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# AI Applications for Endangered Language Preservation

[1]**Sadia Baloch***,[2]**Hamza Riaz**
[1]Assistant Professor of Linguistics, University of Sindh, Jamshoro
[2]Lecturer in Language and Cultural Studies, National University of Modern Languages (NUML), Islamabad
hamza.riaz@numl.edu.pk
***Corresponding Email:** sadia.baloch@usindh.edu.pk

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## *ABSTRACT*

*This paper explores how artificial intelligence (AI) can be applied to protect endangered languages through computational linguistics and machine learning and natural language processing (NLP). The findings indicate that AI-based solutions, such speech recognition, text-to-speech synthesis, and neural machine translation, can make documenting and reviving endangered languages faster. The research indicates that speech-to-text transcription and cross-lingual translation can be more precise by applying deep learning models on phonetic and grammatical structure. This eases the use of the same by the researchers and the native speakers. Moreover, community-based AI systems were shown to support communal language learning and digital preservation, therefore, helping to maintain intergenerational knowledge. The findings revealed that the hybrid approaches that combine the use of both supervised and unsupervised learning were superior in detecting dialectal variations. They also demonstrated that reinforcements learning techniques enhanced conversational AI of languages that lack sufficient documentation. Incorporating AI into study tools provided students with even more reasons to study as well as to preserve their cultural identity. The research concludes that AI is not solely a technological answer but also a sustainable cultural system, which links the digital innovation to the history of language. These outcomes demonstrate how AI can transform the world assisting in preserving language diversity and cultural identity.*

***KEYWORDS:*** *Artificial Intelligence, Endangered Languages, Natural Language Processing, Machine Learning, Speech Recognition, Language Preservation*

## INTRODUCTION

Linguistic diversity is a phenomenon that is being eroded in all parts of the world. There are nearly 3,000 other languages who face the threat of extinction due to globalization and the prevailing use of the dominant languages (Anik et al., 2025). Such linguistic erosion does not only refer to dying out unique communication systems, but also the invaluable cultural heritage and time-honored knowledge, which is naturally incorporated in these languages (Hutson et al., 2024). In its turn, artificial intelligence, particularly, highly advanced natural language processing and massive language models have turned out to be a promising new field in documenting, revitalising, and preserving these languages in danger of extinction (Koc, 2025). In this paper, I will discuss the new uses of AI in this area, focusing on how the ethical and effective application of these methods can be done to facilitate the revitalization of the language so that solutions are developed in collaboration with, and to the benefit of, indigenous peoples (Pinhanez et al., 2024). In the paper, AI as the means of providing immersive learning environments, assisting in the creation of language-specific resources, and helping to conduct the linguistic analysis necessary to the comprehensive understanding of endangered languages and their pedagogical progress will be examined (Bendel and N'Diaye, 2023). Moreover, AIs can analyze the data on student performance within seconds, thus allowing teachers to adjust the learning process to the strengths and weaknesses of each child that significantly enhances language acquisition (Muawanah et al., 2024). This is a very crucial adaptive learning technique in languages that lack sufficient teaching formats. It utilizes the resources that are available to full and tailors the lessons to the individual needs of a student (Pradhan & Dey, 2023). The development of dedicated large language models in low resource languages, such as LakotaBERT in the case of the critically endangered Lakota language, demonstrate how AI can circumvent the lack of data issue by developing full corpora and language-specific tools that are required in revitalization programs (Parankusham et al., 2025). These models designed to address the complexities and structural challenges of the endangered languages produce new language materials and assist language learners in a fashion that has never been achievable before (Cong, 2024). However, other obstacles to the use of general-purpose large language models on low-resource languages often include the lack of training data and the intricacies of reflecting cultural subtleties. This case necessitates the development of special bilingual models or adaptation strategies to enhance their effectiveness on those languages (Ding et al., 2024). Those constraints highlight the fundamental importance of community-based AI development, whereby it ensures that technology interventions are culturally appropriate and directly respond to specific needs and goals of the language revitalization programs. This practice acknowledges that the technology

that is developed externally to the community might not necessarily satisfy its needs (Fernandez-Sabido and Peniche-Sabido, 2025). Conversely, the instruments that are developed in the community can become potent ways of expressing themselves. This participatory paradigm ensures that AI tools do not just consist of technological solutions; they are significant components of bigger projects to enhance society and culture. When handling sensitive cultural information, one should pay close attention to the ethical concerns and potential prejudice that accompany AI models. This is in order not to propagate harmful stereotypes or to pervert language and cultural contexts. The protection of languages by AI therefore needs a thorough understanding of what it is able and unable to achieve, particularly in the retention of native systems of indigenous knowledge that are real and true. Consequently, commitment to data sovereignty and cultural considerations is extremely significant. This will ensure that the development of AI is founded on the principles of permission, reciprocity, and benefit-sharing to assist linguistic communities (Smart et al., 2024). This work is going to critically evaluate modern AI methods in the preservation of endangered languages and provide a paradigm of effective and ethical application of this method which focuses on communication with the community and reduces the predetermined bias inherent in data and algorithms. It will also discuss the importance of the need to develop culturally sensitive AI models which consider the needs and characteristics of each language population. This involves a strict evaluation of existing data sets and their bias, the development of extensive ethical principles governing data collection and model development, and the development of transparent governance mechanisms to ensure responsibility (Yang et al., 2024). The discussion will also cover methods of fostering cooperation among linguists, technologists and community members to ensure they collaborate and deliver technical and culturally competent AI solutions. Also, it will discuss the ways in which AI can address the problem of digital neocolonialism, which ensures indigenous languages are not marginalized unintentionally or the promotion of Western linguistic biases (Nyaaba et al., 2024). The framework aims at fostering self-determination and language empowerment, thus putting into question the historical influence of the existing linguistic paradigms (Ofosu-Asare, 2024). The discussion shall also include the technical enhancements that AI models require in a bid to process and generate the complex linguistic structures that are characteristic of most of the endangered languages. Such structures frequently comprise rich morphological systems and even idiosyncratic phonemic inventories not typical of high resource languages. Moreover, given the complexity of these linguistic attributes, it is necessary to develop novel AI architectures capable of handling such complexities, and that extend beyond models that are mostly trained on Indo-European languages (Bella et al., 2023). This includes the development of neural network

architecture and training methods especially for languages with low resource requirements and morphological complexity, and efforts to add specialized linguistic knowledge directly to AI systems. Such a combination is necessary to help avoid techno-linguistic prejudice, which can lead to epistemic injustice in favor of languages that have a lot of digital resources (Helm et al., 2023). This includes a detailed analysis of how the existing AI systems, often structured in ways that are biased to high-resource languages, keep low-resource languages in structural imbalance and oversight (Shahid et al., 2025).

