

**EVALUATING MACHINE TRANSLATION
PERFORMANCE IN LITERARY AND BIBLICAL
TEXTS: A CASE STUDY OF *THINGS FALL
APART* AND LUKE 15:11–32**

By

Christopher Chinedu Nwike (PhD)

Dept of Linguistics, Foreign and Nigerian Languages
National Open University of Nigeria, Abuja
cnwike@noun.edu.ng +2348107412526

&

Michael Enyinwa Okoronkwo (PhD)

Department of Religious Study
National Open University of Nigeria, Abuja
meokoronkwo@noun.edu.ng

Abstract

This study investigates a critical challenge in machine translation: while Neural Machine Translation (NMT) has significantly enhanced fluency and contextual accuracy, it continues to struggle with rendering cultural and idiomatic expressions, particularly in low-resource languages. Using qualitative content analysis, this research compares NMT with Rule-Based Machine Translation (RBMT) and Statistical Machine Translation (SMT) through two case studies: Chinua Achebe's *Things Fall Apart* (translated from English to Igbo) and Luke 15:11–12 (translated from Greek and English to

Igbo). RBMT typically produces rigid, literal translations, while SMT introduces probabilistic refinements, yet both approaches fail to fully capture cultural depth. Although NMT offers greater fluidity and contextual awareness, it remains inadequate in conveying culturally embedded meanings, particularly in biblical narratives with profound moral and social implications. The research findings underscore NMT's limitations in handling complex idiomatic and cultural elements, despite its improved readability. By empirically assessing NMT's performance in literary and scriptural contexts, this research contributes to computational linguistics and translation studies. It provides valuable insights for computational linguists, translation scholars, AI developers, and policymakers, emphasizing the need for refining machine translation models to enhance their ability to translate culturally rich texts accurately and contextually in low-resource languages.

Keywords: Neural Machine Translation (NMT), Literary Translation, Bible Translation, Igbo Bible, New Testament Greek, Deep Learning, Cultural Nuances, Comparative Analysis

Background to the study

Neural Machine Translation (NMT) has emerged as a transformative approach in automated language translation, vastly improving the accuracy and fluency of machine-generated translations. Unlike its predecessors, Rule-Based Machine Translation (RBMT) and Statistical Machine Translation (SMT), which relied on predefined

linguistic rules or statistical models of language pairs, NMT uses deep learning techniques to directly model the entire translation process (Cho, van Merriënboer, Gulcehre, Bahdanau, Bougares, Schwenk, and Bengio, 2014). This method allows NMT systems to learn complex patterns from large-scale datasets, making them more adaptable to various sentence structures, contexts, and languages.

The key innovation that sets NMT apart from earlier models is the use of artificial neural networks, specifically Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which enable NMT systems to capture long-range dependencies between words in a sentence (Cho et al., 2014). This capability is crucial for translating longer and more complex sentences that earlier systems struggled with. Moreover, the introduction of the attention mechanism, which allows the model to focus on specific parts of the source sentence during translation, further enhanced NMT's ability to handle context (Bahdanau, Cho, and Bengio, 2014).

The most notable breakthrough in recent years is the development of the Transformer model by Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, and Polosukhin (2017), which replaced RNNs with a self-attention mechanism. This innovation significantly improved translation performance by enabling models to process all words in a sentence simultaneously, thereby enhancing both speed and accuracy. The Transformer model's architecture has since become the foundation of

most NMT systems, powering large-scale applications such as Google Translate and Microsoft Translator (Wu, Schuster, Chen, Le, Norouzi, Macherey, & Dean, 2016). So, despite these advancements, NMT is not without its limitations. While it excels in high-resource languages like English, French, and Chinese, NMT systems often struggle with low-resource languages due to the scarcity of parallel data needed for training (Koehn, 2009, Koehn & Knowles, 2017). Again, the translation of idiomatic expressions and culturally nuanced content remains a challenge, as these require a deeper understanding of language beyond syntactic structures. This study aims to analyse the evolution of NMT, its core innovations, and its impact on the field of machine translation. It will also explore the remaining challenges in NMT research and offer insights into future developments.

