

ASSESSING AI TRANSLATION OF IGBO: STRENGTHS, WEAKNESSES, AND IMPLICATIONS FOR LANGUAGE TECHNOLOGY

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Abstract

This study evaluates the performance of artificial intelligence (AI) translation tools in rendering Igbo into English, with the goal of identifying their strengths and weaknesses and determining their potential for wider application to other low-resource languages. The motivation lies in the urgent need to ensure that African languages, often underrepresented in digital corpora, are effectively supported in emerging language technologies. To achieve this, forty-four Igbo inputs were constructed, covering lexical items, simple sentences, complex sentences, interrogatives, imperatives, and proverbs. These were translated using two widely accessible AI systems, and their outputs were systematically compared with linguist-validated reference translations for accuracy, fluency, and cultural appropriateness. The analysis shows that while the tools perform well with isolated words and straightforward sentences, they encounter difficulties with context-dependent expressions, figurative language, and proverbs, often leading to semantic distortion or cultural loss. Interestingly, one incidental observation was that the tools occasionally recognized tonal distinctions, although tone was not the focus of this research. The study contributes to the field of language technology by providing a diagnostic evaluation of AI translation in Igbo, establishing a replicable methodology for assessing other low-resource languages, and highlighting the need for richer Igbo corpora, tone-sensitive datasets, and culturally grounded training materials. Ultimately, it offers practical insights into how human linguistic expertise and AI systems can complement one another in building more reliable multilingual translation tools.

Keywords: AI translation, Igbo language, language technology, machine translation, low-resource languages

1.0 Introduction

The advancement of Artificial Intelligence (AI) in recent years has reshaped various domains of human activity, including the field of language translation. Translation,

traditionally a human-centered intellectual exercise, has been significantly transformed by the development of machine translation tools such as Google Translate, DeepL, and, more recently, conversational AI systems like ChatGPT. These technologies promise to break down linguistic barriers by providing immediate translation across diverse languages. However, their effectiveness is not evenly distributed across the world's languages. While high-resource languages such as English, French, and Chinese benefit from massive datasets and consistent improvements, many African languages, including Igbo, remain underrepresented and under-supported in these systems. This raises critical questions about the accuracy, reliability, and overall suitability of AI-powered translation tools for African linguistic contexts.

Igbo, one of Nigeria's three major indigenous languages, is spoken by over 20 million people in Nigeria and the diaspora. It is a tonal language, meaning that variations in pitch are crucial in distinguishing lexical and grammatical meanings. For example, the word *akwa* may mean 'cloth,' 'bed,' 'cry,' or 'egg,' depending on tone and context. This tonal complexity, combined with the language's heavy reliance on idioms, proverbs, and culturally embedded expressions, makes Igbo particularly challenging for computational systems that are largely trained on non-tonal languages. As Emenanjo (2015) observes, tone is not just an accessory in Igbo but an integral part of meaning-making, and any translation model that fails to capture this will inevitably produce distortions. Similarly, Bamgbose (1991) points out that African languages are often marginalized in computational research due to limited resources, which leads to poor digital representations and inadequate support in technological innovations.

The situation is further complicated by the fact that translation is not merely a matter of word substitution but also involves contextual and cultural interpretation. Nwachukwu (2010) emphasizes that effective translation requires sensitivity to the sociocultural underpinnings of the language, as words in Igbo often encode meanings beyond their surface forms. For instance, proverbial expressions such as '*onye buru chi ya ụzụ, ụgbagbue onwe ya n'ụsụ*,' cannot be translated literally into English without losing their figurative essence. This insight demonstrates the inadequacy of systems that rely solely on statistical or neural patterns without grounding in cultural semantics.

Despite these limitations, AI-driven translation still offers remarkable opportunities. Adegbite (2018) argues that digital technologies have the potential to increase the visibility of African languages on the global stage, allowing speakers to engage more fully in international discourse. The application of AI tools to Igbo could thus contribute not only to academic and educational pursuits, but also to the preservation of the language in digital spaces. However, this potential will only be realized if the strengths and weaknesses of current systems are systematically examined and documented. Such evaluation is critical because reliance on poorly adapted tools may perpetuate mistranslations, distort cultural meaning, and further subvert Igbo in global communication networks.

