https://doi.org/ 10.5281/zenodo.14966955

Ife Journal of Technology, Vol. 29(2), 2024

Phoneme-Based English-Yorùbá Machine Transliteration

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ABSTRACT

One of the challenges in translating English to Yorùbá language is the foreign names and technical terms used in news articles and scientific documents. Many of these names and terms contain letters not used in the orthography of Yorùbá language. We present a rule-based model for the transliteration of English noun words to Yorùbá such that the output respects the morphology and phonology of the target language. The model, which is phoneme-based, relies on the CMU pronouncing dictionary to derive the phoneme for each word. After the implementation of the model, evaluation of the system developed on standardized test set of 55 words yielded an accuracy of 72.7%, recall of 0.98, precision of 0.965 and F score of 0.972. A second test which included works with non-standardized set references has accuracy of 40.7%, recall of 0.91, precision of 0.925 and F score of 0.912. The low accuracy is an indication of several violation of standard Yorùbá orthography found in this bigger set. A few challenges identified with the model include inability to correctly render some of the vowels as required by the phonology of the target language.

KEYWORDS

Conversion
Sound phoneme
Languages

1. INTRODUCTION

The need for transliteration often arises out of the limitations in handling personal, place and technical names that often does not have translation equivalents when working to reproduce lexical content that exist in one language in another language. Translation from English to Yorùbá is a regular activity especially for news media/advertising organizations in Nigeria and manufacturing and service industries also often need to provide information in indigenous languages. Transliteration is therefore a mechanism for handling words which do not have standard translation in such a way that a form of that word can be produced that conforms to the phonology and morphology of that language. Machine transliteration is the automatic method for converting words in originating language (source language, SL) into phonetically equivalent ones in an- other language (target language, TL).

According to Kirschenbaum and Wintner (2009), statistical machine translation systems require terms in the source language to have equivalent ones in target language. However, despite the existence of bilingual dictionary to provide name equivalence, the phenomenon known as Out of Vocabulary (OOV) has been a consistent challenge to Machine Translation since there may be words (new or old) which may not exist as a concept in target language lexical inventory. Most of these OOV are, as previously mentioned, personal names, place names and technical words in different specialized fields. According to Li *et al.* (2009) Transliteration is the conversion of a given name in the source language (a text string in the source writing system or orthography) to a name in the target language (another text string in the target writing system or orthography)" with the requirement that the TL name:

i. achieves close phonemic correspondence to the SL name
ii. complies with the phonology of the TL and
iii. fits in with the user intuition of the equivalence with the SL name.

Huge volumes of work have been undertaken in Machine Transliteration (hence MTlit) as shown by the existing literature that cover several language pairs and techniques. The extent of undertaken work is shown by the NEWS 2009 Machine Transliteration Shared Task and subsequent NEWS workshops. However, a lot of language pairs like English-Yorùbá are still missing from the list of researched language pairs. In fact, to our knowledge, this will be among the first of such research into English-Yorùbá transliteration. The reason is not far-fetched - paucity of data to develop and evaluate models for transliteration of English terms to Yorùbá. Yorùbá is still an under-resourced language with few language processing resources. Some recent efforts in the direction of machine translation of English to Standard Yorùbá have highlighted the need for complementary efforts toward machine transliteration as most named entity in such produced translation do not conform to Yorùbá orthography and phonology. The following, according to Hermjakob, Knight, and Daumè III (2008) are some consequences of having such untranslated named entity within translated documents without transliteration:

i. it affects the quality of the translated document for human readers.
ii. it also affects other systems using machine translation for further information processing.

The remainder of the paper is divided as follows: section 2 discussed related works and introductory background for the source and target languages as is relevant to transliteration. Section 3 describes our proposed model while in section 4, we present the experiments to evaluate the model's performance and thereafter, results emanating from the experiments. In section 5 we discuss the result, errors observed and future work.

2. RELATED WORK

While machine learning techniques can be divided broadly into rule-based approaches and data driven approaches, machine transliteration efforts are grouped into three categories namely: grapheme-based, phoneme-based and hybrid methods (Chen *et al.*, 2018a). Grapheme-based system handles transliteration as straight mapping of graphemes from one orthographic system to another relying on orthographic features of the source and target languages and it is modelled in Equation 1 as:

$$\hat{t} = \underset{t}{argmax} P(t)P(t|s) \quad [1]$$

where $\hat{t}$ is most likely transliteration of the original target word t that must have given rise to the Source word s.

Phonemic transliteration relies on an intermediate step involving mapping of source graphemes to source phonemes before mapping source phonemes to target graphemes. The hybrid transliteration approach could be based on some form of interpolation between source grapheme and source phoneme to

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Received 9 August 2024 | **Received in revised form** 28 October 2024 | **Accepted** 21 November 2024 | **Available online** 10 February 2025

The editor responsible for coordinating the review of this article and approving its publication was *I. P. Gambo*

P-ISSN: 1115-9782 **e-ISSN:** 2536-6807

produce target grapheme or that it could use correspondence between source grapheme and source phoneme to produce transliteration output (Oh, Choi, and Isahara, 2006).

English has been transliterated into wide variety of languages and writing systems being involved in language pairs like English-Chinese; English-Hangul, English-Kanji, English-Vietnamese, Arabic-English, Persian-English, English-Hindi and English-Bangla, amongst others (Karimi, Scholer, and Turpin 2011; Le and Sadat 2018; Chen *et al.* 2018a). The data-driven techniques include statistical approaches like statistical machine translation, joint source channel, (Rama and Gali 2009; Finch and Sumita 2009; Zhang *et al.*, 2011; Singhania *et al.*, 2018), generative tagging and discriminative sequence labelling (Oh and Isahara 2007; Pingali *et al.* 2008; Yang *et al.*, 2009). Other tools like weighted finite state transducers (Wei and Bo 2008; Knight 2009; Noeman and Madkour 2010), Neural Machine translation (Grundkiewicz and Hea eld 2018; Kundu, Paul, and Pal 2018; Najafi *et al.*, 2018) have been the most applied to the task of transliteration and prominent amongst these language pairs.