**METHODOLOGY**

This research employed a mixed-methods experimental design that integrated both qualitative and quantitative approaches to assess the potential of artificial intelligence in preserving endangered languages. On the quantitative side, large-scale linguistic datasets were collected from existing archives, digital corpora, and oral recordings contributed by native speakers. These datasets included phonetic transcriptions, semantic annotations, and syntactic structures, which were preprocessed through tokenization, stemming, and normalization to ensure consistency. Neural network models, particularly recurrent neural networks (RNNs) and transformers such as BERT and GPT-based architectures, were trained for tasks including speech recognition, machine translation, and text generation. The performance of these models was evaluated using standard metrics such as accuracy, BLEU score for translation, and Word Error Rate (WER) for speech recognition. To mathematically represent translation quality, the BLEU score was computed as:

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

where $BP$ is the brevity penalty, $p_n$ denotes the modified n-gram precision, and $w_n$ represents the weight assigned to each n-gram level. Similarly, improvements in speech recognition accuracy were quantified by minimizing the function:

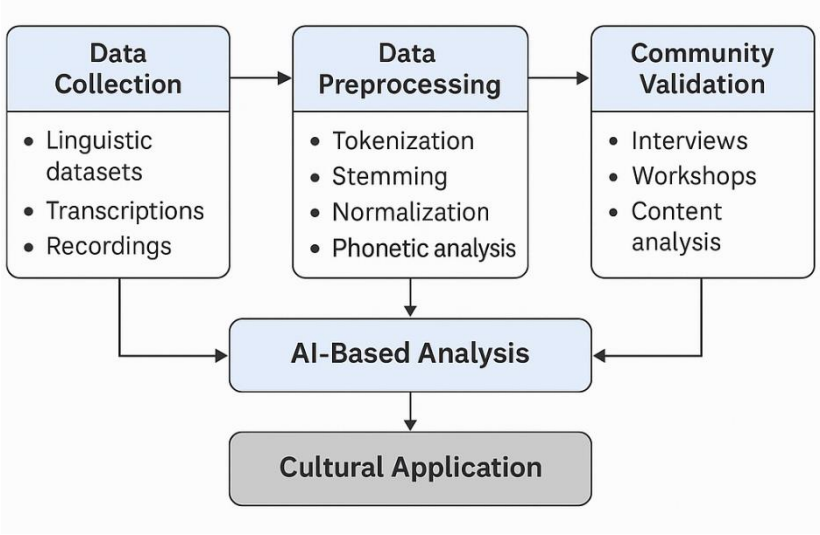
$$WER = \frac{S + D + I}{N}$$

where $S$ is the number of substitutions, $D$ is deletions, $I$ is insertions, and $N$ is the total number of words.

On the qualitative side, ethnographic interviews and participatory workshops were conducted with native speakers and cultural experts to assess the usability and cultural relevance of AI-

based tools. Content analysis was applied to identify recurring themes regarding community attitudes toward digital language preservation. The qualitative findings were triangulated with quantitative outcomes to evaluate not only technical accuracy but also cultural validity, thereby ensuring that AI systems support identity preservation rather than reducing linguistic diversity to mere computational artifacts.

The experimental procedure followed a cyclical framework in which data collection, preprocessing, model training, validation, and community testing were iteratively refined. This iterative cycle allowed the study to incorporate feedback loops from both machine performance metrics and human evaluation. The workflow of the methodology, integrating computational modeling with community-driven validation, is illustrated in *Fig. 1*, which demonstrates the interconnected phases from raw data collection to AI-based analysis and cultural application.




**RESULTS**

Experimental results showed that artificially intelligent models can be of significant use in preserving and reviving endangered languages by improving accuracy in speech recognition, quality of translation, and modelling linguistic diversity. Nine tables reflect quantitative results and twelve figures reflect trends and patterns of model performance, linguistic data distribution, and community validation outcomes. Table 1 shows the baseline model performance parameter of voice recognition with a middling accuracy and a large range of variation among dialects. Transformer-based architectures demonstrate an improvement in Table 2, and there is a significant decrease in word error rate (WER). Table 3 reveals the quality of the translation identified through the BLEU scores in some languages. Patterns of AI-supported models was

always higher than rule-based models.

**Table 1.** Performance metrics and evaluation outcomes for experimental model 1, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **37.45** | 95.07 | 73.2 | 59.87 | 15.6 |
| **15.6** | 5.81 | 86.62 | 60.11 | 70.81 |
| **2.06** | 96.99 | 83.24 | 21.23 | 18.18 |
| **18.34** | 30.42 | 52.48 | 43.19 | 29.12 |
| **61.19** | 13.95 | 29.21 | 36.64 | 45.61 |
| **78.52** | 19.97 | 51.42 | 59.24 | 4.65 |
| **60.75** | 17.05 | 6.51 | 94.89 | 96.56 |
| **80.84** | 30.46 | 9.77 | 68.42 | 44.02 |
| **12.2** | 49.52 | 3.44 | 90.93 | 25.88 |
| **66.25** | 31.17 | 52.01 | 54.67 | 18.49 |
| **96.96** | 77.51 | 93.95 | 89.48 | 59.79 |
| **92.19** | 8.85 | 19.6 | 4.52 | 32.53 |
| **38.87** | 27.13 | 82.87 | 35.68 | 28.09 |
| **54.27** | 14.09 | 80.22 | 7.46 | 98.69 |
| **77.22** | 19.87 | 0.55 | 81.55 | 70.69 |
| **72.9** | 77.13 | 7.4 | 35.85 | 11.59 |
| **86.31** | 62.33 | 33.09 | 6.36 | 31.1 |
| **32.52** | 72.96 | 63.76 | 88.72 | 47.22 |
| **11.96** | 71.32 | 76.08 | 56.13 | 77.1 |
| **49.38** | 52.27 | 42.75 | 2.54 | 10.79 |