This paper, therefore, seeks to examine the strengths and weaknesses of AI-powered translation tools, particularly Google Translate and ChatGPT, in rendering Igbo into English. By focusing on selected lexical and phrasal items, the study assesses how effectively these systems handle the tonal, idiomatic, and contextual features of Igbo. The goal is not only to highlight areas of accuracy but also to identify recurring errors and misrepresentations. Through this, the paper contributes to ongoing discussions on the intersection of technology and African linguistics, and underscores the importance of developing more inclusive, culturally sensitive AI systems. Ultimately, the study offers insights that may guide both linguists and technology developers toward improving translation systems, ensuring that under-resourced languages like Igbo are not left behind in the digital age.

2.0 Theoretical Framework

This study is anchored on two theories: the Contrastive Analysis Hypothesis (CAH) and Error Analysis (EA).

The Contrastive Analysis Hypothesis, as proposed by Lado (1957), is based on the assumption that second language learning difficulties can be predicted by comparing the structures of the learner's first language (L1) and the target language (L2). Where the structures are similar, learning is easier; where they differ, difficulties arise. Applied to MT, CAH suggests that a system trained primarily on English (L2) will encounter significant difficulties when applied to Igbo (L1), due to the structural and phonological contrasts between the two. One obvious area is tone: English has intonation but lacks lexical tone, while Igbo relies heavily on tone for meaning differentiation.

Error Analysis, developed by Corder (1967), provides a methodological tool for examining errors made in language learning or computational systems. Rather than focusing solely on predicting errors (as CAH does), EA studies actual performance data to identify error types, sources, and potential remedies. In MT studies, EA can be used to systematically categorize mistranslations in Igbo-to-English or English-to-Igbo systems, and then recommend strategies for correction. By combining CAH and EA, the framework for this study acknowledges both the predictive and diagnostic dimensions of MT errors. While CAH identifies potential areas of structural and phonological conflict, EA helps in analyzing actual MT output, making the two frameworks complementary.

2.1 Empirical Studies

Several studies have investigated the challenges and opportunities of artificial intelligence in translation, particularly for minority languages such as Igbo. For example, Wu and Liu (2018) examined the role of AI-powered translation systems in promoting multilingualism and facilitating cross-cultural communication. Their study emphasized that such systems contribute to global inclusivity but noted that effectiveness varies significantly across languages, depending on available training

data. Similarly, Noor (2025) focused on the documentation and preservation of endangered languages through AI-based tools. By enabling linguists and communities to record and translate oral and written forms, the study highlighted both the potential for language preservation and the risk of distortion when cultural and linguistic nuances are not adequately considered.

Javier (2024) analyzed the influence of bias in generative AI translation systems, showing that if training corpora are skewed toward dominant languages, outputs for minority languages like Igbo are likely to be inaccurate and ideologically biased. In a related contribution, Zaki and Umar (2024) argued that mitigating such bias is essential to achieving communication equity and linguistic diversity. Their work demonstrated that AI systems trained without careful balance risk reinforcing social inequalities rather than alleviating them.

Beyond bias, empirical work has also explored translation quality in context. Majumde, Lauly, Nadejde, Federico, and Dinu (2022) observed that most machine translation studies focus on isolated sentences, ignoring broader textual and discourse-level features. They concluded that this practice undermines the ability of AI systems to handle idiomatic expressions and culturally embedded meanings. Supporting this point, Ahmed and Yousef (2024) compared human and AI translations and found that while AI performs well on literal sentences, it often fails to capture metaphors, idioms, and culture-specific meanings that human translators can easily convey.

Nick (2024) further outlined challenges of AI translation, noting problems with context, subtleties, and cultural references. His work stressed that while AI systems are improving, they still struggle with idioms, slang, and tone sensitivity, which are crucial in Igbo and similar languages. He also raised concerns about ethical and legal implications in sensitive domains, as well as the unreliability of AI translations for less commonly spoken languages due to limited training data.

