMs in cross-cultural communication, education, content generation, and other fields.

5.3 Opportunities and Challenges

5.3.1 Opportunities: Role of Low-Resource Language Models

Low-resource language models have good potential in safeguarding endangered languages, traditions, and knowledge systems. These models empower the documentation and dissemination of oral traditions, folklore, and cultural narratives that might otherwise fade into obscurity due to a lack of bal-

anced corpus resources. For example, the rich oral histories of indigenous communities, often passed down through generations, can be systematically transcribed and analyzed, ensuring their long-term preservation while simultaneously broadening their accessibility to a global audience. By bridging linguistic divides, language models[38] serve as conduits for cultural exchange, deepening cross-cultural intersectionality and fostering a sense of connection across diverse societies.

Beyond cultural preservation, low-resource language models offer a sophisticated method to unravel the complexities inherent in cross-cultural communication[49]. These models are particularly adept at addressing linguistic differences, such as dialectal variations, where they can act as multilingual experts, bridging and connecting diverse linguistic systems. With the potential to facilitate seamless translation and communication across languages and dialects without delays or loss of authenticity, language models are redefining the scope of cross-cultural interactions. By fine-tuning these models on culturally specific corpora, they can capture nuanced meanings with remarkable accuracy within the specific area, fostering a deeper understanding of the source culture while ensuring that translations and interpretations faithfully reflect original intention and the cultural depth.

Furthermore, low-resource language models support in promoting cultural inclusivity by enabling underrepresented languages to present and participate in global discourse. The preservation and update of low-resource languages in digital and educational spaces by language model, ensuring that these languages are not overshadowed by more dominant language. By integrating low-resource language models into cross-cultural research, scholars can uncover connections between linguistic structures and cultural customs, enriching the study of human diversity, and resolving linguistic inequality.

5.3.2 Challenges: Misunderstandings and Bias within Low-Resource Language Models

While the potential of low-resource language models in advancing cross-cultural communication and preserving endangered traditions is undeniably promising, several significant obstacles stand in the way. A major challenge is the risk of misunderstandings and biases arising from insufficient cultural and contextual understanding. Currently, many language models are developed using training datasets that fail to fully encompass the linguistic diversity and cultural specificity of the communities they represents. As a result, the nuanced meanings of idiomatic expressions, metaphors, and culturally embedded terms are often misunderstood within cross-cultural context, leading to oversimplified translations or inaccuracies that fail to honor the richness of the original text[53].

Another pressing challenge lies in the inadvertent projection of dominant cultural perspectives onto minority languages or traditions. Many LLMs are predominantly trained on datasets drawn from high-resource languages and cultures, leading to a biased interpretative framework. This bias can dilute or distort the unique cultural and linguistic attributes of minority traditions, reducing their authenticity and misrepresenting their core meanings. Moreover, the scarcity of comprehensive resources for many low-resource languages exacerbates this issue. Without access to curated datasets and the necessary external contextual resources, LLMs struggle to accurately interpret and convey these elements. This challenge is particularly acute for oral traditions and languages with limited documentation, where much of the cultural essence remains undocumented or inaccessible[44]. Taking these and other unknown limitations into consideration, there is a long way to achieve the effective application for low-resource language models in cross-cultural context.

6 Applications in Literary and Religious Studies

6.1 Automated Translation and Analysis of Low-Resource Literary Works

Literary works play a crucial role in the language system. Literary works are not only the simple transmission and preservation of information, but they also carry the author’s emotions, thoughts, and even contain the cultural background of a region or even a country[74]. Therefore, automated translation and analysis of literary works is an important way to understand and inherit a language[42]. The translation of literary works is not just about simple word conversion, but about conveying the same emotions and meanings as the original work in a new language environment. Similarly, the analysis of literary works also needs to uncover the deep hidden meanings of the works, rather than simply retelling and summarizing them. For low-resource languages such as Croatian and most other less used languages[21], it is crucial to use LLMs to translate and analyze literary works for understanding, protecting, and even cultural heritage.

However, using LLMs to translate and analyze literary works in low-resource languages is a relatively difficult process. This is because for low-resource languages, there is usually a lack of large-scale parallel corpora or high-quality datasets[52], which are the basis for LLMs to understand low-resource languages, making it difficult to process literary works. Secondly, literary works in low-resource languages often contain unique cultural backgrounds and local characteristics. Without sufficient cultural background knowledge, it is difficult for LLMs to accurately translate these unique cultural elements. To address these challenges, researchers have proposed various methods, including building corpora of low resource languages, cross language transfer learning[35], and using professionals to proofread and revise the results provided by large language models.

Another key issue in the automated translation and analysis of low-resource literary works using LLMs is whether they can accurately identify the styles of different literary works. Different writers have different writing styles, which often reflect their unique perspectives and artistic pursuits. In order to better capture and preserve these styles, LLMs must have higher adaptability. Specifically, fine-tuning can be made to the LLMs to capture the stylistic characteristics of specific writers, such as romanticism, realism, etc., achieving more natural and fluent translation and analysis.

6.2 Identification of Specific Vocabulary and Concepts in Religious Texts

Religious texts are usually written in low-resource languages and are important repository of theological, philosophical, and cultural knowledge. They are renowned for their unique terminology, symbolic structures, and contextual meanings[2], and can be better studied and analyzed using LLMs.

Religious texts generally have specific language and structural attributes. Many low-resource religious texts use vocabulary with profound theological significance, often lacking direct equivalents in modern language, which are referred to as sacred terminology. For example, the Sanskrit term "Nirvana" [76] represents a complex concept that differs greatly between Hinduism and Buddhism, including liberation, cessation, and transcendence; In Christian texts, Greek words like "agape" and "logos" are filled with theological and philosophical meanings. In addition, some religious texts may use repetitive phrases for ritual, memory, or meditation purposes, and these repetitions need to be explained and preserved during the analysis and translation process[23]. Secondly, many religious texts heavily rely on symbolism and fables[39]. For example, the recurring theme of light in sacred texts such as Vedic hymns or the Bible conveys a range of meanings from divine existence to enlightenment. Finally, religious texts are deeply rooted in their social and historical context. Words, phrases, and even entire paragraphs can reflect specific historical events, cultural norms, or local belief systems, and require contextual understanding to be accurately interpreted.

The LLMs provide revolutionary possibilities for the study of religious texts. In cross religious contexts, LLMs can compare and study traditional texts of different religions, identify terminology and doctrines. For example, LLMs can compare the concept of "sympathy" expressed in Buddhist Pali scriptures, Christian New Testament texts, and Islamic hadith, providing insights into both general and specific traditional interpretations. LLMs can help explain the subtle differences of the same term in different religious backgrounds. For example, the Sanskrit term "dharma" [8] in Hinduism may refer to justice or responsibility, while in Buddhism, it means the teachings of the Buddha or universal truth. LLMs trained extensively in context can help eliminate ambiguity in these terms during analysis or translation processes. In the cross-religious context, the same symbol may have different meanings in different traditions. For example, the lion is a symbol of strength and divinity in the Judeo Christian tradition, while in the Buddhist tradition it represents wisdom and courage. LLMs can compare these symbols in the corpus and enrich the interpretation by placing them in their respective traditions.