Oh and Choi (2002) proposed an enhanced rule-based transliteration model. It consists of two sub-models: pronunciation generation (English grapheme to phoneme conversion) model and phoneme conversion (English phonemes to Korean) model. The pronunciation generation model proceeds in two stages, namely:

i. find the most probable sequence of English Pronunciation Units (EPU) in each English word via a probabilistic model and
ii. assigning the appropriate phoneme to the each EPU is the EPU sequence.

The Phoneme to Korean conversion model which was formulated as a rule-based model built on English-to-Korean Standard Conversion Rule composed of 14 rules with each rule further subdivided into sub-rules. A weakness in the Oh and Choi (2002)'s model is the tendency to propagate error from the start point of generating EPUs. Ali and Ijaz (2009) also proposed a rule-based model for English-to-Urdu transliteration which utilized the Carnegie-Mellon University (CMU) pronouncing dictionary to map the English words to their phonemic equivalents. The sequence of phonemes was syllabicated to approximate Urdu syllabication template. Each syllable (of English phonemes) refitted to conform to Urdu syllable template in what was called Urduization before the final process of conversion to Urdu script. A model to handle Out-of-Vocabulary words was also designed. The OOV model and the syllabication intervention together was reported to have improved the system performance by 12.95%. A Punjabi-to-English grapheme-based transliteration model (Deep and Goyal 2011) which maps Punjabi words written in Gurmukhi script to English in a character-to- character manner using a set of rules was developed. The simple rules mapping characters were augmented with contextual constraint rules to improve performance. Tested on two groupings of Named Entities: Personal names and City/State/River names, the model achieved 95.0% and 91.4% accuracies respectively.

Ahmadi (2019) proposed a rule-driven, grapheme-based approach for transliterating between the two (Arabic-based and Latin-based) orthographies used in Sorani Kurdish language. The model was designed for handling all text and not only Named Entities or technical terminologies. The model was able to achieve almost perfect transliteration when the source text is in Latin-based orthography while the target text is Arabic- based orthography as direct grapheme-to-grapheme mapping was efficient, but the reverse direction achieved only 82.79% due to problem in detecting "Bizroke" character that has a detection rate of 38.74%.

While the character or grapheme is the initiating unit for transliteration in most of the literatures reviewed, there are few exceptions that used the syllable instead as the unit for transliteration. Jiang, Sun, and Zhang (2009) was a syllable-based transliteration system for English-Chinese pair by syllabicating the English input word before mapping to Pinyin and hence to Chinese graphemes. Similarly, Wutiwiwatchai and Thangthai (2010); Deep and Goyal (2011) and Zhang, Li, and Zhao (2012), also proposed syllables as the basic transliteration unit for Thai-English, Punjabi-English and English-Chinese pairs respectively. Nevertheless, Balakrishna and Venkatesan (2013) believed syllable-based model is more effective if one of the languages involved utilizes syllabic writing system. A more recent rule-based and rule-extraction system for Polish and English to Lithuanian was presented in Kasparaitis (2023) and a comprehensive review can be found in Yadav et. al (2023).

2.1. Description of the Source and Target Languages

Transliteration, like translation, involves two languages one of which is called the source and the other, target. The source language (SL), the language in which the word or phrase of interest originated, for this research is English while the target language (TL), the language where this 'source word' needed to be presented in such a way that the morphology and phonology is well approximated is Yorùbá. Due to Nigeria's colonial history, a lot of what originally were English terms has become domesticated into the Yorùbá lexicon that it is difficult to trace their English origin. For example, the Yorùbá word bárékè came from the English word barrack. Others, still in the process of total integration, like bread written as búrẹ́dì exist as loan words until they become well integrated into common usage in the target language. The choice of direction of transliteration was dictated more by the fact that it is more common to find information that originated in English that needed to be translated into Yorùbá especially books, news reports and government documents and hence would benefit from transliteration than the other direction.

2.1.1. *Brief Description of the English Language.*

While there are many dialects of the English language, what we describe here is what is generally known as American English which will henceforth be referred to as Standard English (SE) or simply English. The generally accepted number of phonemes in the English language is 39 comprising of 24 consonant phonemes and 15 vowel phonemes. English syllable conforms to the universal syllable template. It is made up of onset and rhyme. The rhyme comprises, most importantly, of a non-optional nucleus and may contain a coda as well or not. If the onset is present in the syllable (as it well be not), the rhyme may be prepended by an onset. English has a syllable structure that allows closed syllables as well as open syllables. A closed syllable has a consonant (or consonant cluster) referred to as coda in the final position following the nucleus while an open syllable does not have a coda. In addition, both open and closed syllables in English can have a consonant (or consonant cluster) referred to as onset occupying the position before the nucleus of the syllable that is mostly composed from vowels. In certain conditions, some sonorant consonants can play the role of nucleus if no vowel is available. The number of consonants in cluster making up an English onset ranges from 1 to 3 while the consonants in the coda can be anything from 1 to 4 (Harrington and Cox 2009). Finally, English is classified as stress- timed language.

Orthographically, there are 21 consonants letters and five vowel letters in the English alphabet. When compared to the phonemic inventory, it is apparent that there is no one- to-one deterministic mapping between the elements in the two inventories. There are some phonemes that have multiple orthographic representations and some single letters that map to more than a single phoneme. This problem of one-to-many and many-to- one mapping between orthographic and phonemic objects causes English to be said to have a deep orthography. An illustrative table of English phones by Weide (1988) is given in Table A1 in the Appendix.