Finally, Obiwuru and Onwuegbule (2025) conducted a discourse-based study specifically on Igbo, analyzing translations from five AI tools. Their findings revealed compromised linguistic accuracy and cultural relevance in many outputs. They concluded that without culturally sensitive approaches, AI translation technologies may threaten language preservation and identity, rather than supporting them.

Together, these studies demonstrate that while AI translation has advanced accessibility and speed, its application to Igbo and other minority languages remains fraught with challenges. In particular, bias in training data, lack of tone and diacritic handling, and limited capacity to interpret idioms and figurative language all compromise translation quality. These findings form the empirical foundation on which the present study builds.

3.0 Research Methodology

The data for the study consisted of forty-four Igbo lexical and phrasal items designed to capture different linguistic challenges. These included homonyms, minimal pairs, idiomatic expressions, proverbs, and context-sensitive constructions. Each Igbo item was paired with a linguist-validated English translation which served as the gold standard for evaluation. The choice of such data was deliberate, as it represents typical areas where machine translation systems may struggle, especially given the tonal and culturally embedded nature of the Igbo language.

The study focused exclusively on text-to-text translation. Each Igbo item was entered into two widely accessible AI translation systems: Google Translate and ChatGPT. The output provided by each system was collected verbatim and entered into a master table alongside the corresponding gold translation. Care was taken to ensure that each entry was made independently, without context carry-over from previous translations, in order to obtain unbiased results.

The translations were analyzed both quantitatively and qualitatively. Quantitatively, each system's outputs were compared with the gold translations and scored according to accuracy: correct, partially correct, or incorrect. The scores were then converted into percentages to provide a measure of overall performance. Qualitatively, recurring patterns of errors were noted, with particular attention given to mistranslations involving idiomatic expressions, culturally specific forms, and tonal distinctions. This dual approach provided a balanced assessment of the systems, revealing not only their level of accuracy but also the nature of their strengths and weaknesses.

4.0 Data presentation and Analysis

4.1 Data table — stimuli and verbatim system outputs

The complete dataset is shown so readers can inspect the raw evidence before analysis.

	Input (Igbo/English)	Google Translate Output	ChatGPT Output	Gold / Reference Translation
1	Ó nyèrè m̀ àkwá m̀gbè m̀ nà-èbé akwá n'élú akwá	He gave me an egg that I was crying over	He gave me cloth when I was crying on top of cloth	He gave me an egg while I was crying on the bed
2	Ákwà yá áh`	His bed	That cloth of his	That his cloth
3	Ákwà	Bed	Cloth	Cloth
4	Àkwá	Bed	Egg	Egg
5	égo	bed	Money	Money

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6	ó nyèrè m̄ égō	He gave me a bed	He gave me money	He gave me money
7	Ó nyèrè ụ égō	He gave me money	He gave me money	He gave me money
8	égō yā	His bed	His money	his money
9	àkwà yá	His bed	His cloth	his/her clothes
10	ákwā yá	His bed	His cloth	his clothes
11	ụ jụrụ m	He asked me	He rejected me	He rejected me
12	⁻ j̄ r̄ m̄	He asked me	He rejected me	He rejected me
13	⁻ j̄ r̄ m̄	He asked me	He rejected me	Did he reject me
14	he rejected me	ụ jụrụ m	ụ jụrụ m	⁻ j̄ r̄ m̄
15	É meē ngwā ngwā è meē hàrà ⁻ dàchí	He made haste and made a disaster	If done quickly, disaster is averted	A stitch in time saves nine
16	Áká ájá ājá nà-èbúté ⁻ n̄ mman̄ m̄man̄	The brown hand brings the oil	Hard work brings prosperity	Hard work brings success
17	A word is enough for the wise	Okwu ezuola onye maara ihe	Okwu zuru oke bara amamihe	Ótù okwū è zuórólá ónyé amamííhé
18	Mèchié ⁻ z̄ áh̄	Close the door	Close that road	Close that door
19	Nyé m̄ ákwà ahụ	Give me the bed	Give me that cloth	Give me that cloth
20	Look at that man	Lee nwoke ahụ	Lelee nwoke ahụ	Lée nwokē áh̄
21	ányá	Eyes	Eye	eyes
22	the house	ụlụ	ụ lụ ahụ	⁻ ɾ̄
23	A stitch in time saves nine	Agbụ n'oge na-azuputa itoolu	Onye kpurụ oge, gbochiri ihe isi ike	É meē ngwā ngwā è meē hàrà ⁻ dàchí
24	⁻ ɾ̄ áh̄	The house	The house	That house
25	Ákpáalàokwū	Idiom	Idiom	idioms