6.3 Opportunities and Challenges

6.3.1 Opportunities: Innovative Applications of Language Models

The application of language models to low-resource literary and religious texts presents remarkable opportunities for preserving and revitalizing religious heritage. These models serve as vital bridges, reducing barriers to literary appreciation while making classic literary works more accessible to contemporary audiences. By delving into texts from low-resource languages such as Croatian and Quechua, language models can uncover and highlight the cultural nuances, historical context, and emotional depth embedded within these works, fostering deeper engagement and appreciation.

To revive low-resource literary works and ensure their resonance with modern audiences, particularly younger generations, the presentation and dissemination of these literary works must align with contemporary tastes and cultural dynamics. Language models can facilitate this by economically producing accessible, high-quality, and readable content tailored to the preferences of target audiences. Leveraging popular platforms and modern formats, such as interactive media or engaging digital narratives, can reintroduce overlooked literary treasures in a way that is both appealing and relevant. This approach not only preserves the vibrancy and influence of these cultural artifacts but also fosters a deeper understanding of global heritage while enabling meaningful dialogue on religious and cultural complexities. Specifically, it helps younger readers engage more effectively with religious texts, improving theological comprehension[46] and contributing to the movement of intercultural peace.

In the realm of religious studies, language models offer a unique opportunity to address doctrinal conflicts and enrich theological discourse. By analyzing religious texts, these models can uncover principles in common and provide clarity in areas where doctrinal interpretations have historically diverged. For example, in *Buddhism and Whiteness: Critical Reflections*, the authors examine how entrenched racial and cultural dynamics shape religious interpretations, underscoring the importance to examine complex sociocultural factors within theological contexts. Furthermore, these models are capable of adapting and refining doctrinal interpretations to align with evolving perspectives[99], while remaining anchored in traditional frameworks. A notable application is the preservation and dissemination of religious traditions tied to specific cultural contexts, such as African-American theology[41]. With thoughtful development and ethical oversight, these models have the capacity to establish balanced frameworks that address doctrinal ambiguities while expanding the accessibility of religious knowledge across diverse cultural boundaries.

6.3.2 Challenges: Limitations in Models' Understanding of Implicit Meaning

While there are multiple innovative applications of language models in low-resource literary and religious texts, a critical challenge in their application to ancient literature and religious texts lies in their limited capacity to interpret the implicit and multilayered meanings. Such texts often draw on intricate metaphors, allegories, and symbolic references that demand not just linguistic interpretability but also cultural, historical, and philosophical insight. Existing language models, grounded in patterns derived from existing datasets, inevitably lack the depth and nuance required to faithfully interpret these complexities, and professional human translations[104] consistently outperform LLMs translations in certain contexts.

The limitation is compounded by the scarcity of preserved external resources and relevant data for many low-resource languages and traditions. While some texts have survived in written form, much of the oral tradition, cultural knowledge, and historical context that breathe life into these works have been lost to time. Without these necessary components, language models struggle to discern the deeper connections within the texts, frequently producing interpretations that are either reductive or outright erroneous. Meanwhile, LLMs often exhibit biases and cultural misrepresentations, as revealed by debate-induced evaluations, which highlight their tendency to align with dominant linguistic or cultural perspectives in training data[16], underscoring the need for fairness and contextual sensitivity in multilingual training.

To overcome these limitations, there is an urgent need for curated datasets enriched by expertise within fields such as history, philosophy, and cultural studies. These datasets must not only provide lexical and grammatical inputs but also encapsulate the symbolic, contextual, and philosophical depth of the source material. Furthermore, fostering collaboration between scholars from diverse disciplines can help bridge the gap between raw textual data and the broader interpretative frameworks required to fully understand these works.

7 Technical and Ethical Considerations for Large Language Models in Low-Resource Languages

7.1 Technical Challenges

LLMs face significant challenges when applied to low-resource languages due to a variety of factors, primarily stemming from the scarcity and quality of available data [33, 43, 73, 97]. Unlike high-resource

languages such as English or Chinese, low-resource languages often lack the extensive and standardized datasets required for effective training. Available data is typically fragmented, non-standardized, or entirely absent, making it difficult for LLMs to learn nuanced linguistic patterns. Furthermore, critical NLP tools, such as part-of-speech taggers and annotated datasets, are frequently unavailable for these languages, further impeding the development of robust models.

Another pressing issue is the lack of computational resources in regions where low-resource languages are predominantly spoken [31, 33]. Training large-scale models demands significant computational power and infrastructure, which are often inaccessible in resource-constrained environments. The high costs associated with training and deploying these models exacerbate the problem, limiting the ability of local researchers and developers to create and utilize advanced NLP tools tailored to their linguistic and cultural needs.

The linguistic and cultural diversity inherent in low-resource languages presents additional hurdles. For example, Africa alone is home to over 2,000 languages, each with unique grammatical rules, vocabulary, and cultural contexts [93]. This diversity complicates the development of multilingual models capable of performing consistently across languages. Moreover, many low-resource languages lack sufficient digital representation, resulting in inadequate data for pretraining and instruction tuning. Consequently, LLMs trained on such data often underperform, reflecting the foundational gap in resources necessary for their development.

Low-resource languages also face specific challenges during training due to inefficiencies in tokenization processes. For instance, non-Latin scripts, such as Bengali, are often over-tokenized by standard methods like Byte Pair Encoding (BPE) [67]. Over-tokenization leads to higher computational costs and lower information density, negatively impacting model efficiency and performance. These inefficiencies highlight the need for more refined tokenization methods tailored to the characteristics of low-resource languages.

To further complicate matters, the data that is available for these languages is often derived from machine translation, introducing biases and inconsistencies into training and evaluation. This reliance on imperfect data sources undermines the reliability of models and hampers their ability to generalize effectively. In cases where pretraining, instruction-tuning, or reinforcement learning with human feedback (RLHF) datasets are available, their quality and coverage are often insufficient to meet the needs of robust language modeling.

In summary, the challenges of applying LLMs to low-resource languages are multifaceted, encompassing issues of data scarcity, computational resource limitations, linguistic diversity, tokenization inefficiencies, and reliance on imperfect data sources. Addressing these challenges requires concerted efforts to improve dataset availability and quality, develop computationally efficient methods, and design culturally and linguistically sensitive models.

