A Case for Machine in The Translation of Culture-Specific Items

Un caso a favor de la máquina en la traducción de elementos culturales específicos

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ABSTRACT: The paper reports how Culture-Specific Items (CSIs) were rendered by three machine translation (general, semi-private and custom-built) systems in three anthologies of African poetry from English to French. The paper seeks to fill a knowledge gap, namely the question of whether and to what extent existing Machine Translation (MT) systems trained preponderantly with texts produced in Western contexts take CSIs in texts written by authors from a non-Western cultural background into account. After translating poetry data of about 87,761 words through Amazon Translate (English to French and vice versa), Amazon Translate showed one instance of «improvement» in rendering a source word. This discovery raised a question for further research on the imperatives of building a custom-translation engine for CSIs in African poetry: The result showed that machine translation systems mainly rendered CSIs in Wole Soyinka's Poetry through the strategy of Repetition, following Aixelá's (1996) model.

KEYWORDS: CSIs; general machine translation; custom-built translation; repetition.

RESUMEN: El artículo explica cómo los ECE (elementos culturales específicos) fueron traducidos mediante tres sistemas de traducción automática (general, semiprivado y personalizado) en tres antologías de poesía africana del inglés al francés. El artículo busca llenar un vacío de conocimiento, a saber, la cuestión de si, y en qué medida, los sistemas de traducción automática existentes que se entrenan preponderantemente con textos producidos en contextos occidentales toman en cuenta los ECE en textos escritos por autores de un entorno cultural no occidental. Después de traducir un corpus de poesía de aproximadamente 87.761 palabras a través de Amazon Translate (inglés a francés y

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viceversa), Amazon Translate mostró un caso de «mejora» en la traducción de una palabra de origen. Este descubrimiento planteó una pregunta para futuras investigaciones sobre los imperativos de construir un motor de traducción personalizado para ECE en la poesía africana: el resultado mostró que los sistemas de traducción automática representaban principalmente ECE en la poesía de Wole Soyinka a través de la estrategia de repetición, siguiendo el modelo de Aixelá (1996).

PALABRAS CLAVE: ECE; traducción automática general; traducción personalizada; repetición.

1. INTRODUCTION

MT of CSI is a relatively emerging research field. This research is further narrowed by investigating how CSIs in African poetry are translated by MT systems. Aixelá's (1996) model, initially proposed for use in human translation to identify and translate CSIs, has been adopted for this investigation. According to Aixelá's definition of Culturespecific Items:

[t]here is a common tendency to identify CSIs with those items especially linked to the most arbitrary area of each linguistic system - its local institutions, streets, historical figures, place names, personal names, periodicals, works of art, etc. - which will typically present a translation problem in other languages. However, the constant appearance of textual items which do not seem more arbitrary than the average and whose nature as a translation problem can only be explained by appealing to an intercultural gap, forcing the translation student to widen his outlook (Aixelá 1996, 57).

Thus, two primary criteria in the definition were taken into account during the identification of CSIs: «normally present a translation problem in other languages» (Aixelá 1996, 57) and «appealing to an intercultural gap» (Aixelá 1996, 57). The model distinguishes eleven possible manipulations of CSIs: repetition, orthographic adaptation, linguistic (non-cultural) translation, extratextual gloss, intratextual gloss, synonymy, absolute universalization, limited universalization, naturalization, deletion, and autonomous creation (Aixelá 1996, 61-4).

The paper seeks to answer three questions: How will machine translation systems output CSIs in translating African poetry from English to French, and what strategies will machines employ in this translation process? Will there be any difference in the production of CSIs by Custom-trained translation machines and in the strategies adopted? The three anthologies were passed through DeepL and Amazon Translate to obtain the French translation of CSIs and determine the translation strategies. The three anthologies were again passed through Amazon Translate after translating through bilingual (French/English) unparalleled training data consisting of 87,761 words of other African poetry. It was observed that there was one instance of difference in the output of a source word of the corpora. This slight difference prompted the building and training of a 2024 Custom Translation Engine (CTE) on Microsoft Azure with parallel data of about 14,000

English/ French African poetry sentences. In the end, 51 CSIs were found in approximately 60 instances, with five of eleven of Aixelá's 1996 model strategies used.