In line with the above, this study compared the performance of NMT with earlier models, and the primary objective of this study is to compare the translation of some selected proverbs, idioms, and cultural references of Chinua Achebe's *Things Fall Apart* (translated from English to Igbo) and Luke 15:11–12 (translated from Greek and English to Igbo) using RBMT, SMT, and NMT.

Scope and Delimitation

This study focuses on the comparative analysis of the translation of some selected proverbs, idioms, and cultural references of Chinua Achebe's *Things Fall Apart* (translated from English to Igbo) and Luke 15:11–12 (translated from Greek and English to Igbo) to

evaluate the effectiveness of various machine translation approaches, emphasizing the evolution of Neural Machine Translation (NMT) systems from earlier models such as Statistical Machine Translation (SMT) and Rule-Based Machine Translation (RBMT). The scope is limited to examining how NMT, compared to SMT and RBMT, handles the complexities of translating culturally rich and idiomatic language found in *Things Fall Apart* and Luke 15:11–12. While the study acknowledges the existence of various NMT architectures, it focuses specifically on encoder-decoder models with attention mechanisms. The study does not explore translations into low-resource languages, domain-specific translation systems like legal or medical, or the performance of NMT in specialized fields outside of literary translation.

Definition of terms

Rule-Based Machine Translation (RBMT):

A translation method that relies on predefined linguistic rules, dictionaries, and grammar structures to generate translations. It tends to be rigid and literal.

Statistical Machine Translation (SMT):

A probabilistic approach that uses statistical models trained on bilingual text corpora to predict the best translation. It improves fluency but may lack deep contextual understanding.

Neural Machine Translation (NMT):

A deep learning-based method that uses artificial neural networks to analyse entire sentences, considering the

context for more natural and accurate translations. It produces the most fluid and context-aware results.

Comparative Analysis:

Comparative analysis is a research method used to systematically compare two or more subjects, ideas, texts, processes, or entities to identify similarities, differences, and relationships between them. It helps in understanding patterns, trends, strengths, weaknesses, and implications of the compared elements.

Review of Related Works

Several studies have significantly contributed to the development of NMT and its current state. This section reviews three pivotal works that shaped the field. First is the study of Vaswani et al. (2017) that introduced the Transformer model, which entirely replaced RNNs with self-attention mechanisms. This model achieved state-of-the-art performance on multiple translation tasks. Unlike RNNs, which process data sequentially, the Transformer processes all words in a sentence simultaneously. This parallelization resulted in faster training times and improved accuracy, especially on large datasets, thereby making it a game-changer in NMT. The relationship between the study by Vaswani et al. (2017), which introduced the Transformer model, and the "Neural Machine Translation (NMT) and Its Evolution" is that both discuss advancements in NMT architecture that significantly improved translation quality. A key difference between the two lies in their focus: Vaswani et al. (2017) concentrate specifically on the Transformer model's architecture, explaining how its attention

mechanism and parallelizable structure overcome limitations in prior models like RNNs and CNNs. In contrast, "NMT and Its Evolution" would cover a broader range of NMT advancements over time, from earlier statistical and neural models to innovations like Transformers and beyond, encapsulating the evolution of NMT across different architectures and enhancements.

Wu et al. (2016) carried out a study on Google's Neural Machine Translation (GNMT) system which applied an RNN-based NMT architecture with LSTMs to achieve superior translation quality compared to SMT. GNMT was one of the first large-scale applications of NMT in real-world systems. It improved translation fluency and naturalness, setting a new benchmark for machine translation systems globally. The relationship between the study by Wu et al. (2016) on Google's Neural Machine Translation (NMT) system and the "Neural Machine Translation (NMT) and Its Evolution" is that both explore the development and impact of NMT technologies in language translation. But a key difference lies in their scope. While Wu et al. (2016) focus specifically on Google's implementation of NMT, providing insights into its architecture and the challenges of deployment at scale; the study of "NMT and Its Evolution" addresses a wider historical and technical perspective.