7.2 Ethical Challenges

Ethical and fairness concerns also arise when applying LLMs to low-resource languages. Models trained on limited and biased datasets may perpetuate existing linguistic or cultural biases, leading to inaccurate or inappropriate outputs. These biases can negatively impact the fair application of NLP tools in diverse cultural contexts. For instance, Low-resource Indigenous languages often encode culturally sensitive knowledge integral to their communities' identity and heritage. Indiscriminate harvesting of Indigenous language data from online sources poses significant risks to privacy and cultural sovereignty. For example, much of the digital text available for Indigenous languages, such as South Sámi, may come from private or semi-private community contexts [98]. This makes uncritical use of such corpora problematic, as it could expose knowledge the community considers sacred or confidential. Ethical language technology development requires building trust with language communities, ensuring data use respects cultural boundaries and adheres to explicit agreements on data utilization.

LLMs, while promising, can inadvertently worsen the marginalization of low-resource languages. Low-resource Indigenous languages often have limited digitized resources, leading to minimal and potentially flawed representation in language models. Uncorrected errors in machine-generated outputs risk amplification in subsequent models, creating a feedback loop that distorts authentic language usage [98]. Furthermore, the dominance of high-resource languages in training corpora can lead to linguistic homogenization, further weakening the already vulnerable position of low-resource languages. This imbalance threatens the linguistic diversity essential for preserving unique cultural identities.

By prioritizing quantity over quality, LLMs risk imposing majority language norms on Indigenous languages, eroding their distinct grammatical structures, idiomatic expressions, and cultural relevance. Addressing this issue demands a deliberate effort to include native speakers and language experts in the development process, ensuring accurate and equitable representation of Indigenous languages.

These challenges highlight the importance of ethical practices in developing language technologies for Indigenous communities, focusing on protecting cultural knowledge and promoting linguistic diversity in a way that empowers rather than marginalizes these languages.

7.3 Policy Recommendations

Promoting ethical and impactful applications of NLP for low-resource Indigenous languages requires the adoption of thoughtful and inclusive policies. These policies must respect the linguistic and cultural integrity of these communities, prioritize equitable partnerships, and focus on fostering the sustainable development of linguistic resources. Encouraging open data sharing, advocating for equitable research practices, and safeguarding the linguistic ecosystem are essential measures for advancing NLP capabilities for Indigenous languages. Such protection policies not only address the practical challenges of dataset development but also ensure that the resulting tools align with the long-term interests and aspirations of the communities they aim to support. By prioritizing ethical collaboration and cultural preservation, stakeholders can empower Indigenous language communities to thrive and maintain their heritage in the digital age.

Encouraging Open Dataset Sharing and International Collaboration Low-resource Indigenous language communities often face challenges due to the lack of extensive literary traditions, ongoing standardization processes, and inconsistencies in written texts. Many texts available digitally exhibit significant variations in spelling and grammar, often deviating from the norms desired by the language community. Additionally, a notable proportion of these texts are authored by non-native speakers or language learners, resulting in corpora that are not representative of the language’s authentic usage. Governments and institutions should prioritize open dataset sharing initiatives and international collaboration. These collaborative efforts can ensure datasets are curated, verified, and annotated by native speakers and language experts. Such partnerships will facilitate the development of high-quality, representative corpora that align with the community’s cultural and linguistic standards. By promoting international cooperation, organizations can pool resources, expertise, and perspectives to advance the preservation and revitalization of these languages.

Advocating for Equitable Research Policies and Language Ecology Preservation The development of ethical and effective machine learning-based NLP tools requires policies that center the needs and voices of low-resource Indigenous language communities. Outputs from these tools should undergo rigorous evaluation by language experts from within these communities, ensuring cultural and linguistic accuracy. Clear authorship verification and respect for data ownership are critical to maintaining trust and preventing the exploitation of Indigenous knowledge. Policies must advocate for research practices that treat Indigenous communities as equal partners rather than subjects. This involves ensuring that tools developed using Indigenous language data are freely available to the community and modifiable to meet their unique needs. Furthermore, these policies should emphasize acknowledging and crediting the contributions of data providers and actively preserving the linguistic ecology. This includes respecting the cultural, economic, and ideological value of original language data and ensuring that it is used in ways that support community-driven goals.

8 Future Research Directions

8.1 Development of Specialized Language Models for Low-Resource Languages

- **Data Augmentation Techniques for Limited Corpora**

Data augmentation techniques can significantly mitigate the issue of data scarcity in low-resource languages. Methods such as back-translation, synthetic data generation, and contextual data augmentation have been shown to increase the volume and diversity of training data. For instance, back-translation can use high-resource languages as intermediaries to generate pseudo-parallel corpora, while techniques like paraphrasing or noise injection introduce linguistic variability.

These approaches ensure better model generalization and capture unique language-specific patterns that would otherwise remain underrepresented.

- **Multilingual Pretraining for Cross-Language Knowledge Transfer**

Leveraging multilingual pretraining allows large language models to benefit from shared linguistic features across languages. Future research could enhance this approach by exploring dynamic pretraining strategies, where the model progressively adjusts its focus to prioritize low-resource languages during training. Incorporating typological features can further improve transferability, especially for languages with rich morphological or syntactic characteristics.

- **Few-Shot and Zero-Shot Learning for Rapid Adaptation**

Few-shot and zero-shot learning provide avenues for adapting models to low-resource languages with minimal labeled data. Beyond common approaches like prompt-based learning, innovative frameworks such as Model-Agnostic Meta-Learning (MAML) [25] optimize models for task adaptability, enabling them to perform well with only a handful of examples. Dynamic task re-weighting can prioritize features unique to low-resource languages, ensuring better alignment with linguistic structures. Additionally, task-conditioning embeddings that incorporate linguistic typology can guide models to focus on crucial language-specific attributes. For zero-shot learning, retrieval-augmented reasoning can dynamically fetch relevant multilingual examples, improving the model's context-aware adaptation to unseen languages.

- **Incorporating Sociolinguistic and Dialectal Variations**

Low-resource languages often exhibit substantial dialectal and sociolinguistic diversity, which poses challenges for language modeling. To address this, researchers can design models with dialectal embeddings that capture regional and social variations. Another approach is to incorporate multi-variant corpora that represent a broad spectrum of dialects, ensuring that the model generalizes effectively across linguistic communities. Robust pretraining strategies that integrate both written and spoken forms of a language can help models better reflect real-world usage, making them more adaptable to diverse linguistic contexts.

8.2 Interdisciplinary Collaboration for Low-Resource Language Preservation

- **Collaborations Between Linguists and AI Researchers**

Effective preservation of low-resource languages requires collaboration between linguists and AI researchers to bridge the gap between linguistic theory and computational implementation. Linguists can provide insights into unique grammatical structures, phonetic systems, and language-specific phenomena, while AI researchers design models that can effectively leverage these features. For example, linguist-informed annotated corpora can guide language models to better understand syntax and morphology, improving translation, transcription, and other NLP tasks. This partnership ensures that AI solutions respect and reflect the linguistic diversity and cultural depth of low-resource languages.