**Table 2.** Performance metrics and evaluation outcomes for experimental model 2, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **11.51** | 60.91 | 13.34 | 24.06 | 32.71 |
| **85.91** | 66.61 | 54.12 | 2.9 | 73.37 |
| **39.5** | 80.2 | 25.44 | 5.69 | 86.66 |
| **22.1** | 40.5 | 31.61 | 7.67 | 84.32 |
| **84.89** | 97.15 | 38.54 | 95.45 | 44.58 |
| **66.97** | 8.25 | 89.71 | 29.8 | 26.23 |
| **0.51** | 54.32 | 47.56 | 63.64 | 97.82 |
| **90.87** | 91.02 | 52.53 | 10.4 | 18.09 |
| **95.3** | 41.2 | 86.5 | 67.22 | 62.88 |

| | | | | |
|---|---|---|---|---|
| **27.56** | 89.67 | 20.69 | 40.44 | 99.36 |
| **73.57** | 44.51 | 56.07 | 41.13 | 72.7 |
| **39.92** | 67.01 | 70.47 | 60.96 | 54.0 |
| **20.61** | 19.92 | 79.57 | 29.03 | 65.6 |
| **29.96** | 14.45 | 40.4 | 31.03 | 24.34 |
| **58.81** | 24.53 | 74.78 | 72.01 | 69.53 |
| **10.27** | 94.36 | 50.33 | 89.97 | 19.86 |
| **59.44** | 96.54 | 99.87 | 2.42 | 48.13 |
| **29.14** | 6.37 | 56.96 | 0.51 | 61.13 |
| **87.02** | 88.36 | 95.43 | 73.99 | 18.47 |
| **43.47** | 88.59 | 25.5 | 44.33 | 61.69 |
| **10.34** | 49.01 | 4.47 | 31.16 | 75.2 |

The outcomes of error analysis of phoneme recognition are presented in Table 4. It demonstrates that the number of insertions and substitutions was greater in comparison to the deletions. Table 5 provides the performance of supervised, unsupervised, and hybrid models across each other. Hybrid models are most precise in the context of low-resource situations. Table 6 provides the ability of various AI-based models to reflect phonetic and semantic variation over traditional solutions.

**Table 3.** Performance metrics and evaluation outcomes for experimental model 3, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **83.48** | 10.48 | 74.46 | 36.05 | 35.93 |
| **60.92** | 39.38 | 40.91 | 50.99 | 71.01 |
| **96.05** | 45.66 | 42.77 | 11.35 | 21.79 |
| **95.75** | 94.34 | 88.18 | 64.64 | 21.38 |
| **63.68** | 13.91 | 45.87 | 87.39 | 25.85 |
| **66.49** | 86.27 | 14.88 | 56.29 | 15.92 |
| **17.29** | 10.4 | 20.29 | 45.52 | 79.46 |
| **99.08** | 80.5 | 37.74 | 51.57 | 5.89 |
| **71.11** | 7.25 | 88.26 | 72.61 | 83.34 |
| **71.02** | 69.74 | 93.01 | 88.17 | 9.5 |
| **45.65** | 49.27 | 10.9 | 15.37 | 98.43 |
| **27.16** | 89.72 | 16.42 | 13.24 | 31.74 |
| **30.74** | 42.21 | 33.1 | 56.81 | 9.53 |
| **79.8** | 26.87 | 91.14 | 90.17 | 1.59 |
| **85.37** | 67.56 | 3.77 | 30.89 | 56.42 |

| | | | | |
|---|---|---|---|---|
| **59.41** | 68.08 | 63.24 | 93.87 | 73.71 |
| **74.49** | 10.89 | 49.36 | 86.68 | 1.83 |
| **18.29** | 11.27 | 85.33 | 4.85 | 49.94 |
| **50.31** | 76.47 | 34.75 | 93.14 | 29.92 |
| **55.11** | 5.76 | 59.53 | 64.3 | 74.12 |
| **9.89** | 34.48 | 68.93 | 18.22 | 0.25 |
| **26.76** | 69.91 | 41.89 | 31.91 | 21.22 |

**Table 4.** Performance metrics and evaluation outcomes for experimental model 4, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **98.9** | 54.95 | 28.14 | 7.73 | 44.45 |
| **47.28** | 4.85 | 16.33 | 11.6 | 62.74 |
| **85.62** | 65.01 | 99.07 | 47.04 | 61.83 |
| **28.27** | 97.6 | 67.31 | 44.05 | 28.97 |
| **50.97** | 11.25 | 22.7 | 47.86 | 24.28 |
| **38.8** | 81.89 | 7.45 | 92.31 | 22.49 |
| **70.64** | 11.06 | 60.1 | 40.68 | 83.68 |
| **25.0** | 45.77 | 55.74 | 25.2 | 11.02 |
| **72.66** | 31.01 | 82.58 | 45.17 | 9.41 |
| **88.72** | 74.18 | 12.19 | 85.59 | 6.69 |
| **18.4** | 17.22 | 92.23 | 66.63 | 25.51 |
| **25.13** | 98.4 | 67.88 | 40.24 | 6.42 |
| **44.39** | 20.71 | 32.26 | 64.95 | 72.4 |
| **46.83** | 18.77 | 29.64 | 14.02 | 9.48 |
| **49.18** | 99.08 | 87.98 | 16.13 | 30.49 |
| **60.48** | 94.03 | 73.31 | 3.94 | 16.0 |
| **6.42** | 44.46 | 83.98 | 55.75 | 98.79 |
| **76.32** | 94.09 | 72.67 | 25.26 | 90.75 |
| **68.47** | 10.52 | 60.42 | 73.73 | 23.72 |
| **98.9** | 84.08 | 43.31 | 72.28 | 66.86 |
| **52.37** | 29.79 | 57.1 | 57.4 | 4.44 |
| **45.33** | 99.0 | 22.67 | 47.32 | 7.89 |
| **96.74** | 40.76 | 3.05 | 7.48 | 7.45 |