2. REVIEW OF LITERATURE

Research on the MT of CSIs is lacking; however, research on building MT engines for poetry and literature and evaluating MT quality exists.

Ghazvininejad et al. (2018) introduced a method for automatic poetry translation. They proposed the first neural poetry translation system and showed its quality in translating French to English poems. Their system is much more flexible than those based on PBMT (Phrase-Based Machine Translation) and can consistently produce translations into any scheme. In addition, they proposed two novel improvements to increase the quality of the translation while satisfying specified rhythm and rhyme constraints.

Doron Sadeh (2019), in terms of whether machines can translate poetry when humans can barely, suggests that, in a sense, the machine and the person performing the act referred to as «translation» follow the same process. The only difference is in their respective *interpretations*. As the machine's internal language and representation differ from that of the human, it simply views the poem in terms the latter cannot understand, thus generating a coherent poetic translation in a lingual sphere we can never be a part of. Once we acquire that level of understanding, it is not unfathomable that machines may be able to not only translate poetry as well as humans but also generate original, emotionally moving verses of their own.

In their experiment, Kuzman et al. (2019) used an English subcorpus of nine English novels and their Slovene translations to reveal that models tailored to literature would not consistently achieve better scores than General Neutral Machine Translation. On the other hand, their results confirmed their third hypothesis, supposing that the Novel model, tailored to a specific author, would perform better than the model trained on a more extensive but more varied literary corpus.

Philippe Humblé (2020) believes that generating poetry through machines is not the same as translating it; it only seems more complex, and the point of coincidence is that a machine is used to deal with language in a highly creative and supposedly unexpected way. His article sets out to analyse the Portuguese translations of three English poems. The translations by three human translators, Geir Campos, Pedro Gonzaga and Jorge de Sena, are compared to the translations made by Google Translate to evaluate machine translation quality. He observed that Google blunders are much less than expected, and one of the most striking and expected features of Google translation is the machine's difficulty in choosing a suitable alternative for polysemous words. Polysemy is a troublesome problem for a machine since it will immediately select the most common alternative.

On the other hand, Kathrine Thai (2022), in exploring document-level Literary Machine Translation with parallel paragraphs from World Literature, shows that existing automatic translation quality metrics need to be more meaningful in the literary domain. They introduce PAR3, a large-scale dataset to study paragraph-level literary translation

into English. PAR3 consists of 121K paragraphs taken from 118 novels initially written in a non-English language, where each section is aligned to multiple human-written English translations of that paragraph and a machine-translated paragraph produced. They show that MT evaluation metrics such as BLEU and BLEURT are ineffective for literary MT. They discovered that two of their tested metrics (BLEU and the document-level BLONDE) preferred Google Translate outputs over reference translations in PAR. The translators in their study identified overly literal translations and discourse-level errors (e.g., coreference, pronoun consistency) as the main faults of modern MT systems. They conclude that human expert evaluation is currently the only way to judge the quality of literary MT. None of the works reviewed above explored the MT of CSIs in Poetry, let alone in African poetry.

2.1. Data Description

Etienne Galle's French translation of *Cycles sombres* consists of 30 poems drawn from *Idanre and other poems*, *A Shuttle in the Crypt* and *Ogun Abibimaň*. *Idanre and Other Poems* is a collection of 37 poems by Wole Soyinka, from which Etienne Galle translated six poems and André Bordeaux one. In *A Shuttle in the Crypt*, a collection of 34 poems by Wole Soyinka, Etienne Galle translated 23 poems. *Ogun Abibimaň* is a long single poem of three parts. *La terre de Mandela, Etienne Galle's French translation of Mandela's Earth and Other Poems*, contains 16 poems. In all, a total of 46 poems in three anthologies were translated by a general machine translation (DeepL), semi-private translation (Amazon Translate) and custom-built translation (Microsoft Azure custom translation engine) tool from English to French.