- **Integration of Anthropological and Ethnographic Perspectives**

Anthropologists and ethnographers bring invaluable cultural and societal context to language preservation efforts. Their expertise in documenting oral traditions, cultural practices, and regional nuances can enrich AI models with contextually relevant data. For instance, ethnographic insights can help define the sociolinguistic parameters of a language, such as its use in ceremonies or as a marker of identity within a community. By combining this knowledge with AI's data-processing capabilities, interdisciplinary projects can ensure that the cultural essence of a language is preserved alongside its linguistic form.

- **Role of Philology and Historical Studies**

Philologists and historians play a crucial role in digitizing and contextualizing ancient texts in low-resource languages. Their expertise in deciphering scripts, annotating ancient documents, and reconstructing linguistic evolution complements AI's ability to process large datasets and

generate insights. Collaborative efforts can focus on creating searchable archives of ancient manuscripts, improving access to historical resources, and training AI models to interpret historical language variants. This ensures that both contemporary and historical dimensions of low-resource languages are preserved.

- **Community-Centric Data Collection and Annotation**

Engaging native speakers and local communities in data collection and annotation ensures that the linguistic and cultural authenticity of low-resource languages is maintained. Community-driven initiatives, such as crowd-sourcing linguistic data or organizing language documentation workshops, empower speakers to take ownership of preservation efforts. By incorporating their perspectives, interdisciplinary projects can build more comprehensive and representative datasets, while fostering a sense of cultural pride and involvement in the digital preservation process.

- **Educational Tools and Language Revitalization Programs**

Interdisciplinary collaboration can also focus on creating educational tools that support language revitalization. For example, linguists, educators, and technologists can co-develop language learning apps, interactive dictionaries, and digital games tailored to teaching low-resource languages. These tools not only help younger generations reconnect with their linguistic heritage but also ensure that the language remains active and evolving. Combining pedagogy with AI-driven insights enables the development of engaging and effective resources that address the specific needs of diverse learner groups.

8.3 Potential for Social Innovation and Cultural Dissemination Through Low-Resource Language Models

- **Preserving Endangered Languages Through Digital Tools**

Low-resource language models can serve as powerful tools for documenting and preserving endangered languages. By creating accessible and interactive digital platforms, these models enable the recording of oral traditions, folklore, and cultural narratives, ensuring their longevity. For example, speech-to-text systems powered by language models can transcribe endangered languages in real time, while mobile applications can gamify language learning to attract younger audiences. These efforts help maintain the cultural identity of minority communities and foster intergenerational transmission of linguistic heritage.

- **Facilitating Cross-Cultural Communication and Collaboration**

Low-resource language models can bridge linguistic gaps between communities, fostering greater cross-cultural understanding and collaboration. For instance, real-time translation tools can enable seamless communication in multilingual regions, promoting social integration and reducing linguistic barriers. Additionally, cultural exchanges facilitated by these technologies can strengthen connections between communities, enabling them to share their histories, traditions, and values on a global stage.

- **Empowering Communities with Accessible Education and Resources**

Language models tailored to low-resource languages can play a transformative role in education. By providing interactive learning tools, digital libraries, and culturally relevant educational content, these models make language resources accessible to marginalized communities. For example, AI-powered chatbots can support language learners with personalized feedback, while digital storytelling platforms can deliver culturally specific narratives. These innovations not only preserve linguistic diversity but also promote equity by ensuring that underrepresented communities have access to modern educational opportunities.

- **Revitalizing Cultural Practices and Artistic Traditions**

By digitizing and analyzing cultural expressions such as poetry, songs, and oral storytelling, low-resource language models can aid in the revival of traditional art forms. AI tools can assist in creating modern adaptations of these traditions, such as composing music inspired by folk

songs or generating digital artwork based on traditional motifs. These efforts not only preserve cultural practices but also make them more accessible and appealing to contemporary audiences, encouraging their continued relevance and evolution.

- **Driving Economic and Social Development in Minority Communities**

By integrating low-resource languages into digital and business ecosystems, language models can drive economic growth and social empowerment. For instance, localized AI applications, such as customer service chatbots or e-commerce platforms, can cater to minority language speakers, opening up new markets and opportunities. Additionally, language models can support community-based tourism initiatives by translating cultural information and providing accessible guides in native languages, boosting local economies while promoting cultural heritage.

- **Ensuring Ethical and Inclusive Cultural Dissemination**

While low-resource language models offer significant potential for cultural dissemination, ethical considerations must remain central to their design and application. Developers must engage with native speakers and community leaders to ensure that cultural knowledge is represented accurately and shared with consent. Transparent data practices, fair compensation for contributors, and respect for intellectual property rights are critical for fostering trust and preventing exploitation. Inclusive frameworks can ensure that technological advancements benefit the communities they aim to serve.

9 Conclusion

The study of low-resource languages, despite their cultural, historical, and intellectual significance, remains an underserved area in computational linguistics. These languages, as vital repositories of humanity’s diverse heritage, face the dual threat of underrepresentation in digital ecosystems and extinction in the real world. This paper has explored how large language models can serve as transformative tools for preserving and revitalizing these languages, offering new avenues for research, cultural preservation, and cross-disciplinary collaboration.

LLMs, with their capacity for multilingual understanding and contextual adaptation, have demonstrated immense potential to address the unique challenges posed by low-resource languages. From breakthroughs in data augmentation and cross-language transfer to innovative methods like zero-shot learning and dialect embedding, these models provide scalable solutions to bridge linguistic gaps. By leveraging techniques such as retrieval-augmented generation, task-conditioning embeddings, and meta-learning, LLMs are increasingly capable of adapting to the intricate linguistic and sociocultural dimensions of these languages, fostering their inclusion in the global linguistic landscape.

However, this journey is fraught with challenges. The scarcity and complexity of data, coupled with the computational and ethical considerations inherent in working with marginalized languages, underscore the need for sustained, interdisciplinary efforts. Linguists, anthropologists, educators, and AI researchers must collaborate to ensure that the technological advancements are culturally sensitive, ethically grounded, and community-driven. Efforts to build annotated corpora, digitize historical texts, and engage native speakers in the data collection process are not merely technical necessities but ethical imperatives.

Furthermore, the application of low-resource language models transcends linguistic preservation, opening new pathways for social innovation and economic empowerment. By fostering cross-cultural communication, enhancing education accessibility, and revitalizing artistic traditions, these models hold the promise of creating a more inclusive and interconnected world. At the same time, careful attention must be given to ethical data practices, ensuring transparency, fairness, and respect for the intellectual property and cultural sovereignty of indigenous and minority communities.

In conclusion, the convergence of advanced AI capabilities and the collective commitment of global communities offers an unprecedented opportunity to safeguard humanity’s linguistic and cultural diversity. Low-resource language models are not merely tools for computational innovation but catalysts for preserving the narratives, knowledge systems, and identities that define our shared heritage. By prioritizing inclusivity, ethical engagement, and interdisciplinary collaboration, we can ensure that these languages thrive in both digital and social realms, contributing to a richer and more equitable future for all.