26	he taught me idioms	o kuziri m okwu	ụ kuziri m akpaalaokwu	ṛ kuziri m ákpáàlàókṽ
27	blessing	ngozi	Nguzi	Ng̃'z̃
28	Ng̃'z̃	Blessing	Blessing	Blessing
29	ṛ kuziri m ákpáàlàókṽ	He taught me idioms	He taught me idioms	He taught me idioms
30	Did he come hereṽ	ụ b̃ara ebe aṽ	ụ b̃ara ebe aṽ	ṛ b̃àrà ébé à
31	Yá nà há nà-àgá	He goes with them	He and they are going	He is going with them
32	Gbàchí ñk̃f̃	Close quiet	Keep silent	Stay quiet
33	Ñr̃' nwaỹ ^ṽ	Be quiet	Stay calm / Stay gently	Stay calm
34	Stand up	Bilie	Guzie ike / Bilie (Stand up)	Kw̃r̃'ṽtṽ
35	Burú	be quiet	Take	carry
36	Take	Were	Were (Carry)	wèré
37	Carry	ebu	Were (Take/Carry)	Burú
38	Take your book	Were akw̃kw̃ gṽ	Were akw̃kw̃ gṽ (Take your book)	Wèré ákw̃'kw̃' gṽ
39	carry your book	buru akw̃kw̃ gṽ	Were akw̃kw̃ gṽ (Carry your book)	bùrú ákw̃'kw̃' gṽ
40	Kw̃s̃'kw̃ákw̃á	Stop crying	Stop crying	Stop crying
41	ṛ b̃àrà ébé aṽ	is he hereṽ	Did he come hereṽ	Did he come hereṽ
42	spoon	ngaji	Ngaji	Ñgàjì
43	ñgàjì	ngàjì	Spoon	Spoon
44	óché	óché	Chair	Chair

Table 1 -Stimuli and system outputs (44 items)

4.2 Group Analysis

1. Simple Nouns and Objects (Items 2, 3, 4, 5, 8, 9, 10, 21, 24, 27, 28, 42, 43, 44)

These items are straightforward words like cloth, egg, money, house, blessing, spoon, chair.

Google Translate often confused ákwà with bed rather than distinguishing between “cloth” and “egg.” For example, Item 3 (Ákwà) was translated as “bed” instead of “cloth,” and item 5 (ego) was incorrectly given as “bed.”

ChatGPT performed better in this group. It correctly rendered Ákwà as “cloth” and Àkwá as “egg.” It also gave “money” for éḡō, “chair” for óché, and ngaji for “spoon”. Observation: Google Translate has difficulty with tonal distinctions and homonyms in Igbo, while ChatGPT was able to pick the more contextually appropriate options.

2. Simple Sentences/Declaratives (Items 1, 6, 7, 8, 11, 12, 13, 19)

These are short statements, usually subject-verb-object structures.

Google Translate misinterpreted item 1 (Ó nyèrè m̀ ákwá mgbè m̀ nà-èbè ákwá n'élú ákwá) as “He gave me an egg that I was crying over,” which fails to capture the intended nuance.

ChatGPT tried but still struggled with item 1, rendering it as “He gave me cloth when I was crying on top of cloth.” The Gold translation was “He gave me an egg while I was crying on the bed,” showing that both tools failed to manage the multiple homonyms (ákwá = cloth/egg/bed).

In items 6 and 7 (Ó nyèrè m̀ égo), Google Translate gave “He gave me a bed” in one case, which is wrong. ChatGPT consistently gave the correct translation “He gave me money.”

For items 11–13 (ń j̣ ń m̀), Google Translate gave “He asked me,” while ChatGPT aligned with the Gold “He rejected me.” The Gold also included an interrogative form (“Did he reject me?”).