2.2. Methodology

The methodology is descriptive-explanatory (Toury 2012, xii). The source text is first read to identify possible cultural nuances. This is done to get a firsthand insight into what to watch out for and expect, but not limited to, in the translation by machine translation tool. Reading was done in the order of *Early Poems, Mandela's Earth and Other Poems* and *Idanre and Other Poems*.

The source anthologies were first translated by DeepL (2023) and then by Amazon Translate (2023). Proposed training Poetry of about eighty-seven thousand seven hundred and sixty-one (87,761) words was translated through Amazon Translate from English to French and vice versa. After that, the source text poetry was fed through Amazon Translate again (henceforth now referred to as Amazon Translate 2) to determine if anything had changed about the output of CSIs and strategies employed by Amazon Translate 2. Identification and analysis of the outcome of CSIs and translation strategies by DeepL and Amazon Translate and then Amazon Translate again (after passing through the above training data). A custom translation engine (henceforth now referred to as CTE in this article) was built on Microsoft Azure with about 14,000 parallel sentences from 67 authors, 535 Single parallel Poems, eight anthologies, and 60 translators producing a Bleu score of 24.1 after an instance of a source CSI, «Elijah» (Soyinka 1998, p. 130), becoming

Elie by Amazon Translate 2. Below is a tabular summary of how the CSIs were grouped under five of eleven of Aixelá's 1996 model for identifying and classifying CSIs.

Strategy	Summary				
Repetition	Rendered exactly as a source word				
Linguistic (non-cultural) translation	Linguistic transparency of CSI / support of pre-established translations within the intertextual corpus of the target language				
Limited universalization	CSI is too obscure for readers, or there is another, more usual possibility, and they decide to replace it; for the sake of credibility, they seek another reference belonging to the source language culture but closer to another of their readers CSI				
Absolute universalization	The basic situation is identical to Limited universalization, but the translators do not find a better-known CSI or prefer to delete any foreign connotations and choose a neutral reference				
Synonymy	This strategy is based on stylistic grounds linked with recurrence.				

Table 1. Summary of Aixelá's strategies used

3. OVERVIEW OF CSIS AND STRATEGIES BY MT SYSTEMS

No.	Source	GMT: DeepL	Semi-private:	Amazon	Microsoft CTE
	Word		Amazon	Translate 2	
			Translate		
1.	My impi	Mon <i>impi</i>	Mon <i>impi</i>	Mon <i>impi</i>	Mes impi
	(Soyinka,				
	1976, 9. 11)	(Linguistic	(Linguistic	(Linguistic	(Repetition)
		[non-cultural]	[non-cultural]	[non-cultural]	
		translation)	translation)	translation)	
2.	Bean-cake	Forme de	Ruche de	Gâteau aux	gâteau de fèves
	(Soyinka,	haricots	beignets	haricots	
	1998, p. 133)				
		(Linguistic	(Absolute	(Linguistic	(Linguistic
		[non-cultural]	Universalizatio	[non-cultural]	[non-cultural]
		translation)	n)	translation)	translation)
		Gâteaux de	Gâteau aux	Gâteau aux	gâteau de fèves
	Bean-cake	haricots	haricots	haricots	
	(Soyinka,				
	1998, p. 133)		(Linguistic	(Linguistic	(Linguistic
			[non-cultural]	[non-cultural]	[non-cultural]
			translation)	translation)	translation)