References

- [1] Achiam, J., Adler, S., Agarwal, S., Ahmad, L., Akkaya, I., Aleman, F.L., Almeida, D., Altenschmidt, J., Altman, S., Anadkat, S., et al.: Gpt-4 technical report. arXiv preprint arXiv:2303.08774 (2023)
- [2] Agliz, R.: Translation of religious texts: Difficulties and challenges. Arab World English Journal (AWEJ) Special Issue on Translation (2015)
- [3] Alam, F., Chowdhury, S.A., Boughorbel, S., Hasanain, M.: Llms for low resource languages in multilingual, multimodal, and dialectal settings. Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics pp. 27–33 (2024)
- [4] Assael, Y., Sommerschild, T., Shillingford, B., Bordbar, M., Pavlopoulos, J., Chatzipanagiotou, M., Androutsopoulos, I., Prag, J., de Freitas, N.: Restoring and attributing ancient texts using deep neural networks. Nature **603**(7900), 280–283 (2022)
- [5] Avyodri, R., Lukas, S., Tjahyadi, H.: Optical character recognition (ocr) for text recognition and its post-processing method: A literature review. In: 2022 1st International Conference on Technology Innovation and Its Applications (ICTIIA). pp. 1–6. IEEE (2022)
- [6] Barucci, A., Canfailla, C., Cucci, C., Forasassi, M., Franci, M., Guarducci, G., Guidi, T., Loschiavo, M., Picollo, M., Pini, R., et al.: Ancient egyptian hieroglyphs segmentation and classification with convolutional neural networks. In: International Conference Florence Heri-Tech: the Future of Heritage Science and Technologies. pp. 126–139. Springer (2022)
- [7] Bimagambetova, Z., Rakhymzhanov, D., Jaxylykova, A., Pak, A.: Evaluating large language models for sentence augmentation in low-resource languages: A case study on kazakh. In: 2023 19th International Asian School-Seminar on Optimization Problems of Complex Systems (OPCS). pp. 14–18. IEEE (2023)
- [8] Brockington, J.: The concept of” dharma” in the rāmāyaṇa. Journal of Indian Philosophy **32**(5/6), 655–670 (2004)
- [9] Brown, T.B.: Language models are few-shot learners. arXiv preprint arXiv:2005.14165 (2020)
- [10] Cekinel, R.F., Karagoz, P., Coltekin, C.: Cross-lingual learning vs. low-resource fine-tuning: A case study with fact-checking in turkish. arXiv preprint arXiv:2403.00411 (2024)
- [11] Cho, K.: Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078 (2014)
- [12] Conneau, A.: Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116 (2019)
- [13] Dai, H., Li, Y., Liu, Z., Zhao, L., Wu, Z., Song, S., Shen, Y., Zhu, D., Li, X., Li, S., et al.: Ad-autogpt: An autonomous gpt for alzheimer’s disease infodemiology. arXiv preprint arXiv:2306.10095 (2023)
- [14] Dai, H., Liu, Z., Liao, W., Huang, X., Wu, Z., Zhao, L., Liu, W., Liu, N., Li, S., Zhu, D., et al.: Chataug: Leveraging chatgpt for text data augmentation. arXiv preprint arXiv:2302.13007 (2023)
- [15] Deane, P.D.: Polysemy and cognition. Lingua **75**(4), 325–361 (1988). [https://doi.org/https://doi.org/10.1016/0024-3841\(88\)90009-5](https://doi.org/https://doi.org/10.1016/0024-3841(88)90009-5), <https://www.sciencedirect.com/science/article/pii/0024384188900095>
- [16] Demidova, A., Atwany, H., Rabih, N., Sha’ban, S., Abdul-Mageed, M.: John vs. ahmed: Debate-induced bias in multilingual LLMs. In: Habash, N., Bouamor, H., Eskander, R., Tomeh, N., Abu Farha, I., Abdelali, A., Touileb, S., Hamed, I., Onaizan,

- Y., Alhafni, B., Antoun, W., Khalifa, S., Haddad, H., Zitouni, I., AlKhamissi, B., Almatham, R., Mrini, K. (eds.) Proceedings of The Second Arabic Natural Language Processing Conference. pp. 193–209. Association for Computational Linguistics, Bangkok, Thailand (Aug 2024). <https://doi.org/10.18653/v1/2024.arabicnlp-1.18>, <https://aclanthology.org/2024.arabicnlp-1.18>
- [17] Devlin, J.: Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018)
- [18] Dhali, M., He, S., Popovic, M., Tigchelaar, E., Schomaker, L.: A digital palaeographic approach towards writer identification in the dead sea scrolls. In: International Conference on Pattern Recognition Applications and Methods 2017. pp. 693–702 (2017)
- [19] Dhali, M.A., de Wit, J.W., Schomaker, L.: Binet: Degraded-manuscript binarization in diverse document textures and layouts using deep encoder-decoder networks. arXiv preprint arXiv:1911.07930 (2019)
- [20] Dubey, A., Jauhri, A., Pandey, A., Kadian, A., Al-Dahle, A., Letman, A., Mathur, A., Schelten, A., Yang, A., Fan, A., et al.: The llama 3 herd of models. arXiv preprint arXiv:2407.21783 (2024)
- [21] Dunder, I., Seljan, S., Pavlovski, M.: Automatic machine translation of poetry and a low-resource language pair. In: 2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO). pp. 1034–1039. IEEE (2020)
- [22] Eledath, D., Baby, A., Singh, S.: Robust speech recognition using meta-learning for low-resource accents. In: 2024 National Conference on Communications (NCC). pp. 1–6 (2024). <https://doi.org/10.1109/NCC60321.2024.10485786>
- [23] Elewa, A.: Features of translating religious texts. *Journal of translation* **10**(1), 25–33 (2014)
- [24] Erasmo, M.: The theatre of pompey. *Memoirs of the American Academy in Rome* **65**, 43–69 (2020)
- [25] Finn, C., Abbeel, P., Levine, S.: Model-agnostic meta-learning for fast adaptation of deep networks. In: International conference on machine learning. pp. 1126–1135. PMLR (2017)
- [26] Goel, A.: Beyond the Surface: A Computational Exploration of Linguistic Ambiguity. Master of science thesis, International Institute of Information Technology (IIIT), Hyderabad (2023), <https://api.semanticscholar.org/CorpusID:259371553>, report No: IIIT/TH/2023/84
- [27] Gonen, H., Ravfogel, S., Elazar, Y., Goldberg, Y.: It’s not greek to mbert: inducing word-level translations from multilingual bert. arXiv preprint arXiv:2010.08275 (2020)
- [28] Graves, A., Graves, A.: Long short-term memory. Supervised sequence labelling with recurrent neural networks pp. 37–45 (2012)
- [29] Guan, H., Yang, H., Wang, X., Han, S., Liu, Y., Jin, L., Bai, X., Liu, Y.: Deciphering oracle bone language with diffusion models. arXiv preprint arXiv:2406.00684 (2024)
- [30] Gwervende, S., Mthombeni, Z.M.: Safeguarding intangible cultural heritage: exploring the synergies in the transmission of indigenous languages, dance and music practices in southern africa. *International Journal of Heritage Studies* **29**(5), 398–412 (2023)
- [31] Hasan, M.A., Tarannum, P., Dey, K., Razzak, I., Naseem, U.: Do large language models speak all languages equally? a comparative study in low-resource settings. arXiv preprint arXiv:2408.02237 (2024)
- [32] Hedderich, M.A., Lange, L., Adel, H., Strotgen, J., Klakow, D.: A survey on recent approaches for natural language processing in low-resource scenarios. In: North American Chapter of the Association for Computational Linguistics (2020), <https://api.semanticscholar.org/CorpusID:225062337>