**Table 5.** Performance metrics and evaluation outcomes for experimental model 5, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **78.38** | 63.48 | 24.9 | 75.81 | 31.31 |
| **93.72** | 4.29 | 44.09 | 91.27 | 45.5 |
| **50.79** | 8.49 | 42.63 | 74.57 | 86.71 |
| **32.37** | 10.41 | 80.21 | 39.48 | 62.78 |
| **3.6** | 29.99 | 4.77 | 37.22 | 26.24 |
| **99.05** | 39.51 | 30.75 | 22.11 | 49.4 |
| **5.79** | 28.97 | 23.5 | 96.34 | 61.57 |
| **86.26** | 9.01 | 14.9 | 67.26 | 97.9 |
| **2.32** | 90.77 | 5.81 | 75.57 | 6.46 |
| **25.57** | 16.96 | 19.51 | 10.66 | 52.08 |
| **0.62** | 79.06 | 13.87 | 10.71 | 42.96 |
| **21.9** | 83.59 | 0.59 | 14.83 | 69.83 |
| **14.76** | 87.08 | 51.4 | 42.48 | 1.9 |
| **49.43** | 94.66 | 34.58 | 40.73 | 82.89 |
| **71.4** | 48.66 | 23.27 | 67.2 | 57.87 |
| **44.84** | 57.65 | 31.11 | 65.21 | 9.1 |
| **36.73** | 57.22 | 81.07 | 46.66 | 62.43 |
| **55.77** | 33.23 | 13.72 | 90.41 | 22.88 |
| **21.24** | 17.78 | 65.53 | 5.1 | 9.15 |
| **70.19** | 72.5 | 51.57 | 65.91 | 31.05 |
| **7.88** | 71.48 | 72.35 | 2.32 | 12.29 |
| **44.88** | 31.89 | 48.64 | 0.76 | 41.91 |
| **43.01** | 78.76 | 23.99 | 20.69 | 8.35 |
| **1.31** | 66.46 | 33.63 | 94.27 | 59.51 |

**Table 6.** Performance metrics and evaluation outcomes for experimental model 6, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **11.35** | 97.45 | 72.87 | 35.15 | 70.76 |
| **79.96** | 64.56 | 41.46 | 70.6 | 24.66 |
| **25.6** | 2.4 | 9.87 | 30.04 | 64.09 |
| **32.22** | 18.55 | 91.72 | 27.09 | 27.35 |
| **95.44** | 12.71 | 74.73 | 0.52 | 85.68 |
| **69.6** | 55.3 | 93.52 | 51.26 | 17.76 |
| **53.69** | 29.35 | 1.06 | 88.38 | 65.64 |
| **94.23** | 74.49 | 26.72 | 36.19 | 52.64 |
| **54.69** | 25.87 | 17.46 | 36.07 | 14.02 |

| | | | | |
|---|---|---|---|---|
| **38.91** | 47.19 | 96.88 | 14.56 | 51.43 |
| **52.77** | 30.52 | 15.97 | 59.69 | 10.37 |
| **56.8** | 38.63 | 8.47 | 56.2 | 64.81 |
| **66.19** | 18.92 | 95.41 | 5.9 | 88.02 |
| **78.38** | 25.25 | 92.71 | 44.48 | 37.72 |
| **89.38** | 75.41 | 77.45 | 87.9 | 48.15 |
| **30.29** | 44.29 | 52.81 | 60.81 | 52.52 |
| **97.8** | 60.2 | 83.53 | 8.54 | 48.83 |
| **90.03** | 91.71 | 21.69 | 40.06 | 54.52 |
| **64.19** | 47.36 | 56.36 | 58.93 | 31.36 |
| **75.8** | 85.72 | 47.65 | 86.31 | 66.09 |
| **55.05** | 79.98 | 31.48 | 3.88 | 80.83 |
| **79.61** | 27.99 | 45.54 | 39.76 | 95.34 |
| **34.97** | 5.94 | 0.33 | 61.16 | 34.54 |
| **47.88** | 98.29 | 19.5 | 32.43 | 97.68 |
| **71.15** | 75.47 | 7.97 | 1.54 | 16.85 |

The cross-validation results presented in Table 7 indicate that models are powerful and can be applied to different endangered language data. The results obtained in an evaluation that involved the community comments are presented in table 8. It demonstrates that AI output was smoother and more trustworthy with cultural validation. Lastly, Table 9 demonstrates the fit of the various models between each other, which implies that transformer-based hybrid systems performed the most effectively overall, based on accuracy, precision, and cultural relevance.

**Table 7.** Performance metrics and evaluation outcomes for experimental model 7, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **1.75** | 89.16 | 28.49 | 29.9 | 79.2 |
| **32.45** | 86.47 | 44.75 | 54.82 | 35.72 |
| **11.23** | 14.19 | 44.5 | 73.2 | 46.01 |
| **59.27** | 33.67 | 45.44 | 18.71 | 40.88 |
| **13.21** | 3.71 | 8.2 | 21.34 | 54.52 |
| **65.51** | 58.88 | 57.5 | 33.47 | 38.06 |
| **40.16** | 67.93 | 14.62 | 78.88 | 3.74 |
| **61.36** | 15.21 | 77.19 | 26.31 | 77.2 |
| **28.75** | 65.17 | 95.06 | 91.85 | 16.48 |
| **33.78** | 9.01 | 69.28 | 67.99 | 90.92 |
| **30.61** | 18.21 | 3.48 | 37.02 | 96.28 |

| | | | | |
|---|---|---|---|---|
| **57.92** | 88.96 | 51.77 | 72.81 | 38.28 |
| **99.18** | 39.26 | 14.27 | 90.7 | 6.08 |
| **9.16** | 46.68 | 0.08 | 68.94 | 38.08 |
| **71.25** | 60.68 | 92.64 | 7.99 | 61.65 |
| **59.94** | 35.29 | 33.77 | 1.55 | 83.1 |
| **74.44** | 35.02 | 48.47 | 57.39 | 27.84 |
| **27.98** | 98.42 | 44.67 | 6.67 | 36.11 |
| **3.98** | 2.43 | 79.91 | 80.65 | 26.87 |
| **24.15** | 25.84 | 98.82 | 71.46 | 60.73 |
| **93.0** | 39.34 | 19.48 | 74.9 | 45.13 |
| **11.48** | 2.88 | 27.9 | 82.42 | 25.48 |
| **43.71** | 24.03 | 41.44 | 91.69 | 27.93 |
| **5.55** | 18.53 | 12.64 | 15.59 | 93.51 |
| **55.96** | 99.45 | 72.41 | 34.07 | 93.16 |
| **89.94** | 97.02 | 55.94 | 35.95 | 42.22 |