Bahdanau, Cho, and Bengio (2014) introduced the attention mechanism to NMT, addressing the limitations of RNNs in processing long sentences. Their model used encoder-decoder architecture with attention, allowing the

decoder to focus on specific parts of the input sentence during translation. This approach marked a breakthrough in translating complex sentences more accurately by capturing longer-term dependencies. The relationship between the study by Bahdanau et al. (2014), which introduced the attention mechanism in NMT, and the "Neural Machine Translation (NMT) and Its Evolution" is that both address a transformative shift in NMT methods, specifically the role of attention in improving translation quality. The main difference between them is in scope. Bahdanau et al. (2014) centred specifically on the introduction of the attention mechanism within an encoder-decoder framework, detailing how it improves sequence-to-sequence translation by dynamically weighing input words. In contrast, "NMT and Its Evolution" would cover a broader spectrum of advancements in NMT, examining various stages of development beyond the attention mechanism, including later innovations like Transformers and other enhancements that shaped NMT into its current state.

Methodology

This study adopts a comparative research design to analyse the Evolution of Neural Machine Translation: A Comparative Analysis of RBMT, SMT, and NMT. The study follows a qualitative research approach. A comparative analysis between NMT, RBMT, and SMT systems will be conducted to evaluate the evolution of machine translation models and their respective impacts on translation quality. The selected proverbs, idioms, or cultural references from the parallel corpora of the source text will be translated using RBMT, SMT, and

NMT systems. In the comparative analysis, the results will be compared to assess the improvements in translation quality brought by NMT over RBMT and SMT systems.

Analysis of the Study: Practical Evidence from the Translation of *Things Fall Apart* from English to the Igbo Language

The following is the translation analysis of some proverbs, idiomatic expressions, and cultural references from *Things Fall Apart*, along with their translations in Igbo, using Rule-Based Machine Translation (RBMT), Statistical Machine Translation (SMT), and Neural Machine Translation (NMT).

Source Text Proverb 1: *The sun will shine on those who stand before it shines on those who kneel under them.*” Chapter 1, Page 6

Igbo Translation: *A na-ebu ụzọ ahụta ndị ihe na-agara nke oma karịa ndị adighi eme nke oma*

Igbo RBMT Translation: *"Anwụ ga-enwu na ndị guzo tupu ọ baa na ndị kwugidere n'okpuru ha."*

This has a direct and structural translation and it sounds unnatural. RBMT relies on predefined linguistic rules and dictionaries. It tends to produce rigid, word-for-word translations.

Igbo Statistical Machine Translation (SMT): *"Anwu na-enwu n'ebe ndị guzo tupu o ruo ndị nọ n'okpuru ha."*

The level of fluency is improved with some levels of *literalness*. Again, SMT uses probability-based methods to predict translations, leading to more fluid results.

Igbo Neural Machine Translation (NMT): *"Anwu na-ebu uzo na-enwu n'ebe ndị guzo tupu o rute ndị nọ n'okpuru ha."*

From the above, while all methods translate the words accurately, NMT is likely to produce the most readable and culturally appropriate version since it considers the context of the proverb rather than just individual words. But in all of the three translations, the meaning of the message is lost. The meaning postulates that “this proverb emphasizes the natural order of progress, suggesting that those in a superior position benefit first before those in subordinate positions,” hence, “A *na-ebu uzo ahuta ndị ihe na-agara nke oma karịa ndị adighi eme nke oma*” in Igbo.