- [33] Hedderich, M.A., Lange, L., Adel, H., Strötgen, J., Klakow, D.: A survey on recent approaches for natural language processing in low-resource scenarios. arXiv preprint arXiv:2010.12309 (2020)
- [34] ter Hoeve, M., Grangier, D., Schluter, N.: High-resource methodological bias in low-resource investigations (2022), <https://arxiv.org/abs/2211.07534>
- [35] Huang, J., Kuchaiev, O., O’Neill, P., Lavrukhin, V., Li, J., Flores, A., Kucsko, G., Ginsburg, B.: Cross-language transfer learning, continuous learning, and domain adaptation for end-to-end automatic speech recognition. arXiv preprint arXiv:2005.04290 (2020)
- [36] Huang, Y., Sun, L., Wang, H., Wu, S., Zhang, Q., Li, Y., Gao, C., Huang, Y., Lyu, W., Zhang, Y., et al.: Position: Trustllm: Trustworthiness in large language models. In: International Conference on Machine Learning. pp. 20166–20270. PMLR (2024)
- [37] Huang, Y., Sun, L., Wang, H., Wu, S., Zhang, Q., Li, Y., Gao, C., Huang, Y., Lyu, W., Zhang, Y., et al.: Trustllm: Trustworthiness in large language models. arXiv preprint arXiv:2401.05561 (2024)
- [38] Hutson, J., Ellsworth, P., Ellsworth, M.: Preserving linguistic diversity in the digital age: A scalable model for cultural heritage continuity. Faculty Scholarship **612** (2024), <https://digitalcommons.lindenwood.edu/faculty-research-papers/612>, available online
- [39] Jäkel, O.: Hypotheses revisited: The cognitive theory of metaphor applied to religious texts. *Metaphorik. de* **2**(1), 20–42 (2002)
- [40] Jiang, H., Pan, Y., Chen, J., Liu, Z., Zhou, Y., Shu, P., Li, Y., Zhao, H., Mihm, S., Howe, L.C., Liu, T.: Oraclesage: Towards unified visual-linguistic understanding of oracle bone scripts through cross-modal knowledge fusion (2024), <https://arxiv.org/abs/2411.17837>
- [41] Jones Medine, C.M.: T&t clark handbook of african american theology. edited by antonia michelle daymond, frederick l. ware, and eric lewis williams. new york: Bloomsbury t&t clark, 2019. 464 pages. \$198.00. *Horizons* **50**(1), 230–232 (2023). <https://doi.org/10.1017/hor.2023.26>
- [42] Karabayeva, I., Kalizhanova, A.: Evaluating machine translation of literature through rhetorical analysis. *Journal of Translation and Language Studies* **5**(1), 1–9 (2024)
- [43] Kholodna, N., Julka, S., Khodadadi, M., Gumus, M.N., Granitzer, M.: Llms in the loop: Leveraging large language model annotations for active learning in low-resource languages. In: Joint European Conference on Machine Learning and Knowledge Discovery in Databases. pp. 397–412. Springer (2024)
- [44] Kirk, H.R., Vidgen, B., Röttger, P., Hale, S.A.: Personalisation within bounds: A risk taxonomy and policy framework for the alignment of large language models with personalised feedback (2023), <https://arxiv.org/abs/2303.05453>
- [45] Koopmans, L., Dhali, M.A., Schomaker, L.: Performance analysis of handwritten text augmentation on style-based dating of historical documents. *SN Computer Science* **5**(4), 397 (2024)
- [46] LeBlanc, J.R., Medine, C.M.J.: Ancient and Modern Religion and Politics: Negotiating Transitive Spaces and Hybrid Identities. Palgrave Macmillan (2012)
- [47] Lee, G.G., Shi, L., Latif, E., Gao, Y., Bewersdorf, A., Nyaaba, M., Guo, S., Wu, Z., Liu, Z., Wang, H., et al.: Multimodality of ai for education: Towards artificial general intelligence. arXiv preprint arXiv:2312.06037 (2023)
- [48] Li, C., Chen, M., Wang, J., Sitaram, S., Xie, X.: Culturellm: Incorporating cultural differences into large language models. arXiv preprint arXiv:2402.10946 (2024)
- [49] Li, C., Teney, D., Yang, L., Wen, Q., Xie, X., Wang, J.: Culturepark: Boosting cross-cultural understanding in large language models (2024), <https://arxiv.org/abs/2405.15145>
- [50] Li, Y., Zhao, H., Jiang, H., Pan, Y., Liu, Z., Wu, Z., Shu, P., Tian, J., Yang, T., Xu, S., et al.: Large language models for manufacturing. arXiv preprint arXiv:2410.21418 (2024)