2.1.2. Brief Description of the Yorùbá Language.

Like the situation in English, there are also several dialects of spoken Yorùbá languages. The written dialect that is used for educational purposes, mass media, government publications, other formal sectors and intercommunication amongst the people of different regional dialects is called the Standard Yorùbá (SY) and it is not tied to any specific regional location. There are 31 phonemes in Standard Yorùbá made up of 18 consonant phonemes, 12 vowel phonemes and one syllabic consonant phoneme. In addition to the phonemes, Yorùbá is a tonal language that uses tone for lexical contrast and thus has three tonemes in its phonology. Yorùbá is an open syllable structured language such that no coda is allowed in the syllable. In addition, the onset can only have a single consonant, and syllabic consonant can also stand as a syllable nucleus but without any onset. Yorùbá is a syllable-time language

The Yorùbá orthography is somewhat close to the English orthography, it has 25 letters in its alphabet (one short of English's 26). However, the alphabet comprises 19 consonant letters and 7 vowel letters (for indicating only oral vowels). The remaining four vowels sounds are nasal vowels, and they are indicated in writing by appending the letter n to the oral equivalent. Note that the phoneme ɔ̃ has two representations in the orthography 'an' and 'ọn'. The syllabic consonant is represented by letter n or m, depending on the context. A table showing the Yorùbá letters and phonemes using IPA symbols and their equivalent context-free mapping to ARPABET symbols can be found in Table A2 in the Appendix..

A comparison of some of the phonological of the source and target languages are shown in Table 1. The table shows English has almost 42% more phonemes than Yorùbá as a whole. The disparity is more pronounced for the vowel phonemes which showed a disparity of 67% while the consonant disparity was 33%. The disparity was narrowed when comparing at letter level where English has 11% more consonants than Yorùbá. Yorùbá has more vowel letters than English with Yorùbá having 40% more vowel letters. At syllable level, Yorùbá operates only open syllable structure while English has both open and closed syllables. $C_{0-3}VC_{0-4}$ is used to indicate that English may have between zero to three consonants at the onset position and and zero to four consonants at the code. Yorùbá, on the other hand can have at most one consonant in the onset position or none and no consonant in the coda position. More importantly, the number of onset and nucleus phonemes in Yorùbá syllables are restricted to only one each but English has wide variety.

Table 1: Comparing the Characterization of English and Yorùbá Languages

Parameter	English	Yorùbá
Number of phonemes	44	31
Consonant phonemes	24	18
Vowel phonemes	20	12
Consonant letters	21	19
Vowel letters	5	7
Syllable Structure	Closed	Open
Syllable	$C_{0-3}VC_{0-4}$	$C_{0-1}V$, n
Prosodic feature of timing	Stress-timed	syllable-timed

3. METHODS

The method applied to addressing the English-to-Yorùbá transliteration is knowledge intensive. Data were gathered for analysis and understanding of the patterns that shows how graphemes and phones in English and Yorùbá are related and then we proceeded to model formulation using the acquired knowledge. The model was then implemented as a transliteration system so that the performance of model could be evaluated. Therefore, the system developed was a rule-driven, phoneme-based transliteration system.

3.1. Data

The data used in the research were gathered from several sources but the 'gold' standard were extracted from the following published papers: Ufomata (1991), Kenstowicz (2006), Adedun and Shodipe (2011), Komolafe (2014) and Tijani (2015). From these papers we extracted two hundred and seventy-three (273) transliteration-pairs out of which 34 English words were repeated by two authors and three by four authors making a total of 38 repeated word pairs. 21 of the 37 repetitions were equally matched while 17 of them either differed due to one of the vowels being doubled in one version or a syllabic nasal was absent in one version and present in the other. Two of the entries are not phonemically or orthographically related being words that were used as in place (as translation by extension of meaning) of the English entry. Five of the words contained consonant clusters that represented exceptions violating the rule that forbid consonant clusters. Table 2 shows data pairs with violations such as consonant clusters (Serial number 1 attested in usage and literature), consonant final (serial 2) and illegal letter in transliteration (serial numbers 3 and 4). Other issues are vowel difference and vowel doubling instead of one. It is to be noted that the remaining 228 data pairs were used as the basis for formulating the rule-base that formed the core of the system.

Table 2: English-Yorùbá transliteration pairs with violations or multiple rendering

SN	English	Yorùbá T1	Yorùbá T2	Comment
1	apostolic	Apostoliiki		consonant cluster
2	hospital	ọsipitu	ọsibitul	consonant final
3	computer	cọmputa		illegal letter
4	Bulb	Gilobu		non-transliteration
5	plaster	Pulasita	pilaster	vowel variation
6	Alum	aalọmu	alọmu	vowel length
7	Free	Firii	firi	vowel length

3.2. Model

A phoneme-based model of English-to-Yorùbá (Eng2Yor) transliteration was formulated using the Carnegie-Mellon University Pronunciation dictionary (abbreviated CMU-Dict) and a rule-base of engines for mapping and alignment. The rule base encodes expert knowledge extracted from several publications and knowledge gotten from patterns observed in the data gathered for the research. The rule-base was divided into three different engines each handling an aspect of the transliteration process.

The four processes involved in English to Yorùbá transliteration consist of the following, given an input of an English word to be transliterated:

i. extract phonemic transcription of input word from dictionary resource
ii. apply preliminary mapping rules to the phonemes extracted from the dictionary.
iii. apply final mapping rules to outcome of application of preliminary mappings.
iv. align the outcome of final mapping to Yorùbá phonological and orthographical system and produce outcome as output.

The processes above are presented as a visual model in Figure 1. The DICTIONARY in Figure 1 is "an open-source pronouncing dictionary originally created by the Speech Group at Carnegie Mellon University (CMU) for use in speech recognition research" known as the CMU pronouncing dictionary which we retrieved from http://www.speech.cs.cmu.edu/cgibin/cmudict. The process: PHONEME EXTRACTION corresponds to stage 1 while INITIAL MAPPING RULES handles stage 2 in the process above. Stage 3 and 4 are handled by the processes FINAL MAPPING RULES and ALIGNMENT ENGINE respectively