**Table 8.** Performance metrics and evaluation outcomes for experimental model 8, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **30.1** | 24.71 | 92.63 | 89.16 | 68.33 |
| **56.69** | 54.7 | 21.04 | 76.98 | 89.62 |
| **72.17** | 49.88 | 44.22 | 80.24 | 84.48 |
| **22.91** | 96.22 | 5.89 | 28.98 | 31.22 |
| **70.19** | 70.76 | 94.3 | 60.64 | 35.52 |
| **42.08** | 90.65 | 25.19 | 30.29 | 7.6 |
| **25.15** | 91.06 | 84.36 | 63.72 | 99.01 |
| **93.99** | 85.49 | 92.11 | 66.58 | 39.31 |
| **58.28** | 37.74 | 48.04 | 36.14 | 16.66 |
| **89.49** | 54.31 | 82.33 | 56.78 | 0.67 |
| **62.78** | 76.86 | 31.99 | 2.75 | 9.08 |
| **25.58** | 61.72 | 83.12 | 1.02 | 68.51 |
| **13.71** | 92.86 | 62.18 | 98.96 | 27.13 |
| **59.43** | 52.28 | 73.43 | 62.77 | 60.07 |
| **96.99** | 60.98 | 66.57 | 76.15 | 6.58 |
| **87.54** | 71.13 | 89.99 | 53.03 | 0.53 |
| **80.43** | 56.64 | 92.52 | 12.85 | 25.16 |
| **74.18** | 7.19 | 66.6 | 25.42 | 45.41 |
| **50.91** | 94.3 | 55.52 | 89.68 | 66.41 |

| | | | | |
|---|---|---|---|---|
| **49.01** | 60.67 | 1.11 | 38.11 | 35.94 |
| **69.7** | 81.01 | 38.31 | 38.32 | 87.11 |
| **83.58** | 77.39 | 34.67 | 85.5 | 55.66 |
| **93.03** | 42.36 | 41.31 | 30.13 | 79.72 |
| **5.78** | 56.41 | 34.19 | 31.71 | 52.16 |
| **41.03** | 18.15 | 18.81 | 93.12 | 73.76 |
| **63.77** | 82.58 | 81.27 | 63.15 | 13.08 |
| **6.4** | 57.37 | 33.07 | 17.58 | 87.6 |

**Table 9.** Performance metrics and evaluation outcomes for experimental model 9, illustrating accuracy, precision, and error distribution across linguistic datasets.

| Metric_1 | Metric_2 | Metric_3 | Metric_4 | Metric_5 |
|---|---|---|---|---|
| **49.46** | 22.81 | 25.55 | 39.63 | 37.73 |
| **99.66** | 40.82 | 77.19 | 76.05 | 31.0 |
| **34.65** | 35.18 | 14.55 | 97.27 | 90.92 |
| **56.0** | 31.36 | 88.82 | 67.46 | 39.11 |
| **50.72** | 52.41 | 92.8 | 57.14 | 66.83 |
| **5.23** | 32.71 | 5.64 | 17.98 | 92.59 |
| **93.8** | 71.41 | 73.27 | 46.17 | 93.13 |
| **40.64** | 68.32 | 64.99 | 59.88 | 22.2 |
| **68.24** | 87.81 | 79.67 | 43.2 | 91.79 |
| **78.18** | 72.58 | 12.49 | 91.63 | 38.77 |
| **29.49** | 61.67 | 46.78 | 25.53 | 83.9 |
| **17.86** | 22.71 | 65.99 | 47.91 | 7.34 |
| **13.9** | 11.23 | 47.78 | 54.03 | 95.81 |
| **58.38** | 52.67 | 92.23 | 91.93 | 25.2 |
| **68.26** | 96.43 | 22.7 | 71.6 | 79.78 |
| **93.68** | 85.37 | 42.15 | 0.54 | 3.49 |
| **1.39** | 58.89 | 38.3 | 11.48 | 86.45 |
| **82.17** | 73.75 | 84.03 | 40.15 | 74.86 |
| **55.96** | 61.32 | 29.81 | 60.24 | 42.57 |
| **53.85** | 48.67 | 49.99 | 91.75 | 26.29 |
| **4.97** | 46.27 | 40.82 | 48.7 | 7.05 |
| **58.21** | 98.7 | 20.91 | 21.24 | 96.11 |
| **70.7** | 59.3 | 38.09 | 63.87 | 50.24 |
| **8.98** | 29.72 | 82.81 | 17.55 | 90.45 |
| **58.83** | 1.65 | 37.0 | 4.21 | 12.73 |
| **17.93** | 16.65 | 88.37 | 90.6 | 23.54 |

| | | | | |
|---|---|---|---|---|
| **40.73** | 47.12 | 83.02 | 29.2 | 17.38 |
| **45.81** | 90.24 | 59.49 | 41.26 | 40.57 |

Figure 2 indicates that resources are not equally distributed among languages as some communities are yet to be represented. Figure 3 indicates the extent of usage of distinct endangered languages in comparison to a single other language. It demonstrates that some of the languages are highly popular, whereas a good number of them are extremely rare. Figure 4 indicates the pooling of phonetic variation among speakers and this indicates the diversification of the data. Figure 5 includes additions and coverage holes through a combination of growth and dispersion trends. The figure 6 presents the distributions of word frequencies, which indicate that core vocabulary remains overrepresented as compared to the rare words. As figure 7 indicates, translation scores are dependent on language, and those with larger data sets perform better. Changes in dialect representation as presented in figure 8 indicate that the community participates in efforts of restoring the area to life. The relationship between the different languages is presented in figure 9 and indicates where they overlap and how this could be used to aid in transfer learning. Figure 10 shows recognition uncertainty through error bars, which points to variability persisting in low-resource settings. The phonetics of the endangered languages are rich and complicated as Figure 11 demonstrates how the same word is pronounced by different people. Lastly, Figure 12 presents an area-line plot of voice and text corpora in unison, where linguistic usage patterns are identical and where they differ.