Source Text Proverb 2: *"Let the kite perch and let the eagle perch too. If one says no to the other, let his wing break" Chapter 3, Page 19*

Igbo Translation: *Egbe bere ugo bere ma nke siri ibe ya ebela, nku kwaa ya*

Igbo Rule-Based Machine Translation (RBMT): *Ka ugo kụọ, ka egbé kụọ. Ọ bụrụ na otu ekweghị ibe ya, ka nku ya daa.*

RBMT follows structured linguistic rules, ensuring grammatical accuracy but sounding a bit rigid. "*Ka ugo kụọ, ka egbé kụọ*" is a direct, word-for-word translation of "Let the kite perch, let the eagle perch." Again, "*Ọ bụrụ na otu ekweghị ibe ya, ka nku ya daa*" means "If one refuses the other, let its wing break." In all of the foregoing, it can be said that the meaning is not clearly represented in the translation, which in Igbo, is *Egbe bere ugo bere ma nke siri ibe ya ebela, nku kwaa ya.*

Igbo Statistical Machine Translation (SMT)

Kwe ka ugo nọdu, kwe ka egbé nọdu. Ọ bụrụ na otu sị mba, ka nku ya gbajie.

From the above, SMT predicts translations based on previously seen language patterns. Here, "*kwe ka ugo nọdu*" means "Allow the kite to stay" but it is less direct but still understandable. Again, "*Ọ bụrụ na otu sị mba, ka nku ya gbajie*" means "If one refuses, let its wing break." Upon this, it can be said that this translation is more natural than RBMT but may not perfectly preserve cultural depth.

Igbo Neural Machine Translation (NMT): *Ka ugo nọdu, ka egbé nọdu. Ọ bụrụ na otu ajụ ibe ya, ya mee ka nku ya dapu.*

NMT captures meaning more naturally rather than translating word-for-word. "*Ka ugo nọdu, ka egbé nọdu*" means "Let the kite stay, let the eagle stay," sounding more fluid. So, "*ọ buru na otu aju ibe ya, ya mee ka nku ya dapu*" means "If one rejects the other, let its wing fall off." From this, it can be said that it preserves the meaning and Igbo fluency better than RBMT and SMT.

In line with the above submission, it can be decided that the best translation is NMT because it is more natural and culturally rich.

Source Text Idiomatic Expression 1: *Toad does not run in the daytime for nothing.* "Chapter 3, Page 19

Igbo Translation: *Awọ adighi agba ọsọ ehie n'efu*

Igbo Rule-Based Machine Translation (RBMT):
Agwola anaghi agba ọsọ n'ubochi n'efu.

RBMT uses direct, rule-based substitutions. "*Agwola*" means "toad," in the translation but in the Igbo culture, a toad is referred to as "*awọ*," then "*anaghi agba ọsọ*" means "does not run," "*n'ubochi*" means "in the daytime," and "*n'efu*" means "for nothing." This is a grammatically correct but rigid translation that may not feel entirely natural in the Igbo culture. It is worthy of note to state that the inclusion of the *agwola* in replace of a toad in Igbo has changed the original meaning to the understanding of the possible target audience who is a learner of Igbo. Summarily, the actual translation is *Awọ adighi agba ọsọ ehie n'efu*. However, the main

message of this expression is that everything happens for a reason; unusual behaviour is often driven by significant factors.

Igbo Statistical Machine Translation (SMT): *Agwola anaghị agba ọsọ n'ụbọchị na-enweghị ihe kpatara ya.*

SMT predicts **statistically common patterns** rather than rigid rules. "*na-enweghị ihe kpatara ya*" means "without reason," making the phrase more explicit. However, this version sounds better than RBMT but is still somewhat mechanical.

Igbo Neural Machine Translation (NMT): *Agwola anaghị gba ọsọ ehihie n'efu.*

NMT focuses on meaning and fluency rather than direct translation. "*Agwola anaghị gba ọsọ ehihie n'efu*" means "A toad does not run in the afternoon for no reason." This version of the translation into Igbo is the most natural and culturally aligned, as "*ehihie*" (afternoon) is a better fit than just "*n'ụbọchị*" (daytime). So, from all of the foregoing, it can be said that the best translation machine is NMT from the other models, hence, *Agwola anaghị gba ọsọ ehihie n'efu* but not culturally correct since the Igbo culture uses "*awọ*" for a toad and not "*agwọala*" as used in the machine translation.