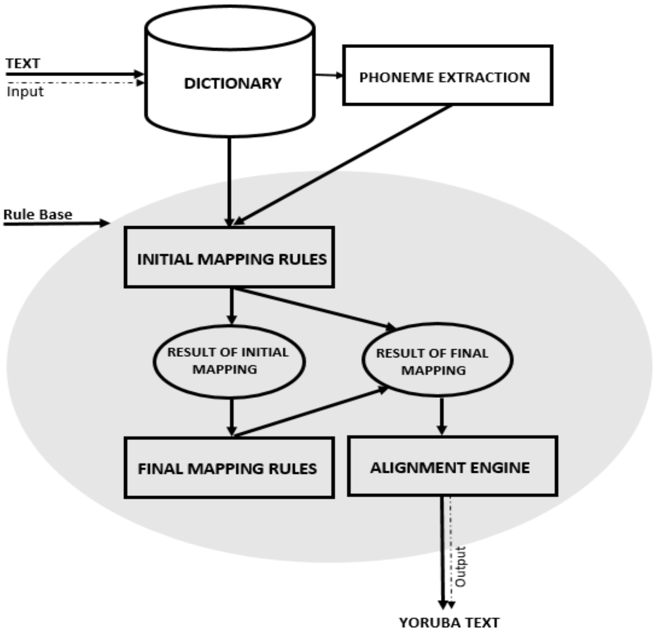


Figure 1: English-Yorùbá Phoneme-Based Transliteration Model. (adapted from (Oh, Choi, and Isahara 2006))

The processing stages were formulated as a set of context-sensitive rewrite rules, adopting Oh, Choi, and Isahara (2006) approach, as shown in Equation 2. This mean that the focus English phoneme $EngPhone_{focus}$ can be written as Yorùbá grapheme $YorGrapheme$ in the presence of preceding and succeeding contexts $EngPhone_{-1}$ and $EngPhone_{+1}$ respectively. Each of major processes here mentioned are discussed in more details in the following sections.

$$(EngPhone_{-1})\ EngPhone_{focus}\ (EngPhone_{+1}) \stackrel{\text{def}}{=} YorGrapheme \quad [2]$$

3.2.1. *Preliminary Mapping.*

The mapping of English phonemes to Yorùbá letters are either one-to-one mapping or one-to-many. The English phones with one-to-one mapping are shown in Table A3 in the Appendix. The rule-case for these phonemes with one-to-one mapping is not presented here in the work since it is straight forward, and the context re-write rules make both $EngPhone_{-1}$ and $EngPhone_{+1}$ to take null values to rewrite $EngPhone_{focus}$.

The one-to-many mapping of English phonemes to Yorùbá letter is shown in Table A4 in the Appendix. The phonemes involved in one-to-many mapping require explicit context of rewrite of Equation 1. For example, the following words and their corresponding phonemes (using ARPABET) extracted from CMU Dictionary:

i. TECHNOLOGY gives T EH0 K N AA1 L AH0 JH IY0
ii. UNIVERSITY gives Y UW2 N AH0 V ER1 S AH0 T IY093
iii. NIGERIA gives N AY0 JH IH1 R IY0 AH0
iv. COMPUTER gives K AH0 M P Y UW1 T ER0
v. LINGUISTICS gives L IH0 NG G W IH1 S T IH0 K

From the output generated, the phoneme /AH0/ is produced from the second English grapheme o in the word Technology, the same phoneme is produced by graphemes i, and a from the words University and Nigeria respectively. The various re-write rules used in preliminary mapping algorithm are presented in Table A5 in the Appendix and the resolution of AH0 presented in Table A6 in the Appendix. The context re-write rules were implemented using logical/conditional(if-else-then) statements.

The preliminary mapping preprocesses the extracted phonemes to ensure that letter mapping does not map to wrong graphemes. The first rule in Table A5, for instance, deletes letter H and attendant phoneme H that starts the character and phoneme sequences of the input English word. Table A6 contains the mapping that resolves the occurrences of phoneme 'AH0 (and sometimes 'AH1 and 'AH2') within the context of other phonemes and graphemes. This was necessary since this phoneme has a one-to-many mapping to Yorùbá graphemes. The English phone\AH\ maps to all seven oral vowels in the Yorùbá language depending on its context of occurrence. It is very important to note that while our approach is essentially phonemic- based, graphemic information from the letters of the original input word were utilized to make reliable mapping as indicated by the eWrd terms in nine out of the ten rules in the Preliminary rules.

3.2.2. *Final Mapping*

Final Mapping. The final mapping rule is completed with the application of transliteration rule for English phonemes that have one-to-one mapping. The rule for the final mapping involves the mapping of the English phonemes with one-to-one relationship to Yorùbá letters as presented in Table A3 in Appendix and Final mapping rules presented in the Table A7 in the Appendix that guide the transliteration of English phonemes that require contextual information to correctly map to the expected Yorùbá letters.

To illustrate both the preliminary and final mapping that takes place during English- to-Yorùbá transliteration, we take an English name Victor and show what is happening in each mapping stage.

The word "**Victor**" is supplied as input English word to be transliterated

Equivalent phonemes sequence retrieved from (CMUDict): V IH1 K T ER0

Applying Preliminary rule mapping: Phoneme ER0 transliterated by Rule 4 of Table A5, hence,

V IH1 K T ER0 =⇒ V IH1 K T ọ

Final mapping module utilizes rows 26, 4, 18 and 25 of Table A3 respectively for one-to-one correspondence mapping of phonemes

V ⇒ f,
IH ⇒ i,
K ⇒ k
T ⇒ t

With the preliminary rule above, 'V IH K T ER0' ➔ f i k t ọ

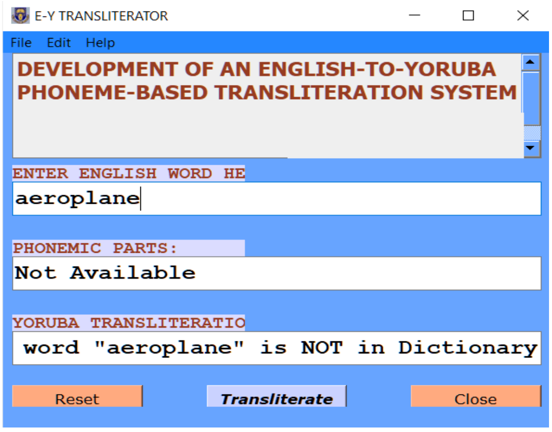
3.2.3. *Final Alignment*

This phase deals with the adjustments applied to the output of mapping, to make the final word conform to Yorùbá orthography and phonology. Yorùbá does not allow consonant clusters, hence, there is a need to adjust any output that contains such clusters. From the preceding illustration, "**f i k t ọ**" contains the cluster "**k t**" not allowed in Yorùbá orthography. The issue raised by any consonant cluster is addressed by the insertion of an epenthetic vowel, the choice of which is limited to letters **i**, u and in isolated cases e. The epenthetic vowel to be inserted is dependent on the context within the word itself. The system scans through the word to find the last seen vowel before the cluster and based on that decides on what vowel to insert. In the given illustration, an i is inserted between k and t as the vowel before the cluster is also an i. The epenthetic vowel "**I**" is inserted for a, e, ẹ and i otherwise, u is inserted. The insertion of i in the illustration causes the transliteration to be completed with "**f i k t ọ**" becoming "**f i k i t ọ**".