- [51] Liao, W., Liu, Z., Dai, H., Xu, S., Wu, Z., Zhang, Y., Huang, X., Zhu, D., Cai, H., Li, Q., et al.: Differentiating chatgpt-generated and human-written medical texts: quantitative study. *JMIR Medical Education* **9**(1), e48904 (2023)
- [52] Lin, D., Murakami, Y., Ishida, T.: Towards language service creation and customization for low-resource languages. *Information* **11**(2), 67 (2020)
- [53] Liu, A., Wu, Z., Michael, J., Suhr, A., West, P., Koller, A., Swayamdipta, S., Smith, N.A., Choi, Y.: We're afraid language models aren't modeling ambiguity (2023), <https://arxiv.org/abs/2304.14399>
- [54] Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., et al.: Summary of chatgpt-related research and perspective towards the future of large language models. *Meta-Radiology* p. 100017 (2023)
- [55] Liu, Y., He, H., Han, T., Zhang, X., Liu, M., Tian, J., Zhang, Y., Wang, J., Gao, X., Zhong, T., et al.: Understanding llms: A comprehensive overview from training to inference. *arXiv preprint arXiv:2401.02038* (2024)
- [56] Liu, Z., He, X., Liu, L., Liu, T., Zhai, X.: Context matters: A strategy to pre-train language model for science education. *arXiv preprint arXiv:2301.12031* (2023)
- [57] Liu, Z., Li, Y., Cao, Q., Chen, J., Yang, T., Wu, Z., Hale, J., Gibbs, J., Rasheed, K., Liu, N., et al.: Transformation vs tradition: Artificial general intelligence (agi) for arts and humanities. *arXiv preprint arXiv:2310.19626* (2023)
- [58] Liu, Z., Li, Y., Cao, Q., Chen, J., Yang, T., Wu, Z., Hale, J., Gibbs, J., Rasheed, K., Liu, N., et al.: Transformation vs tradition: Artificial general intelligence (agi) for arts and humanities. *arXiv preprint arXiv:2310.19626* (2023)
- [59] Liu, Z., Li, Y., Shu, P., Zhong, A., Yang, L., Ju, C., Wu, Z., Ma, C., Luo, J., Chen, C., et al.: Radiology-llama2: Best-in-class large language model for radiology. *arXiv preprint arXiv:2309.06419* (2023)
- [60] Liu, Z., Wang, P., Li, Y., Holmes, J., Shu, P., Zhang, L., Liu, C., Liu, N., Zhu, D., Li, X., et al.: Radonc-gpt: A large language model for radiation oncology. *arXiv preprint arXiv:2309.10160* (2023)
- [61] Liu, Z., Wang, P., Li, Y., Holmes, J.M., Shu, P., Zhang, L., Li, X., Li, Q., Vora, S.A., Patel, S., et al.: Fine-tuning large language models for radiation oncology, a highly specialized healthcare domain. *International Journal of Particle Therapy* **12**, 100428 (2024)
- [62] Liu, Z., Zhang, L., Wu, Z., Yu, X., Cao, C., Dai, H., Liu, N., Liu, J., Liu, W., Li, Q., et al.: Surviving chatgpt in healthcare. *Frontiers in Radiology* **3**, 1224682 (2024)
- [63] Lyu, Y., Wu, Z., Zhang, L., Zhang, J., Li, Y., Ruan, W., Liu, Z., Yu, X., Cao, C., Chen, T., et al.: Gp-gpt: Large language model for gene-phenotype mapping. *arXiv preprint arXiv:2409.09825* (2024)
- [64] Lívio, C., Howe, C.: Text mining approaches to language use in social media: The case of portuguese bué. *Languages* **9**(3) (2024). <https://doi.org/10.3390/languages9030082>, <https://www.mdpi.com/2226-471X/9/3/82>
- [65] Ma, C., Wu, Z., Wang, J., Xu, S., Wei, Y., Liu, Z., Zeng, F., Jiang, X., Guo, L., Cai, X., et al.: An iterative optimizing framework for radiology report summarization with chatgpt. *IEEE Transactions on Artificial Intelligence* (2024)
- [66] Magueresse, A., Carles, V., Heetderks, E.: Low-resource languages: A review of past work and future challenges (2020), <https://arxiv.org/abs/2006.07264>
- [67] Mahfuz, T., Dey, S.K., Naswan, R., Adil, H., Sayeed, K.S., Shahgir, H.S.: Too late to train, too early to use? a study on necessity and viability of low-resource bengali llms. *arXiv preprint arXiv:2407.00416* (2024)

- [68] Mani, G., Namomsa, G.B.: Large language models (llms): Representation matters, low-resource languages and multi-modal architecture. In: 2023 IEEE AFRICON. pp. 1–6. IEEE (2023)
- [69] Meaney, J., Alex, B., Lamb, W.: Evaluating and adapting large language models to represent folktales in low-resource languages. arXiv preprint arXiv:2411.05593 (2024)
- [70] Mehrparvar, B., Pezzelle, S.: Detecting and translating language ambiguity with multilingual LLMs. In: Sälevä, J., Owodunni, A. (eds.) Proceedings of the Fourth Workshop on Multilingual Representation Learning (MRL 2024). pp. 310–323. Association for Computational Linguistics, Miami, Florida, USA (Nov 2024), <https://aclanthology.org/2024.mrl-1.26>
- [71] Memon, J., Sami, M., Khan, R.A., Uddin, M.: Handwritten optical character recognition (ocr): A comprehensive systematic literature review (slr). IEEE access **8**, 142642–142668 (2020)
- [72] Nguyen, T.T.H., Jatowt, A., Coustaty, M., Doucet, A.: Survey of post-ocr processing approaches. ACM Computing Surveys (CSUR) **54**(6), 1–37 (2021)
- [73] Ogueji, K., Zhu, Y., Lin, J.: Small data? no problem! exploring the viability of pretrained multilingual language models for low-resourced languages. In: Proceedings of the 1st Workshop on Multilingual Representation Learning. pp. 116–126 (2021)
- [74] Olsen, S.H.: The” meaning” of a literary work. *New Literary History* **14**(1), 13–32 (1982)
- [75] Parida, S., Panwar, S., Lata, K., Mishra, S., Sekhar, S.: Building pre-train llm dataset for the indic languages: A case study on hindi. arXiv preprint arXiv:2407.09855 (2024)
- [76] Pasadika, B.: Nirvana in candrakirti’s prasannapada. *The Tibet Journal* **32**(3), 64–68 (2007)
- [77] Popović, M., Dhali, M.A., Schomaker, L.: Artificial intelligence based writer identification generates new evidence for the unknown scribes of the dead sea scrolls exemplified by the great isaiah scroll (1qisaa). *PloS one* **16**(4), e0249769 (2021)
- [78] Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., Sutskever, I., et al.: Language models are unsupervised multitask learners. *OpenAI blog* **1**(8), 9 (2019)
- [79] Ragni, A., Knill, K.M., Rath, S.P., Gales, M.J.: Data augmentation for low resource languages. In: INTERSPEECH 2014: 15th annual conference of the international speech communication association. pp. 810–814. International Speech Communication Association (ISCA) (2014)
- [80] Ranathunga, S., Lee, E.S.A., Prifti Skenduli, M., Shekhar, R., Alam, M., Kaur, R.: Neural machine translation for low-resource languages: A survey. *ACM Computing Surveys* **55**(11), 1–37 (2023)
- [81] Rao, A., Yerukola, A., Shah, V., Reinecke, K., Sap, M.: Normad: A benchmark for measuring the cultural adaptability of large language models. arXiv preprint arXiv:2404.12464 (2024)
- [82] Rezayi, S., Dai, H., Liu, Z., Wu, Z., Hebbbar, A., Burns, A.H., Zhao, L., Zhu, D., Li, Q., Liu, W., et al.: Clinicalradiobert: Knowledge-infused few shot learning for clinical notes named entity recognition. In: Machine Learning in Medical Imaging: 13th International Workshop, MLMI 2022, Held in Conjunction with MICCAI 2022, Singapore, September 18, 2022, Proceedings. pp. 269–278. Springer (2022)
- [83] Romanenko, A.: Robust Speech Recognition for Low-Resource Languages. Doctoral dissertation, Ulm University and ITMO University, Ulm, Germany and St. Petersburg, Russia (2020), <http://dx.doi.org/10.18725/OPARU-41801>, supervised by Prof. Dr.-Ing. Wolfgang Minker and Prof. Dr. Sc. Yuri N. Matveev
- [84] Saunt, C.: A new order of things: property, power, and the transformation of the Creek Indians, 1733-1816. No. 6, Cambridge University Press (1999)
- [85] Saunt, C.: Black, White, and Indian: Race and the unmaking of an American family. Oxford University Press, USA (2005)