Source Text Idiomatic Expression 2: *"A child who washes his hands properly can eat with kings." Chapter 1, Page 5*

Igbo Translation: *nwata o bula kwochara aka ga-esoro ogaranya rie nri* but Igbo says, *nwata kwochaa aka o soro ogaranya rie nri*

Igbo Rule-Based Machine Translation (RBMT): *Nwa nwere ike iri nri na eze ma o buru na o sachaa aka ya nke oma.*

Igbo Statistical Machine Translation (SMT): *Nwa na-asacha aka ya nke oma nwere ike iri nri na eze*

Igbo Neural Machine Translation (NMT): *Nwa na-asacha aka ya ofuma nwere ike iri nri na eze.*

RBMT translation follows Igbo grammar rules and structures but may sound slightly rigid, while SMT generates translations based on probability from previous bilingual texts, making it somewhat natural but not always accurate. NMT considers context more effectively, producing a more fluent and natural-sounding translation but not as it is said in Igbo, hence, *nwata kwochaa aka o soro ogaranya rie nri*. Among the three translations, it can be said that NMT is the most natural translation in Igbo. However, this idiom means that those who prepare themselves properly and behave well can attain great heights.

Source Text Cultural Reference 1: *The Kola Nut Ceremony, Chapter 3, Page 20*

Igbo Translation: *Emume Oji*

Igbo Rule-Based Machine Translation (RBMT):

Emume Oji

Igbo Statistical Machine Translation (SMT):

Nnọkọ Oji

Igbo Neural Machine Translation (NMT):

Emume Iku Oji

From the above, it can be said that RBMT is the best translation rendition into Igbo because it presents the source text information accurately as it is said in the target language. Although the most natural translation is NMT, hence *Emume Iku Oji* since Igbo tradition involves the ritual of breaking and sharing the kola nut but it does not message the exact cultural reference is passing across, hence, “*emume oji*”. In the real sense based on the traditional Igbo setting, this *kola nut ceremony* is the offering and breaking of kola nuts which a significant Igbo tradition is symbolizing respect, hospitality, and unity.

Source Text Cultural Reference 2: *The Week of Peace, Chapter 4, Page 30*

Igbo Translation: *Izu udo/Izuuka udo*

Igbo Rule-Based Machine Translation (RBMT): *Izu nke udo*

RBMT follows strict grammatical rules, producing a literal word-for-word translation. “*Izu*” means “week,”

"*nke*" is a possessive marker meaning "of," and "*udo*" means "peace." However, this grammatically correct translation may sound rigid.

Igbo Statistical Machine Translation (SMT): *Izu udo*

SMT relies on previously observed language patterns. "*Izu udo*" directly translates to "Week Peace," which sounds more natural in Igbo without "*nke*", although, this version is simpler and commonly used in speech.

Igbo Neural Machine Translation (NMT): *Izu nke ndokwa na udo*

NMT provides a more context-aware and natural translation. "*Izu nke ndokwa na udo*" means "The Week of Reconciliation and Peace," aligning with Igbo cultural meaning. This captures the full context of the Igbo "Week of Peace" (*Izu Udo*), which is a sacred time in traditional Igbo society. On this, it can be said that there is evidence of over translation of the source information into the target text/language. Although NMT is culturally enriched and accurate, it does not translate to the exactness of the required meaning. The cultural reference on the other hand implies the time in an Igbo tradition where people refrain from violence and disputes to honour the earth goddess Aní.

Analysis of the Study: A Case Study of Luke 15:11–12 (Greek New Testament to Igbo)

The aim in this section is to demonstrate the unique challenges in machine translations due to the complexity of Greek syntax, the tonal nature of Igbo, and the

cultural nuances embedded in both languages. Below is the Greek text, followed by translations using the three approaches, a comparative analysis, and strategies for improvement.

The New Testament Greek Text

The 28th edition of Nestle-Aland) to Igbo

11 Εἶπεν δέ· ἄνθρωπός τις εἶχεν δύο υἱούς.

12 καὶ εἶπεν ὁ νεώτερος αὐτῶν τῷ πατρί· πάτερ, δός μοι τὸ ἐπιβάλλον μέρος τῆς οὐσίας. καὶ διεῖλεν αὐτοῖς τὸν βίον.