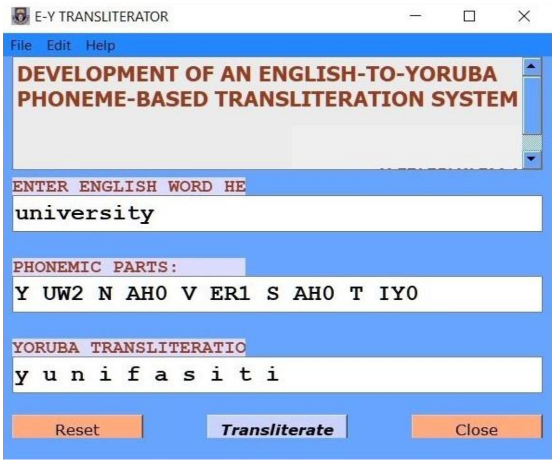
In a case where the consonant cluster is encountered before the first vowel, the vowel inserted is dependent on the first vowel encountered after the clustered consonants. Notwithstanding the vowel, if the first consonant in the cluster is a b, then u is always used as the cluster breaker. Finally, the last issue concerning the alignment must deal with is that Yorùbá words do not end with consonants. The same approach to dealing with consonant clusters is also applied to terminal consonants by adding an epenthetic vowel to resolve such cases following the same concept of last seen vowel.

4. IMPLEMENTATION, EXPERIMENT AND RESULT

In this section, a little detail of the implementation of the model as a transliteration system called E-Y Transliterator is given. The E-Y Transliterator was used to evaluate the performance of the model as earlier discussed.



(a)



(b)

Figure 2 GUI forE2Y Transliterator (a) Not in dictionary (b) Word transliteration

4.1. Implementation

The formulated model was implemented using Python version 3.6.4 and a graphical user interface (GUI) with PyQt5. The system takes an English word as its input. The input is checked against the CMU Pronouncing Dictionary made available in the execution directory. If the input word is not found, a statement to that effect will be displayed within the GUI. Otherwise, the phonetic transcription is retrieved and displayed along with the final output which is the word transliterated according to the constraints of Yorùbá language's phonology and morphology. Figure 2 show the two possible instances of the system either not finding the input word in the database or finding the input word in the database. Figure 2a shows that the input: **aeroplane** is not in the database as American English refers to it as **airplane** while Figure 2b indicates that the input: university was found in the database and a transliteration was returned for it.

4.2. Experiments and Result

We conducted two sets of experiments to evaluate the performance of the E-Y Transliterator. The first experiment is to evaluate the performance of the system on the data that was used to develop the rules within the model while the second experiment evaluated the system using an expanded testing data set. Wherever the author has two or more reference transliterations for an English word, both are used as alternative transliteration, but none is ranked as first reference. The exception to that is in the situation where any of the candidates has a violation of Yorùbá spelling like consonant clusters or consonant ending that do not indicate nasal vowels.

The test data for the first experiment comprised fifty-five (55) words drawn from the works of various authors mentioned in section 3.1. In this first dataset, the number of English words with only a single reference transliteration is forty-three (43) while those with multiple reference transliteration are twenty-two (22). The test data for the second experiment is a superset of the dataset for the first experiment. Additional data was from additional literatures especially, those written as text for teaching Yorùbá language and for literate Yorùbá speakers using personal knowledge of the proficiency of the subjects. In the second dataset, the number of English words with only a single reference transliteration is 126 while the number of English words with multiple reference transliteration is 235 making a total of 311 unique English words. The nature of the model that we developed allowed the system to return only one possible candidate transliteration. A candidate is considered valid if there exists one reference that it matches. A sample of the test data showing entries with either single or multiple references can be found in Table A8 in the Appendix.

4.3. Result

The evaluations presented here were computed using a part of the standard metrics for transliteration developed for the NEWS 2018 Named Entity Transliteration Shared Task (Chen *et al.* 2018b). The following metrics were used: Word Accuracy in Top-1 (ACC) and Fuzziness in Top-1 (Mean F-score) defined by equations 3 to 9:

$$ACC = \frac{1}{N}\sum_{i=1}^{N}\begin{Bmatrix} 1 \ if \ \exists r_{i,j} : r_{i,j} = c_i; \\ 0 \ otherwise \end{Bmatrix} \quad [3]$$

$$LCS(c,r) = \frac{1}{2}(|c| + |r| - ED(c,r)) \quad [4]$$

$$r_{i,m} = argmin_j \left(LCS\left(c_i, r_{i,j}\right) \right) \quad [5]$$

$$R_i = \frac{LCS(c_i, r_{i,m})}{r_{i,m}} \quad [6]$$

$$P_i = \frac{LCS(c_i, r_{i,m})}{c_i} \quad [7]$$

$$F_i = 2\frac{R_i * P_i}{R_i + P_i} \quad [8]$$

$$\begin{Bmatrix} R = \frac{1}{N}\sum_{i=1}^{N} R_i \\ P = \frac{1}{N}\sum_{i=1}^{N} P_i \\ F = \frac{1}{N}\sum_{i=1}^{N} F_i \end{Bmatrix} \quad [9]$$

ACC in equation 32 also known as Word Error Rate measures how much of the candidates generated for each input word matches at least one of the reference transliterations for that input word. Value of ACC ranges between 1 (all the candidates have a reference) and 0 (none of the candidates matched any of their possible references). *i* is index for the input test word while *j* is index for a reference transliteration. *j* could take either a single value 1 when there is only one reference provide for an input test word or two values 1 and 2 or three values 1 -3 for test words with two and three references respectively.