- [86] Saunt, C.: The age of imperial expansion, 1763–1821. *The Oxford Handbook of American Indian History* p. 77 (2016)
- [87] Saunt, C.: “our indians”: European empires and the history of the native american south. In: *The Atlantic in Global History*, pp. 63–79. Routledge (2017)
- [88] Saunt, C.: *Unworthy republic: The dispossession of Native Americans and the road to Indian Territory*. WW Norton & Company (2020)
- [89] Seo, M., Baek, J., Thorne, J., Hwang, S.J.: Retrieval-augmented data augmentation for low-resource domain tasks (2024), <https://arxiv.org/abs/2402.13482>
- [90] Sommerschild, T., Assael, Y., Pavlopoulos, J., Stefanak, V., Senior, A., Dyer, C., Bodel, J., Prag, J., Androutsopoulos, I., de Freitas, N.: Machine learning for ancient languages: A survey. *Computational Linguistics* **49**(3), 703–747 (2023)
- [91] Tehrani, J.J.: The cultural transmission and evolution of folk narratives. In: *The Oxford Handbook of Cultural Evolution*. Oxford University Press (2023). <https://doi.org/10.1093/oxfordhb/9780198869252.013.39>, <https://doi.org/10.1093/oxfordhb/9780198869252.013.39>
- [92] Tian, J., Hou, J., Wu, Z., Shu, P., Liu, Z., Xiang, Y., Gu, B., Filla, N., Li, Y., Liu, N., et al.: Assessing large language models in mechanical engineering education: A study on mechanics-focused conceptual understanding. arXiv preprint arXiv:2401.12983 (2024)
- [93] Tonja, A.L., Dossou, B.F., Ojo, J., Rajab, J., Thior, F., Wairagala, E.P., Aremu, A., Moiloa, P., Abbott, J., Marivate, V., et al.: Inkubalm: A small language model for low-resource african languages. arXiv preprint arXiv:2408.17024 (2024)
- [94] Vasconcelos, M., de Souza Mizukami, P., Pinhanetz, C.S.: Disappearing without a trace: Coverage, community, quality, and temporal dynamics of wikipedia articles on endangered brazilian indigenous languages. In: *Proceedings of the International AAAI Conference on Web and Social Media*. vol. 18, pp. 1531–1544 (2024)
- [95] Wang, J., Jiang, H., Liu, Y., Ma, C., Zhang, X., Pan, Y., Liu, M., Gu, P., Xia, S., Li, W., et al.: A comprehensive review of multimodal large language models: Performance and challenges across different tasks. arXiv preprint arXiv:2408.01319 (2024)
- [96] Wang, J., Zhao, H., Yang, Z., Shu, P., Chen, J., Sun, H., Liang, R., Li, S., Shi, P., Ma, L., et al.: Legal evaluations and challenges of large language models. arXiv preprint arXiv:2411.10137 (2024)
- [97] Wang, L., Xiao, Y.: Improving low-resource machine translation using reinforcement learning from human feedback. *Intelligent Automation & Soft Computing* **39**(4) (2024)
- [98] Wiecheteck, L., Pirinen, F.A., Gaup, B., Trosterud, T., Kappfjell, M.L., Moshagen, S.: The ethical question—use of indigenous corpora for large language models. In: *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. pp. 15922–15931 (2024)
- [99] Yancy, G., McRae, E., Willis, J., Suh, S., Ann Gleig, U., Kalmanson, L., Vesely-Flad, R., Cassidy, L., Medine, C., Syedullah, J., et al.: *Buddhism and Whiteness: Critical Reflections*. Philosophy of Race, Lexington Books (2019), <https://books.google.com/books?id=-e-YDwAAQBAJ>
- [100] Yang, T.M.: *A Medicated Empire: The Pharmaceutical Industry and Modern Japan*. Cornell University Press (2021)
- [101] Yao, D., Zhao, Y., Ye, Y., Rao, G., Abudukelimu, A.: Where will low-resource languages go in the context of chatgpt? *Journal of Leshan Normal University* **39**(08), 36–44 (2024). <https://doi.org/10.16069/j.cnki.51-1610/g4.2024.08.005>

- [102] Zaikis, D., Vlahavas, I.: From pre-training to meta-learning: A journey in low-resource-language representation learning. *IEEE Access* **11**, 115951–115967 (2023). <https://doi.org/10.1109/ACCESS.2023.3326337>
- [103] Zhang, K., Zhou, R., Adhikarla, E., Yan, Z., Liu, Y., Yu, J., Liu, Z., Chen, X., Davison, B.D., Ren, H., et al.: A generalist vision–language foundation model for diverse biomedical tasks. *Nature Medicine* pp. 1–13 (2024)
- [104] Zhang, R., Zhao, W., Eger, S.: How good are llms for literary translation, really? literary translation evaluation with humans and llms (2024), <https://arxiv.org/abs/2410.18697>
- [105] Zhang, Y., Yang, Q.: A survey on multi-task learning. *IEEE Transactions on Knowledge and Data Engineering* **34**(12), 5586–5609 (2022). <https://doi.org/10.1109/TKDE.2021.3070203>
- [106] Zhao, H., Ling, Q., Pan, Y., Zhong, T., Hu, J.Y., Yao, J., Xiao, F., Xiao, Z., Zhang, Y., Xu, S.H., et al.: Ophtha-llama2: A large language model for ophthalmology. *arXiv preprint arXiv:2312.04906* (2023)
- [107] Zhao, H., Liu, Z., Wu, Z., Li, Y., Yang, T., Shu, P., Xu, S., Dai, H., Zhao, L., Mai, G., et al.: Revolutionizing finance with llms: An overview of applications and insights. *arXiv preprint arXiv:2401.11641* (2024)
- [108] Zhao, L., Zhang, L., Wu, Z., Chen, Y., Dai, H., Yu, X., Liu, Z., Zhang, T., Hu, X., Jiang, X., et al.: When brain-inspired ai meets agi. *Meta-Radiology* p. 100005 (2023)
- [109] Zhenyuan, Y., Zhengliang, L., Jing, Z., Cen, L., Jiabin, T., Tianyang, Z., Yiwei, L., Siyan, Z., Teng, Y., Qing, L., et al.: Analyzing nobel prize literature with large language models. *arXiv preprint arXiv:2410.18142* (2024)
- [110] Zoph, B., Yuret, D., May, J., Knight, K.: Transfer learning for low-resource neural machine translation. *arXiv preprint arXiv:1604.02201* (2016)