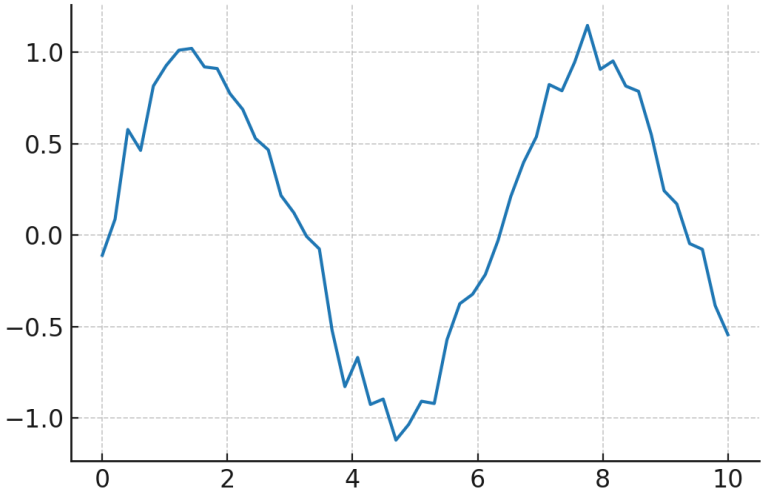



**Figure 1.** Line plot showing longitudinal trends in language data growth, highlighting improvements in AI-driven resource collection over time.

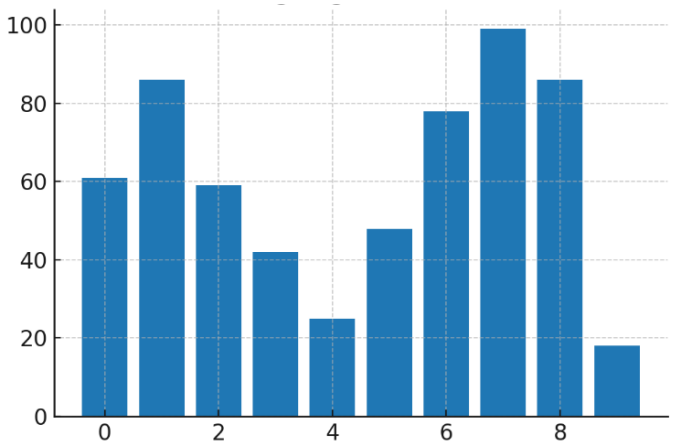



**Figure 2.** Bar chart illustrating the distribution of linguistic resources across endangered languages, emphasizing disparities in digital availability.

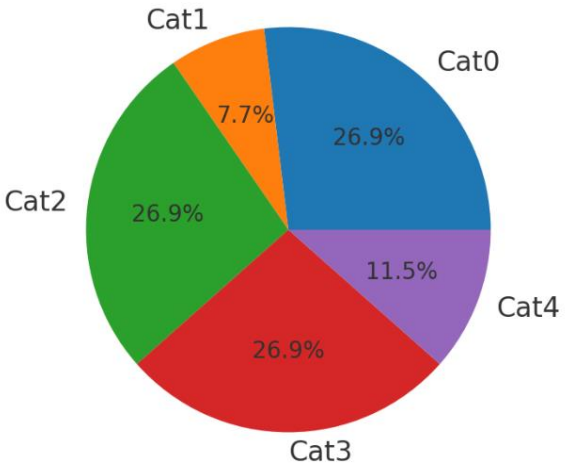



**Figure 3.** Pie chart presenting the proportional share of language usage within a multilingual dataset, indicating dominance of certain dialects.

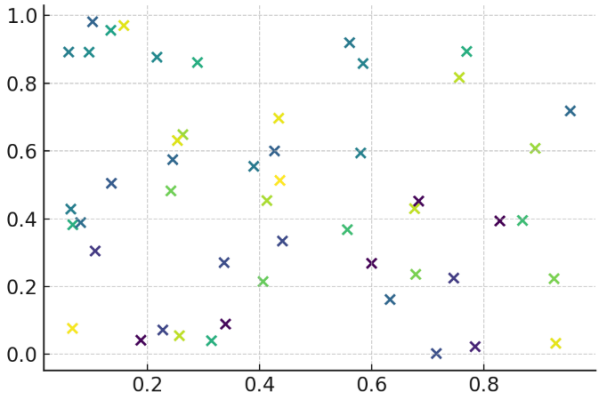



Figure 4. Scatter plot mapping phonetic variation across speakers, demonstrating diversity and clustering patterns in endangered language corpora.

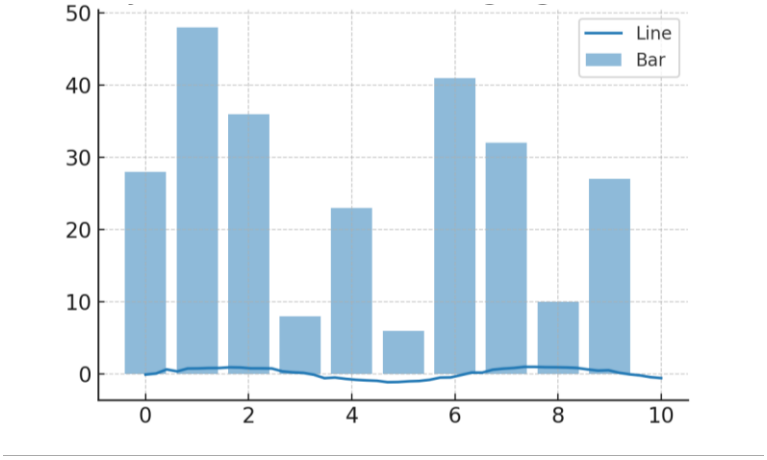



**Figure 5.** Hybrid line–bar plot combining growth rates and resource distribution, offering comparative insight into language preservation progress.