Given two strings, LCS (Longest Common Subsequence) is the longest sequence of characters which appears in order in both strings. This is defined by equation 4 and the term $ED(c, r)$ in the equation refers to the edit distance between reference *r* and candidate *r*. Edit distance is the minimum number of single-character edits required to change one string into another one. $|x|$ is the length of string *x*. The particular reference that is chosen for the computation in equations 6 to 8 is the one that yield the minimum LCS according to equation 5. For each test word, Recall R_i and Precision P_i are calculated from LCS and the F-score F_i from P_i and R_i according to equations 6 to 8 respectively. System-level values for Recall, Precision and F-score are calculated by applicable components of equation 9. A sample of the report for some of the test words in experiment 1 is presented in Table 3 and the summary of the system-level performance follows it. Similarly, the sample of the report for some of the test words in experiment 2 is presented in Table 5 and the summary of its system-level performance are in Table 4 and 6 respectively.

Table 3: Computation for sample words in Experiment E1

SN	Key	Reference	Candidate	R_i	P_i	F_i
1	Blender	blẹnda	bulẹnda	1.000	0.857	0.923
2	Chancellor	ṣansẹlọ	ṣanselọ	0.929	0.929	0.929
3	Computer	kọmputa	kọmputa	1.000	1.000	1.000
4	Egypt	ijipiti	Ijipiti	1.000	1.000	1.000
5	Helicopter	ẹlikọputa	ẹlikọputa	1.000	1.000	1.000
6	Maternity	mataniti	mataniti	1.000	1.000	1.000
7	Phoneme	fonimu	fonimu	1.000	1.000	1.000
8	Pink	pinki	Pinki	1.000	1.000	1.000
9	Silver	silifa	Silifa	1.000	1.000	1.000
10	Technology	t kin l ji	t kin l ji	1.000	1.000	1.000

Table 4: Result of Data on E1

	Experiment 1 (E1)	Variance on Mean
No of items processed	55	
ACC of E2Y	0.727	
Recall of E2Y	0.980	0.003
Precision of E2Y	0.965	0.004
F1 Score of E2Y	0.972	0.003

Table 5: Computation for sample words in Experiment E2

SN	Key	Reference	Candidate	R_i	P_i	F_i
1	Abram	aburamu	aburamu	1.000	1.000	1.000
2	Barber	baba	baaba	1.000	0.800	0.889
3	Center	sẹnta	sẹnta	1.000	1.000	1.000
4	Delay	dilee	dile	0.800	1.000	0.889
5	Freedom	firidọọmu	firidọmu	0.889	1.000	0.941
6	Incubator	inkubetọ	inkubetọ	1.000	1.000	1.000
7	Methodist	mẹtọdiisi	mẹtadisiti	0.889	0.800	0.842
8	Parcel	pasu	paaseli	0.875	0.500	0.636
9	Purple	pọpu	papu	0.875	0.875	0.875
10	Sweater	suwẹta	swẹta	0.833	1.000	0.909

Table 6: Result on Data of E2

	Experiment 2 (E2)	
No of items processed	307	
ACC of E2Y	0.407	
Recall of E2Y	0.910	0.015
Precision of E2Y	0.925	0.011
F1 Score of E2Y	0.912	0.011

4.4. Discussions

Comparing the values computed from Tables 3 and 5, we found that performance trend followed expected patterns as the E-Y Transliterator has better performance when tested on the data that formed the basis for formulating the English-to-Yorùbá transliteration model (Experiment E1) than on data outside the development data (Experiment E2). Accuracy for E1 was 0.727 or 72.7% while for E2, the accuracy was 0.407 (40.7%). One explanation for this observation is that data in E1 has been the object of several research while data in E2 are just dependent on one or two authorities. In addition, the data in E2 has more words with more than one references. This may indicate that it is yet to stabilize to single and generally accepted form. Furthermore, as observed in subsequent discussion in this section, proficient Yorùbá speakers, whose opinion we consulted, indicated that the output of the E-Y Transliterator on several cases were equally valid or even better than given references considering the standard constraints on phonology and morphology of Yorùbá language.

Despite the wide difference in word-level accuracies for experiments E1 and E2, the recall and precision for the two experiments were relatively high. In addition to the above general results, we have noted the following through a closer investigation of the pattern of correct or wrong transliteration by the E-Y Transliterator. The investigations are presented in Tables 7 to 10.

Table 7: Transliterating of Positions Requiring Doubling of Vowel

Reference contains	Candidate contains	Count	Comment
double vowels	Not double vowel	59	FN_d
double vowels	double vowels	16	TP_d
Not double vowel	double vowels	11	FP_d
Not double vowel	Not double vowel	251	TN_d

Table 8: Transliterating of Positions Requiring only Single Vowel

Reference contains	Candidate contains	Count	Comment
not single vowel	single vowel	59	FP_s
not single vowel	not single vowel	16	TN_s
single vowel	not single vowel	11	FN_s
single vowel	single vowel	251	TP_s

From Table 7, we calculated R_d, P_d and F_d, the Recall, Precision and F1 of transliterating double vowels respectively. Similarly, from the Table 8 we calculated the Recall (R_s), Precision (P_s) and F 1 score (F_s) for correctly mapping vowels that were expected to be single vowels respectively:

$$R_d = TP_d/(TP_d + FN_d) = 0.213$$
$$P_d = TP_d/(TP_d + FP_d) = 0.593$$
$$F_d = (R_d * P_d)/(R_d + P_d) = 0.313$$
$$R_s = TP_s/(TP_s + FN_s) = 0.958$$
$$P_s = TP_s/(TP_s + FP_s) = 0.810$$
$$F_s = (R_s * P_s)/(R_s + P_s) = 0.878$$

Using the F-score parameter to compare the performance of the E-Y Transliterator on mapping to double or single vowels from the English phonemes, single vowels were almost as three times correctly mapped than double vowels. This might be linked to the difference in American English (AME) and Nigerian English also called Standard Nigerian English (SNE), including the fact that transliteration is mostly pronounced to fit into the tonal structure of the first language of SNE users.