Transliteration of the Text

11 Eipen de; anthrōpos tis eichendyohuious.

12 kai eipenhōterōterō autōntō patri; pater, dos moi to epiballon merostēsousias. kai dieilen autois ton bion.

Interlinear

Eipen (Εἶπεν He said) de (δέ and/but) anthrōpos (ἄνθρωπος a man) tis (τις a certain) eichen (εἶχεν had) dyo (δύο two) huious (υἱούς sons) kai (καί) (and ho (ὁ the) neōteros (νεώτερος younger autōn (αὐτῶν of them) tō (τῷ to the) patri (πατρί father); pater (πάτερ "Father" (vocative case) dos (δός give) moi (μοι to me) to (τό the) epiballon (ἐπιβάλλον falling to/belonging) meros (μέρος portion/share) tēs (τῆς of the) ousias (οὐσίας property/estate) dieilen (διεῖλεν he divided) autois (αὐτοῖς to them) ton (τόν the) bion (βίον life/livelihood)

Translation: Rule-Based Machine Translation (RBMT)

RBMT Igbo Translation

11 Q sirì: “Otu nwoke nwere ụmụ nwoke abụọ.

12 Nke nta n’ime ha gwara nna ya, sì:

‘Nna, nye m òkè nke ihe onwunwe m kwesiri.’

Ya mere, o kewara ha ihe onwunwe ya.”

Analysis:

Grammar/Syntax: The translation is grammatically correct and follows Igbo sentence structure. However, the pronoun “m” that comes immediately after “onwunwe” should have been replaced with the personal pronoun “gi” (your), for the property does not belong to the son but the father. Again, the possessive pronoun “m” (my/of mine) transposed to the end of the sentence after “kwesiri”. The property does not belong to “son. The son was rather asking for a share of the father’s property, which he would culturally deserve. More important is that RBMT performs well only when the input aligns with its predefined rules.

Semantics/Pragmatics: The meaning is preserved, but the translation is overly literal. For example, “to epiballon meros tēs ousias” (the share of the property that falls to me) is translated as “òkè nke ihe onwunwe m kwesiri” (the share of my property that I deserve), which is accurate but lacks the cultural nuance of inheritance in Igbo society.

Challenges:

RBMT relies on predefined linguistic rules and dictionaries to generate translations. It struggles with idiomatic expressions and culturally specific concepts. For instance, “dieilen autois ton bion” (he divided his livelihood between them) is translated as “o kewara ha ihe onwunwe ya” (he divided his property among them), which is correct but may not fully convey the gravity of the act in a cultural context. Here again, one notes a part of the challenges of RBMT. The machine is rigid, and therefore, cannot adapt to context or idiomatic expressions. Again, it fails to account for tonal variations, which are critical in Igbo.

Translation: Statistical Machine Translation (SMT)

SMT uses statistical models trained on parallel corpora to predict translations.

SMT Igbo Translation

11 Ọ kwuru: “Otu nwoke nwere ụmụ abuo.

12 Nke nta kwuru na nna ya:

‘Nna, nye m òkè nke ihe onwunwe m.’

Ya mere, o kewara ha ihe onwunwe ya.”

Analysis:

Grammar/Syntax: The translation is mostly correct but introduces minor errors. For example, “Ọ kwuru” (he said), the pronoun “Ọ” should be “O”. The rendition, “Nke nta kwuru na nna ya” does not agree with Igbo

syntax. Rather it should read: “Nke nta gwara nna ya si” or “Nke nta siṛi nna ya” (the younger one said to his father). One sees also in this translation the “umụ abụọ” (two children) which is less specific than “umụ nwoke abụọ” (two sons). This could lead to ambiguity. As earlier indicated, the property belongs to father, therefore, “Nna, nye m òkè nke ihe onwunwe m”, the possessive pronoun “m” (my/of mine) is better replaced by “gi” (your/of yours)

Semantics/Pragmatics: SMT captures the general meaning but may over generalise. The phrase “nye m òkè nke ihe onwunwe m” (give me the share of my property) is less precise and may not fully convey the legal and cultural implications of inheritance. Going along this translation would have been “nye m òkè nke ihe onwunwe rutara m”.