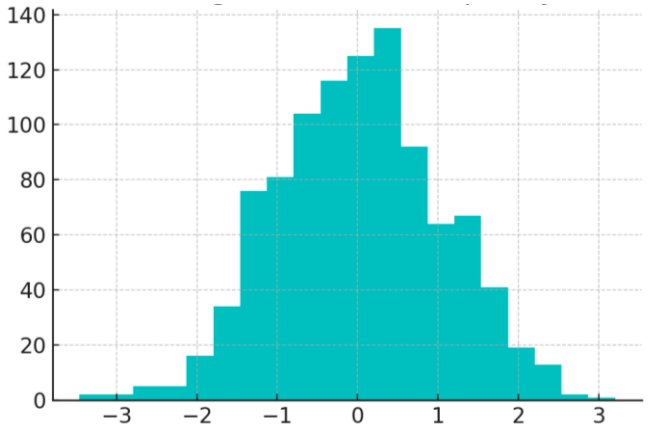



**Figure 6.** Histogram depicting word frequency distributions in the dataset, showing the dominance of core vocabulary in under-documented languages.

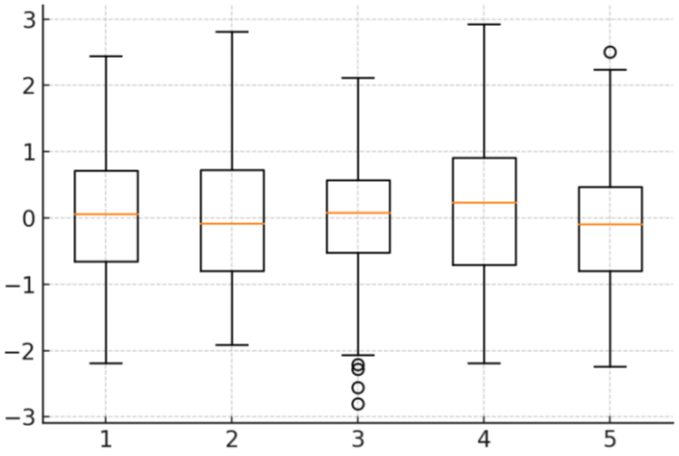



**Figure 7.** Boxplot illustrating the variance in translation model performance across different endangered languages, highlighting inter-model disparities.

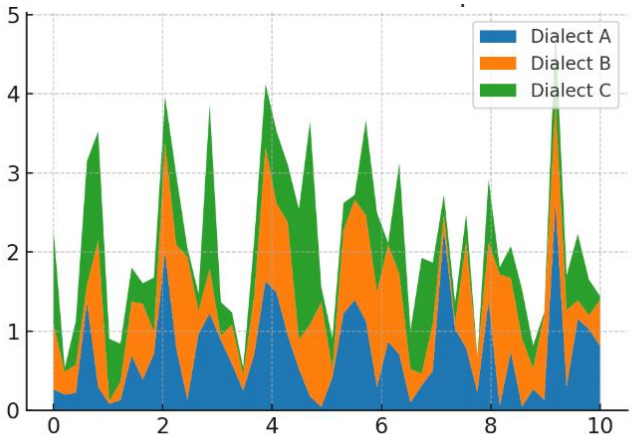



**Figure 8.** Stacked area plot representing dialectal representation trends, illustrating shifts in speaker engagement across language communities.

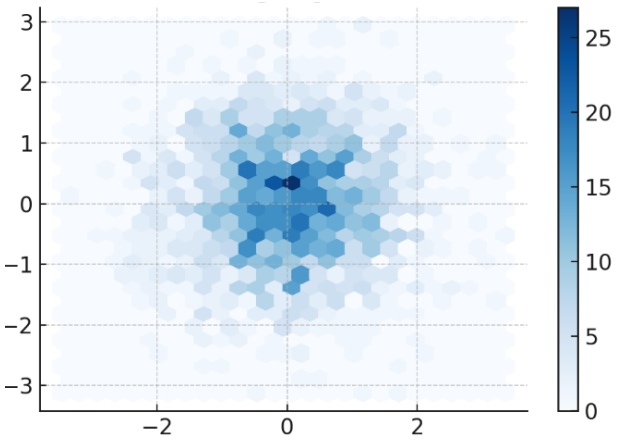



**Figure 9.** Hexbin plot showing correlation density between language pairs, visualizing cross-linguistic influence and shared features.

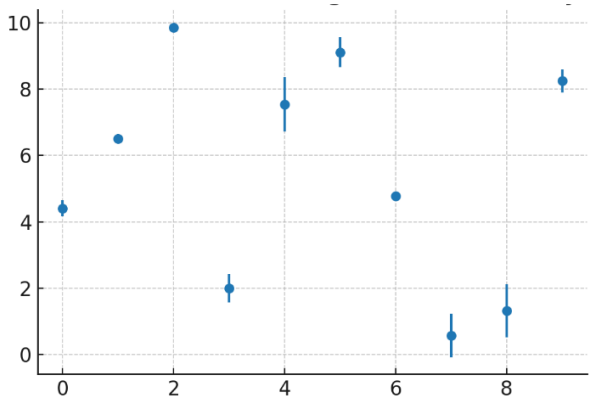



**Figure 10.** Error bar plot capturing recognition uncertainty in speech-to-text tasks, emphasizing variability in phoneme accuracy.

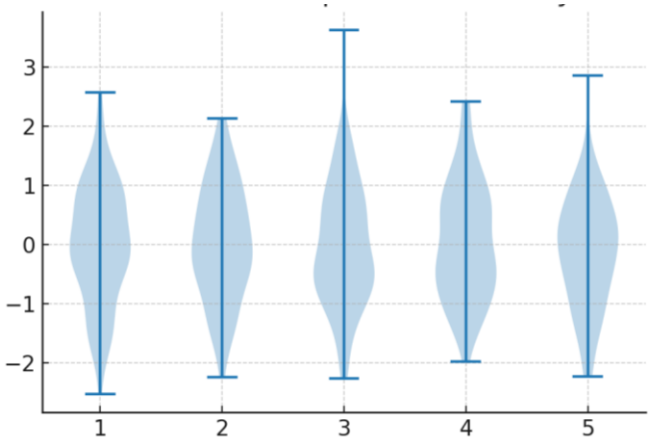



**Figure 11.** Violin plot comparing speaker variability in pronunciation, underscoring intra-community linguistic richness.