Observation: Google Translate often chooses the “commonest” English form (e.g., “asked”) without tonal sensitivity, while ChatGPT shows better contextual awareness but sometimes overgeneralizes.

3. Idiomatic Expressions and Proverbs (Items 15, 16, 17, 23, 25, 26)

These are culturally rooted and carry meanings beyond literal words.

Google Translate gave literal, often awkward outputs:

Item 15 (É méé ngwá ngwá è méé hàrá́ dáchí) → “He made haste and made a disaster.”

Item 16 (Áká ájá ājá nà-èbuté' n' mman' mman') → “The brown hand brings the oil.”

ChatGPT, by contrast, attempted to give functional equivalence:

Item 15 É mée ngwā ngwā è mée hará' dàchí → “If done quickly, disaster is averted,” closer to the Gold “A stitch in time saves nine.”

Item 16 Áká ájá ājá nà-èbuté' n' mman' mman' → “Hard work brings prosperity,” close to the Gold “Hard work brings success.”

Item 17 A word is enough for the wise → “Okwu zuru oke bara amamihe” close to the Gold “Òtù ókwù è zuórolá ónyé àmàmiíhé.”

Observation: ChatGPT is much better at capturing idiomatic and proverbial meanings, while Google Translate sticks to literal translations that sound unnatural and often misleading.

4. Imperatives / Commands (Items 18, 32, 33, 34, 35, 36, 37, 38, 39, 40)

These are instructions or commands such as close the door, keep silent, take, carry, stand up Google Translate often gave partial or broken translations like “close quiet” (item 32) instead of “Stay quiet.”

ChatGPT rendered them more naturally, e.g., “keep silent,” “stay calm,” “stop crying,” “take your book.”

A few inconsistencies appear, for instance, item 34 (kw' r' tū) → ChatGPT gave both “Stand up” and “Rest,” showing some confusion.

Observation: ChatGPT handles imperatives far better than Google Translate, though occasional inconsistencies remain.

5. Interrogatives / Questions (Items 14, 30, 41)

These include yes/no questions.

Google Translate output for Item 41 (ɔ̃ b' àrà ébé à) was “is he here?”

ChatGPT gave “Did he come here?” which aligns better with the Gold.

For Item 14 (ɔ̃ j' r' m̃), both tools struggled, but the Gold “Did he reject me?” makes the intended meaning clear.

Observation: ChatGPT generally produces more accurate interrogatives, while Google Translate often misses nuances in tense and intent.

4.3 General Observations

1. Tone Sensitivity: Google Translate repeatedly failed where Igbo tones disambiguate meaning (e.g., ákwà = cloth, àkwá = egg, ákwá = cry, ákwà = bed). ChatGPT performed better but still struggled with multiple homonyms.

2. Literal vs. Functional Translation: Google Translate prefers literal outputs even for proverbs and idioms, leading to awkward translations. ChatGPT showed greater awareness of context and produced more natural equivalents.

3. Consistency: ChatGPT was more consistent in handling repeated items e.g., “He gave me money”, whereas Google Translate varied unnecessarily (sometimes “bed,” sometimes “money”).

4. Cultural Knowledge: Proverbs and idioms highlighted the biggest difference—Google Translate gave direct/literal versions, while ChatGPT managed to provide meaningful equivalents closer to the Gold.

4.4 Summary of Findings

From the 44 test items, the performance of the two systems showed clear differences. Google Translate had an overall accuracy of about 32%. Its main weakness was a heavy reliance on literal translations, which made it struggle with tonal distinctions, idioms, and proverbs. This shows that the tool is not yet adapted to handle the complexity of Igbo meanings and expressions.

ChatGPT performed better, with an accuracy of about 73%. It was able to handle many idiomatic and contextual translations more effectively than Google Translate. However, it still made errors, especially with tone-sensitive words like *ákwà* (cloth/cry/egg/bed) and in some interrogative sentences. This indicates that while ChatGPT shows more awareness of context, it also needs further improvement to fully capture the depth and variety of Igbo. Both tools demonstrate useful strengths but also reveal significant weaknesses. They are far from perfect and require more advancement, especially in areas of tone recognition, idiomatic usage, and context sensitivity, to become truly reliable for Igbo-English translation.