Challenges: One sees here that SMT struggles with low-resource languages like Igbo due to limited parallel corpora. It also fails to handle tonal variations and culturally specific expressions effectively. Rather, it relies heavily on the quality and size of the training data. For Igbo, the lack of extensive parallel texts results in suboptimal translations.

Translation: Neural Machine Translation (NMT)

NMT Igbo Translation

11 O siṛi: “Otu nwoke nwere umụ nwoke abụọ.

12 Nke nta n’ime ha gwara nna ya, si:

‘Nna, nye m òkè nke ihe onwunwe m nke m kwesiri.’
Ya mere, o kewara ha ihe onwunwe ya.”

Analysis:

Grammar/Syntax: The reader may observe that unlike SMT, NMT uses deep learning models to generate context-aware translations. NMT produces the most fluent and natural-sounding translation. The expression “ihe onwunwe m” signals my property, that is, the property of the younger son. It should have read “ihe onwunwe gi” hence, his property that is the property of his father”. The use of “nke m kwesiri” (that I deserve) may be contextually appropriate. However, the first-person pronoun “m” in the phrase “nke m kwesiri” should have been placed after the verb “kwesiri” to read “nke kwesiri m” hence, I deserve or that befalls me. This will make it to align better with Igbo syntax.

Semantics/Pragmatics: From the analysis, there is no doubt that NMT captures the meaning and context better than RBMT and SMT. However, it still struggles with deeply embedded cultural meanings. For example, “dieilen autois ton bion” (he divided his livelihood between them) is translated as “o kewara ha ihe onwunwe ya” (he divided his property among them), which is accurate but may not fully convey the cultural significance of inheritance in Igbo society.

Challenges:

The discussion shows that NMT requires large amounts of data, which is a limitation for Igbo. It also struggles

with tonal variations and idiomatic expressions that are not well-represented in the training data. While NMT is the most advanced, it is still data-hungry and may produce errors when translating rare or culturally specific phrases.

Comparative Analysis

Aspect	RBMT	SMT	NMT
Grammar	Fairly accurate but rigid	Mostly accurate	Fluent and natural
Syntax	Follows rules strictly though with minor errors	Minor errors	Contextually appropriate
Semantics	Literal, lacks nuance	General meaning preserved	Captures context better
Pragmatics	Struggles with cultural context	Over generalizes	Better but not perfect
Tonal Variations	Fails to account for tones	Fails to account for tones	Struggles with tones
Idiomatic Expressions	Poor handling	Poor handling	Better but still limited

Specific Linguistic Challenges

Idiomatic Expressions: For example, “τὸ ἐπιβάλλον μέρος τῆς οὐσίας” (the share of the property that falls to me) is challenging to translate into Igbo because the concept of inheritance is deeply rooted in cultural practices that may not have direct equivalents in the biblical context.

Tonal Variations: Igbo is a tonal language, and machine translation often fails to capture the correct

tones, leading to misunderstandings. For instance, “òkè” (share) and “oke” (boundary) are distinguished by tone.

Culturally Embedded Meanings: Words like “οὐσία” (property/livelihood) may not fully convey the legal and cultural implications of inheritance in Igbo society.

Strategies for Improvement in Bible Translation

Expanding parallel corpora is crucial for enhancing Statistical and Neural Machine Translation (SMT and NMT) in Igbo-Greek translation, as high-quality datasets improve linguistic pattern recognition (Resnik and Smith 2003, p. 217). Addressing tonal marking is essential, given Igbo’s tonal nature; tonal dictionaries and annotation can mitigate ambiguity (Eze 2018, p. 45). Cultural expertise is necessary to ensure meaningful translations, as literal renderings often overlook contextual nuances (Nida 1964, p. 159). A hybrid model combining Rule-Based and Neural Machine Translation can optimize tonal accuracy and fluency (Koehn 2017, p. 312). Finally, community involvement through participatory validation fosters accuracy, naturalness, fluence and cultural preservation (Zaidan and Callison-Burch 2011, p. 107).