The last vowel in candidates either generated by mapping or epenthetically introduced for alignment to Yorùbá phonology were mostly correct. The number of entries transliterated that was expected to an oral vowel ending is 330 out of these 318 oral endings were correctly mapped. That is 318 oral vowels have their correct values while only twelve (12) have oral vowels but not of correct value giving an accuracy of 0.963076923. Conversely, all the seven (7) entries that were expected to have a nasal vowel in word- final position were wrongly aligned by inserting epenthetic vowels yielding an accuracy of 0.0. These are nasal vowels as shown in Table 9 and the last column represents what would have been the correct word- final nasal vowels been underlined.

Table 9: Word- final Nasal Vowels de-nasalized by the Insertion of Epenthetic Vowel

SN	English	Reference	Candidate	Corrected
1	Dressing	dirẹsin	dirẹsini	dirẹsin
2	Equation	ikuesọn	ikwesani	ikwesan
3	Occasion	okesọn	ọkesọnu	ọkeson
4	Operation	ọpuresọn	apẹresọnu	apẹreson
5	Television	tẹlifisan	tẹlafisani	tẹlafisan
6	Washington	wọṣintin	wọṣintini	wọṣintin

Table 10: Exceptions for letter 'W' and letter sequance 'UR'

SN	English	Phonemic Transcription	Reference	Candidate
1	equation	/IH0 K W EY 1 ZH AH0 N /	ikuesọn	ikwesani
2	choir	/K W AY 1 ER0/	kuaya	kwaya
3	sweater	/S W EH1 T ER0/	suẹta	swẹta
4	father	/F AA1 DH ER0/	fada	f da
5	further	/F ER1 DH ER0/	fọda	fada
6	nurse	/N ER1 S/	nọọsi	nasi
7	purple	/P ER1 P AH0 L/	pọpu	papu
8	manufacture	/M AE2 N Y AH0 F AE1 K CH ER0/	manufakisọ	manufakiṣa

The English phoneme *W* was treated as a consonant phoneme but during evaluation, we noticed that there were instances where it was expected to become of Yorùbá letter 'u'. We encountered three such situations, shown in Table 10, serial numbers 1, 2, 3. These are instances in which letter 'w' or phoneme 'W' succeed a consonant phoneme, in these cases: *K*, *S* and *K*. Similarly, all appearance of the letter sequence 'ur' in any English word were wrongly transliterated as letter 'a' whereas the reference letter expected in the context was **'ọ'**.

Table 11: SNE contrasted with AME for grapheme ER

Word	ARPABET(AME)	IPA(SNE)	ARPABET(SNE)
Purse	/P ER1 S/	/pɔ:s/	/P AO1 S/
Purge	/P ER1 JH/	/pɔ:ʤ/	/P AO1 JH/

Four of such instances are shown in rows 5 to 8 of Table 10. These are cases of pronunciation difference between AME and SNE. We illustrate this particular difference with two of the entries: purse and purge , with IPA as spoken in SNE, taken from A dictionary of Nigerian English with IPA notation as spoken in SNE (Adegbite, Udofot, and Ayoola 2014).

The entry in row 4 of Table 10 was included for contrast with entry in row 5. Thus, the challenge of transliteration extends beyond getting a valid dictionary of pronouncing to being able to adapt the dictionary resource to the local dialect of the source language that target language is often more related to. Finally, the following issues were identified to have contributed to the low performance of the model implemented:

According to reliable opinions from two proficient Yorùbá first language speakers, out of the 185 words without exact references, 48 of them were valid transliterations and 15 were linguistically better than the references provided. These would have caused the model's performance to change from 126 correct words to 174, equivalent to 15% improvement. Furthermore, eleven of the incorrect transliterations are directly the outcome of incorrect mapping phoneme AH0 to target Yorùbá letters. In addition, three words were also incorrectly transliterated due to wrong mapping of the ER0 phoneme.

Finally, CMU Dict encode the pronunciation of English word according to the American English accent and style while the target language users have a dialect of English with accents and style that is clearly recognized as distinct and known as Standard Nigeria English (SNE). A large part of the error in transliteration can be shown to be due to the way English words are pronounced and thereby transliterated by Nigerians There exist several literature on SNE (Bamgbose, 1992), (Adegbija, 1989), (Gut, 2008), (Jowitt, 2018), (Sunday and Oyemade, 2021). Some of the features identified of the SNE include, amongst others, reduced vowel system that leads to phonetic substitutions, replacement of stress-timed rhythm with syllable-timed rhythm since most of the first languages in Nigeria are syllable-timed, insertion of epenthetic vowels, and consistent spelling pronunciation of word ending "mb" for example in bomb, climb and plumber (Bamgbose, 1992).

5. CONCLUSION AND FURTHER WORK

In this work, the study and analysis of Yorùbá texts and English texts with no direct equivalent in Yorùbá, with focus on extracting the knowledge needed for developing an English-to-Yorùbá phoneme-based transliteration system have been carried out. The result shows that the English to Yorùbá transliteration process has a systematic concept underlying it, and that this concept can be specified, analyzed and represented computationally.

5.1. Conclusion

In this study, we found out the following: The peculiarity of the spoken English of a typical Nigerian English-Yorùbá bilingual poses a major transliteration challenge as available source pronunciation dictionaries reflect either the British or American pronunciation. Kenstowicz (2006) asked the following questions as quoted:

> *"To what extent are the adaptation patterns observed in loans also reflected in Nigerian English? Can Nigerian English be viewed as the proximate source for loans?"*

Our result and the analysis of the model's performance seem to have shown that Nigerian English have serious effect on the adaptation patterns observed and that indeed, it is a proximate source for English loan words to Yorùbá.