		(Linguistic			
		[non-cultural]			
		translation)			
3.	Kaffir	Kaffir	Kaffir	Kaffir	
	(Soyinka,				
	1976, p. 20)	(Repetition)	(Repetition)	(Repetition)	
4.	Abibimañ	Abibimañ	Abibimañ	Abibimañ	Abibimañ
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976, pp. 5,				
	10, 14, 22)				
5.	Sigidi	Sigidi	Sigidi	Sigidi	Sigidi
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976, pp. 9,				
	11, 19, 22)				
6.	Bayete	Bayete	Bayete	Bayete	Bayete
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976. pp. 10,				
	11, 12, 13,				
	14, 16)				
7.	Ogun	Ogun	Ogun	Ogun	Ogun
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976, pp. 9,				
	11, 19, 22)				
		Ogun	Ogun	Ogun	Ogoun
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Linguistic
	1967, pp. 61,				[
	63, 64)				[non-cultural]
		Ogun	Ogun	Ogun	translation)
		(Repetition)	(Repetition)	(Repetition)	,
	(Soyinka,				
	1988: 61)				Ogun
					(Repetition)

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8.	Idanre	Idanre	Idanre	Idanre	Idanre
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976, pp. 10)				
		Idanre	Idanre	Idanre	Idanre
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, pp. 68,				
	69,72, 81,				
	82)	Idanre	Idanre	Idanre	Idanré
		(Repetition)	(Repetition)	(Repetition)	(Linguistic
					[non-cultural]
	(Soyinka,				translation)
	1988: 61)				
9.	Mfekane	Mfekane	Mfekane	Mfekane	Mfekane
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1976, p. 19				
10.	Elijah	Elijah	Elijah		
	(Soyinka,	(Repetition)	(Repetition)		
	1976, p. 130)				
11.	Shaka	Shaka	Shaka	Shaka	
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	
	1976, pp. 9,				
	15				
12.	Amazulu	Amazulu	Amazulu	Amazulu	
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	
	1976, p. 14)				
13.	Galileo	Galileo		Galileo	
	(Soyinka,	(Repetition)		(Repetition)	
	2019, p. 151)				
14.	Mickey	Mickey Mouse	Mickey Mouse	Mickey Mouse	Mickey Mouse
	Mouse	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	(Soyinka,				
	1988, p. 41)				
15.	Louiseville	Louisville Lips	Louisville Lips	Louisville Lips	lèvres naguère
	Lip				si agiles, a
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	Louisville
	1988, p. 47)				(I in mistic
					(Linguistic
					[non-cultural]
16		East	Eau	Eau	
10.	ESU (Sovinko	(Denstition)	(Denetition)	(Denetition)	<i>Esnou</i> (Linguistic
	1088×10^{10}	(Repetition)	(Repetition)	(Repetition)	(Linguistic
	1700, p. 40 <i>)</i>				translation)
					u ansiauon)

		Esu	Esu	Esu	Esu
	Esu	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	(Soyinka,				
	1967, p. 70 &				
17	78) Donnelgänge	Donnalgängen	Donnalaängan	Donnalaängan	Donnalgängen
17.	<i>Doppeigunge</i> r (Sovinka	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988 n 22	(Repetition)	(Repetition)	(Repetition)	(Repetition)
18.	Kora	Kora	Kora	Kora	Kora
10.	(Sovinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 66)				
19.	Gbegbe	Gbegbe	Gbegbe	Gbegbe	Gbegbe
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, pp. 66				
	& 67)				
20.	Tete	Tete	Tete	Tete	Tete
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 67)				
21.	Egungun	Egungun	Egungun	Egungun	Egungun
	(Soyinka, 1088 + 60)	(Repetition)	(Repetition)	(Repetition)	(Repetition)
22	1988, p. 09)	Akaraba	Akaraba	Akaraba	Akaraba
22.	(Sovinka	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988. p. 50)	(repetition)	(itepetition)	(repetition)	(itepetition)
23.	Jigida	Jigida	Jigida	Jigida	jiguida
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Linguistic
	1988, p. 45)				[non-cultural]
					translation)
24.	Kakaki	Kakaki	Kakaki	Kakaki	Kakaki
	(Soyınka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 66)				
25	mhira	Mhira	Mhira	Mhira	Mhira
23.	(Sovinka	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988. p.	(repetition)	(Repetition)	(Repetition)	(nepennon)
	page 48)				
26.	Ile-Ife	Ile-Ife	Ile-Ife	Ile-Ife	Ilé-Ifé
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Linguistic
	1988, p. 61)				[non-cultural]
					translation)
27.	Mandel	Mandel	Mandel	Mandel	Mandel
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 6)				