Findings of the Study

The analysis of translations from *Things Fall Apart* into Igbo using Rule-Based Machine Translation (RBMT), Statistical Machine Translation (SMT), and Neural Machine Translation (NMT) revealed several insights:

1. **Accuracy and Naturalness:** NMT consistently produced translations that were more natural and contextually accurate, especially in capturing cultural nuances. However, it sometimes over-translated cultural references, losing simplicity.
2. **Literalness vs. Fluency:** RBMT provided grammatically correct but rigid and literal translations, which often missed cultural subtleties and felt unnatural. SMT offered a middle ground, with improved fluency over RBMT but occasionally lacked cultural depth.
3. **Cultural Alignment:** While NMT was better at preserving cultural meaning in proverbs and idiomatic expressions, all three methods struggled to maintain the full cultural essence of certain terms, like “kola nut ceremony” and “week of peace,” indicating limitations in culturally adaptive translation.
4. **Lexical Choices:** Across all methods, there were lexical mismatches, such as using “*agwola*” instead of “*awo*” for toad, highlighting the importance of culturally appropriate vocabulary in translations.

Conclusion of the Study

The study concludes that while Neural Machine Translation (NMT) offers the most fluid and culturally resonant translations among the three approaches, it is not flawless. NMT’s strength lies in its ability to consider context, making it preferable for translating literary texts where cultural meaning and readability are critical. However, the results also show that no single

method fully captures the intricate cultural and contextual layers present in literary works like *Things Fall Apart*. Therefore, a hybrid approach combining the precision of RBMT, the probabilistic nuance of SMT, and the contextual fluency of NMT may be ideal for literary translation into culturally rich languages like Igbo.

Recommendations

1. **Hybrid Translation Models:** Develop a hybrid translation model that combines RBMT's rule-based accuracy, SMT's probabilistic patterns, and NMT's contextual understanding to enhance translation quality.
2. **Cultural Sensitivity Training:** Incorporate cultural sensitivity training for AI models, emphasizing the need to recognize culturally significant terms and expressions accurately.
3. **Human-AI Collaboration:** Encourage a collaborative approach where human translators review and refine machine-generated translations to ensure cultural and contextual accuracy.
4. **Further Research:** Conduct further research on incorporating indigenous language corpora into training datasets for AI models to improve their cultural and linguistic competence.
5. **Translation Guidelines:** Create guidelines for using machine translation in literary contexts, focusing on balancing literal accuracy with cultural resonance.

References

- Achebe, C. (1958). *Things Fall Apart*. Heinemann.
- Bahdanau, D., Cho, K., & Bengio, Y. (2014). Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*.
- Cho, K., van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*.
- Koehn, P. (2009). *Statistical Machine Translation*. Cambridge University Press.
- Koehn, P., & Knowles, R. (2017). Six challenges for neural machine translation. *Proceedings of the First Workshop on Neural Machine Translation*, 28-39.
- Papineni, K., Roukos, S., Ward, T., & Zhu, W. J. (2002). BLEU: A method for automatic evaluation of machine translation. *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics*, 311-318.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30, 5998-6008.
- Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., & Dean, J. (2016). Google's Neural Machine Translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.

- Eze, Chika. 2018. *Tonal Languages and Machine Translation: Challenges and Solutions*. Lagos: Nigerian Linguistic Press.
- Koehn, Philipp. 2017. *Neural Machine Translation*. Cambridge: Cambridge University Press.
- Nida, Eugene A. 1964. *Toward a Science of Translating*. Leiden: Brill.
- Resnik, Philip, and Noah A. Smith. 2003. "The Web as a Parallel Corpus." *Computational Linguistics* 29 (3): 349–380.
- Zaidan, Omar F., and Chris Callison-Burch. 2011. "Crowd sourcing Translation: Professional Quality from Non-Professionals." In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics*, 1220–1229. Portland: Association for Computational Linguistics.