5. Conclusion

This study evaluated the performance of Google Translate and ChatGPT in translating Igbo language data, using a dataset of forty-four items that included lexical homonyms, declarative and interrogative sentences, imperatives, and proverbs. The analysis revealed that while both systems handled simple declaratives and imperatives reasonably well, significant weaknesses emerged with lexical items that rely on tone and diacritics, as well as with proverbs and idiomatic expressions. Google Translate consistently defaulted to literal renderings, often distorting meaning and missing context, whereas ChatGPT produced more context-sensitive outputs and captured idiomatic sense more effectively, though sometimes at the expense of precision. Overall, Google Translate achieved about 27% accuracy, while ChatGPT reached approximately 73%, underscoring the gap in their performance. These findings demonstrate that although AI translation tools hold promise for supporting Igbo and

other Nigerian languages, their current limitations hinder accurate documentation and effective communication. To make them more useful for African languages, improvements are needed in handling tones, diacritics, and culturally embedded forms such as proverbs. By addressing these gaps, AI systems can better contribute to language preservation, education, and cross-cultural communication in multilingual contexts, and such improvements would not only benefit Igbo but also enhance the effectiveness of global translation technology as a whole.

References

- Abbott, Jade, and Laura Martinus. 2019. “*Benchmarking Neural Machine Translation for Southern African Languages*.” Proceedings of the Workshop on African NLP.
- Adebara, Ibrahim, and Muhammad Abdul-Mageed. 2022. “*Translating African Languages: Building and Benchmarking Neural Machine Translation for Low-Resource Settings*.” Transactions of the Association for Computational Linguistics 10: 150–166.
- Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. 2015. “*Neural Machine Translation by Jointly Learning to Align and Translate*.” Proceedings of the International Conference on Learning Representations (ICLR).
- Bamgbose, Ayo. 1991. *Language and the Nation: The Language Question in Sub-Saharan Africa*. Edinburgh: Edinburgh University Press.
- Bird, Steven. 2020. “*Decolonising Speech and Language Technology*.” Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (ACL): 5183–5197.
- Crystal, David. 2008. *A Dictionary of Linguistics and Phonetics*. 6th ed. Malden, MA: Blackwell.
- Emenajo, E. Nolue. 2015. *A Grammar of Contemporary Igbo: Constituents, Features, and Processes*. Port Harcourt: M & J Grand Orbit Communications.
- Hutchins, John, and Harold L. Somers. 1992. *An Introduction to Machine Translation*. London: Academic Press.
- Javier, C., (2024). The impact of Generative AI on minority languages. <https://www.linkedin.com/pulse/impact-generative-ai-minority-languages-javier-ca%C3%B1estrouz1m>
- Obiwuru, L. and Chinyere Gift Onwuegbule, C. (2025). *Assessing the impact of artificial intelligence translation on igbo language: a critical discourse analysis* EKETE: International Journal of Advanced Research Volume 3 Number 2, March 2025

- Nick, S., (2024). *14 Best AI Translation Tools & Online Translators to Use Right Now*. TranslatePress. <https://translatepress.com/best-ai-translation-tool>
- Nida, Eugene A. 1964. *Toward a Science of Translating: With Special Reference to Principles and Procedures Involved in Bible Translating*. Leiden: Brill.
- Noor, M., (2025). Machine Learning for Endangered Language Preservation. Trend Research and Advisory Report, <https://trendsresearch.org/insight/machine-learning-for-endangered-languagepreservation/#:~:text=AI%2Dbased%20translation%20tools%20facilitate,resources%20that%20were%20previously%20unattainable>.
- Nwachukwu, P. Akujuobi. 2010. *Towards an Igbo Literary Standard*. Aba: Nwamife Publishers.
- Orife, Iroro, et al. 2020. “*Towards Neural Machine Translation for African Languages*.” Proceedings of the Workshop on African NLP.
- Wu, L., & Liu, S. (2021). User Feedback and Continuous Improvement in AI Translation Systems: Lessons Learned from a Large-Scale Deployment. *Journal of Information Systems*, 43(2), 215-230