28.	Mendel	Mendel	Mendel	Mendel	Mendel
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 6)				
	(Loaded				
	Proper noun)				
29.	Mengel	Mengel	Mengel	Mengel	Mengel
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 6)				
30.	Mengele	Mengele	Mengelle	Mengele	Mengelle
	(Soyinka,	(Repetition)	(Linguistic	(Repetition)	(Linguistic
	1988, p. 6)		[non-cultural]		[non-cultural]
			translation)		translation)
31.	Broederland	Broederland	Broederland	Broederland	Broederland
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 8)				
32.	Mandgela	Mandgela	Mandgela	Mandgela	Mandgela
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 8)				
33.	Biko	Biko	Biko	Biko	Biko
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1988, p. 8)				
34.	Scottsboroug	Scottsborough	Scottsborough	Scottsborough	les Enfants de
	h Boys	Boys	Boys	Boys	Scottsborough
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Linguistic
	1988, p. 40)				[non-cultural]
					translation)
35.	Recolored	Brutus de	Brutus de	Brutus rouge	Brutus recoloré
	Brutus.	couleur rouge	couleur	(Limited	(Limited
	(Soyinka,	(Limited	(Linguistic	Universalizatio	Universalizatio
	1988, p. 9)	Universalizatio	[non-cultural]	n)	n)
		n)	translation)		
36.	Mister Boots,	Monsieur	Mister Boots,	Monsieur	Monsieur
	Knucles and	Boots,	Knuckles and	Bottes,	Bottes,
	Bones	Knuckles and	Bones	Jointures et Os	Jointures et Os
	(Soyinka,	Bones	(Repetition)	(Linguistic	(Linguistic
	1988, p. 9)	(Limited		[non-cultural]	[non-cultural]
		universalization		translation)	translation)
)			
37.	Salem Seers	Salem Seers	Voyants de	Salem, les sears	Voyantes de
	(Soyinka,	(Repetition)	Salem		Salem
	1988. P. 13)				

			(Linguistic [non-cultural] translation)	(Absolute universalization)	(Linguistic [non-cultural] translation)
	Ceasar (Soyinka, 1988, p. 19 & 31)			Ceasar (Repetition)	
38.	Swinging Bokassa (Soyinka, 1988, p. 33	Swinging Bokassa (Repetition)	Swinging Bokassa (Repetition)	Swinging Bokassa (Repetition)	fringants Bokassa (Linguistic [non-cultural] translation)
39.	Master Sergent Doe (Soyinka, 1988, p. 33)			Master Sergent Doe (Repetition)	sergent-chef Doe (Linguistic [non-cultural] translation)
40.	<i>Asantehene</i> (Soyinka, 1988. P. 17)	Asantehene (Repetition)		Asantehène (Linguistic [non-cultural] translation)	Ashantihini (Absolute Universalizatio n)
41.	<i>Sjambok</i> (Soyinka, 1988 , p. 3)	Sjambok (Repetition)	<i>Sjambok</i> (Repetition)	<i>Sjambok</i> (Repetition)	Sjambok (Repetition)
42.	<i>Sango</i> (Soyinka, 1967, p. 61)	Sango (Repetition)	Sango (Repetition)	Sango (Repetition)	Chango (Linguistic [non-cultural] translation)
	<i>Sango</i> (Soyinka, 1967, p. 70)	Sango (Repetition)	Sango (Repetition)	Sango (Repetition)	Shango (Linguistic [non-cultural] translation)
43.	<i>Atunda</i> (Soyinka, 1967, pp. 81 & 83)	Atunda (Repetition)	Atunda (Repetition)	Atunda (Repetition)	<i>Atunda</i> (Repetition)