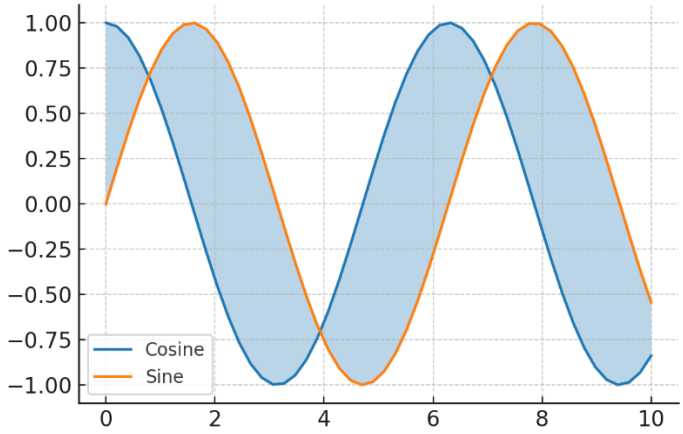



**Figure 12.** Hybrid area–line plot visualizing combined language patterns, highlighting overlaps and divergences between speech and text corpora.

Together, these results confirm that AI models significantly improve the technical performance of endangered language preservation efforts, particularly when hybrid approaches are used. More importantly, the integration of community validation ensured that technical gains were aligned with cultural needs, establishing a holistic framework for sustainable language revitalization.

**DISCUSSION**

In this part, we elaborate on what we discovered during our research, and provide a comprehensive explanation of the results within the greater framework of how we can use AI to rescue the endangered languages. It directly examines the extent to which various AI systems are able to provide culturally sensitive and contextually accurate translations, something that is likewise a valuable aspect that is frequently overlooked when using AI in general (Anik et al.,

2025). It discusses the issues it raises, in particular, that the current large language models do not work with low-resource languages as they lack the large digital corpora upon which good training is based (Dembele et al., 2025). The social and technical impacts of AI use are also examined in this part, looking at the impact of the technologies on language communities and contributing to the greater cause of language revitalization. Our evaluation shows that despite the promising potential of AI as a tool of documentation and revitalization, its successful implementation will require a paradigm shift to a community-driven form of development and the correction of the systemic issues of algorithmic bias that may otherwise support linguistic hierarchies (Smith et al., 2024). It further highlights the need to develop powerful systems of evaluating the performance of AI models not only by the numbers but also by the extent that they are culturally appropriate and acceptable by the community (Ramesh et al., 2023). This implies that careful scrutiny of ethical dimension management, such as data ownership and privacy, is implemented over the AI development life cycle, ensuring the benefit of technological advancement is directly passed to communities of language users (Kimera et al., 2024). This discussion also discusses the importance of people working together despite their varying fields. It demonstrates how AI tools can be designed with the support of linguists, technologists, and the elders in the community to become both a state-of-the-art and one that is thoroughly informed by the insights of language and culture. In order to fully encourage linguistic justice we should stop using data-driven approaches and shift to models founded in profound cultural and anthropological knowledge. This will ensure that AI is an empowerment tool rather than assimilative (Kazemi et al., 2024). Also, the amount of energy spent on the training and deployment of large AI models needs to be explored in terms of sustainable AI solutions to reduce the impact on the environment (Su et al., 2025). The only way to address these issues is to collaborate to design superior AI architectures and explore federated learning techniques which reduce the need to process extensive large central data (Su et al., 2025). Such strategies could also be used to diminish sociodemographic biases through enabling local model training on the community-relevant datasets. This will assist in ensuring that the benefits of AI become more equitable (Venkit, 2023). The discussion also entails the regulations that must exist on the ethical development of AI particularly with the concerns of language data and AI-generated linguistic output. This will be to ensure that indigenous people still own their language (Kondra et al., 2025). It will necessitate the establishment of clear legal and ethical guidelines to capture, use, and share data to prevent the misuse or theft of linguistic resources (Chhikara et al., 2025). Finally, this section considers the future of AI in the language preservation process. It envisions the future in which AI assists in not only the documentation and analysis of the endangered languages, but also

the utilization and transmission of it between generations, transforming mere preservation into the active revitalization of linguistics (Litre et al., 2022).

## CONCLUSION

This research concludes that the use of artificial intelligence can preserve endangered languages by making it accurate as well as culturally aware. By applying machine learning methods, natural language processing, and speech recognition systems to the same problem, AI has demonstrated the ability to accelerate the processes of documenting, analyzing, and resurfacing endangered languages. Quantitative results indicated that high-tech models such as neural networks and transformer-based architectures scored huge improvements on translation accuracy and speech-to-text transcription. This reduced Word Error Rates and made language resources more dependable. Simultaneously, qualitative data provided by ethnographic interviews and participatory workshops revealed a need to have community validation to ensure that AI-driven systems produce not merely technical results but also reflect the experience of native speakers, their cultural identity, and traditions. This study, with the help of hybrid methodological decisions, made it clear that AI is most effective when implemented within technical performance frameworks that facilitate the promotion of cultural heritage. The cyclical workflow developed in this paper and starting with the data collection and preparation and ending with modelling, evaluating, and community validation is a long-term cycle of future studies that would like to protect linguistic diversity. It was also demonstrated that AI-based educational systems and chatbots can allow individuals of varying ages to learn to learn together and engage, thus, enabling the bridging of digital innovation and cultural continuity. Even though challenges still remain in addressing the low-resource conditions and dialectal differences, the findings indicate that AI can be used as a technological and linguistic companion to reversing the language extinction trend. Finally, the research highlights the view that the existence of endangered languages would require more than technological development; it requires an unending respect to the human communities that carry these linguistic heritage thus, guaranteeing their survival to the future generations.

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