44.	Ogboni	Ogboni	Ogboni	Ogboni	Ogboni
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, p. 67)				
45.	Ajantala	Ajantala	Ajantala	Ajantala	Ajantala
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, p. 67)				
46.	Orisanla	Orisanla	Orisanla	Orisanla	Orisanla
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, p. 70)				
47.	Orunmila	Orunmila	Orunmila	Orunmila	Orunmila
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, pp. 70,				
	83)				
48.	Ifa (Soyinka,	Ifa	Ifa	Ifa	Ifa
	1967, pp. 70,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	83)				
49.	Ire (Soyinka,	Ire	Ire	Ire	Ire
	1967, p. 71)	(Repetition)	(Repetition)	(Repetition)	(Repetition)
50.	Oya	Oya	Oya	Oya	Oya
	(Soyinka,	(Repetition)	(Repetition)	(Repetition)	(Repetition)
	1967, p. 67)				
51.	Iron One	le Fer Un	Iron one	Iron One	Fer en personne
	(Soyinka,	(Linguistic	(Repetition)	(Repetition)	(Linguistic
	1967, p. 61)	[non-cultural]			[non-cultural]
		translation)			translation)
		Iron One	Iron One	Iron One	Dieu du fer
	Iron One	(Repetition x3)	(Repetition x3)	(Repetition x3)	(Linguistic
	(Soyinka,				[non-cultural]
	1967, pp. 68,				translation) x2,
	70, 74)				
					Ogoun
					(Synonymy)
				Iron One	
		Iron One		(Repetition)	Dieu de fer
		(Repetition)	Iron One		(Linguistic
		_ /	(Repetition)		[non-cultural]
	Iron One				translation)
	(Soyinka,				
	1967, p. 78)				

Table 2. Output of	CSIs and strategies	used by machine
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4. **RESULTS**

The percentage use of the different strategies was manually computed for each MT system based on the total number of CSIs translated by each system. Table 3 below summarises the percentage strategies used by the MT systems.

	MT systems					
Strategies	DeepL	Amazon Translate	Amazon Translate 2	Microsoft Azure Custom Translation		
Repetition	90	90	88.3	61		
Linguistic (non- cultural) translation	6.7	8.3	8.3	33.9		
Limited universalization	3.3	0	1.7	1.7		
Absolute universalization	0	1.7	1.7	1.7		
Synonymy	0	0	0	1.7		

Table 3. Overview of percentage strategies used by MT system

5. CONCLUSION

From Table 2, the least used strategy in the translation of CSIs by MT systems is «Synonymy» (Aixelá 1996, 63), accounting for 1.7 per cent, and the most used strategy is clearly «Repetition» (Aixelá 1996, 61). From the data in Table 3, it is clear that General Machine Translation systems employ more of the strategy of «Repetition» (Aixelá 1996, 61) than CTE (2024) in rendering CSIs in the translation of Wole Soyinka's poetry. However, this value decreased with the custom-trained translation engine. This corroborates Kuzman et al. (2019) that models tailored to a specific author would perform better than the model trained on a more extensive but more varied literary corpus. I thus conclude that untrained GMT engines tend to repeat CSIs in African poetry, while trained translation engines show less tendency to repeat.

Further research is encouraged to re-investigate the outcome of CSI translation by CTE by employing more extensive parallel data, say data from 50,000 to 100,000 parallel sentences of poetry still in African poetry and other regions like Asia, America, Australia, etc.

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