The differences in the syllable structure of English and Yorùbá language also poses a transliteration challenge: Yorùbá being an open syllable language, requires a consistent need for adapting the source word to meet this structure. The identified challenges should form a basis for further investigation to improve the performance of the system. It is obvious, from this research, that while Yorùbá loan words have phonemic correspondence to their English source words, the correspondence is via Nigerian English pronunciation which have large graphemic input. Consequently, the borrowing device can be hybrid in nature instead of being fully phonemic. This transliteration system and subsequent improvements should be able to serve, in addition to standard purposes, as a pedagogical tool to support language development and the teaching of linguistic borrowing and transliteration to students with interest in Yorùbá.

5.2. Further Work

This implementation of an English-to-Yorùbá phoneme-based system is the first documented attempt to address this problem, hence, there is much work to be done to improve on the system and the entire process. The work did not consider tone marks because much of the available data do not have tone marks. Additionally, the process of mapping from a language that is primarily based on intonation to one based on tone is research in progress. Effort to include tone-marks should be of utmost importance as Standard Yorùbá uses tones for pronunciation and meaning.

The transliteration produced with the outside data showed that there is room for improvement and research should be carried out to improve on this by expanding the rule base and revisiting old rules. A study should also be carried out to compare the performance of a system based on pronouncing dictionary with British dialect with that of American dialect-based CMU dictionary. A study should be carried out to produce digital lexicon for Nigerian English or to develop a model that can adapt the CMU pronunciation dictionary to Nigerian pronunciation which can then be used for the transliteration system. Also, both grapheme-based and hybrid transliteration models have been proposed for other language pairs as reported in this study, these approaches could be explored on English-Yorùbá language pair to compare the result with those presented by this work. As more data is gathered, the application of cutting-edge machine learning algorithms will become feasible and e ort should therefore also focus on building a large corpus of English-Yorùbá word pairs that will hopefully include variant Yorùbá targets for many of the English source words.

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6. APPENDIX

Table A1: English Phonemes, Example Words and Phonetic Transcriptions

Phoneme	Example	Transcription
AA	Odd	AA D
AE	At	AE T
AH	Hut	HH AH T
AO	Ought	AO T
AW	Cow	K AW
AY	Hide	HH AY D
B	Be	B IY
CH	Cheese	CH IY Z
D	Dee	D IY
DH	Thee	DH IY
EH	Ed	EH D
ER	Hurt	HH ER T
EY	Ate	EY T
F	Fee	F IY
G	Green	G R IY N
HH	He	HH IY
IH	It	IH T
IY	Eat	IY T
JH	Gee	JH IY
K	Key	K IY
L	Lee	L IY
M	Me	M IY
N	Knee	N IY
NG	Ping	P IH NG
OW	Oat	OW T
OY	Toy	T OY
P	Pee	P IY
R	Read	R IY D
S	Sea	S IY
SH	She	SH IY
T	Tea	T IY
TH	Theta	TH EY T AH
UH	Hood	HH UH D
UW	Two	T UW
V	Vee	V IY
W	We	W IY
Y	Yield	Y IY L D
Z	Zee	Z IY
ZH	Seizure	S IY ZH ER

Table A2: Yorùbá Phonemes in IPA, Standard Orthography and ARPABET

Ipa	Orthography	ARPABET	Example
a	A	AA	ata
b	B	B	bàtà
d	D	D	de
e	E	EY*	epo
ɛ	ẹ	EH	ja
ɛ̃	ẹn		ìyẹn
f	F	F	fìlà
g	G	G	gèlè
$\widehat{gb}$	Gb		gbọ́
h	H	HH OR H	họ
i	I	IY	igi
ĩ	In		dín
ʤ	J	JH	jẹun
k	K	K	ká
l	L	L	lẹ́tà
m	M	M	mẹ́rin
n	N	N	ní
ŋ	n, m	NX OR NG	n (ng), bím̀bọ́
o	O	OW	oko
ɔ	ọ	AO	ọká
ɔ̃	ọn, an		b n, ad an
$\widehat{kp}$	P		pańpẹ́
r	R	R	ráńpẹ́
s	S	S	ṣábàbí
ʃ	S	SH	ṣeré
t	T	T	tata
u	U	UW	iṣu
ũ	Un		wàrà
w	W	W	wàhálà
j	Y	Y	yunifásítí

Table A3: Phonemes with One-to-One Correspondence to Graphemes

No	English Phoneme	Yorùbá Grapheme
1	'AE'	'a'
2	'AO'	'ọ'
3	'EH'	'ẹ'
4	'IH'	'i'
5	'UH'	'u'
6	'CH'	'ṣ'
7	'DH'	'd'
8	'HH'	'h'
9	'JH'	'j'
10	'SH'	'ṣ'
11	'TH'	't'
12	'ZH'	's'
13	'B'	'b'
14	'D'	'd'
15	'F'	'f'
16	'G'	'g'
17	'H'	'h'
18	'K'	'k'
19	'L'	'l'
20	'M'	'm'
21	'N'	'n'
22	'P'	'p'
23	'R'	'r'
24	'S'	's'
25	'T'	't'
26	'V'	'f'
27	'W'	'w'
28	'Y'	'y'
29	'Z'	's'

Table A4: English Phonemes that transliterate to several Yorùbá grapheme

No	Transcription	SY Equivalent
1	AA	a, ọ
2	AH	a, e, ẹ, i, o, ọ, u
3	AW	a, ao, aw
4	AY	a, ai, ay
5	ER	a, ọ
6	EY	e, ei, ey
7	NG	n, ng
8	OW	o, ow
9	OY	ọ, i, oy
10	UW	u, uw

Table A5 Algorithm1 for Preliminary Mapping Rules

<table>
<tr><th>No</th><th>Conditions</th><th>Action to take</th></tr>
<tr><td>1</td><td>if eWrd sswt('H') & ePhon sswt('H')</td><td>del H</td></tr>
<tr><td>2</td><td>if len(eWrd) > 3 & eWrd eswt('AL')</td><td>del L</td></tr>
<tr><td>3</td><td>if ePhon eswt('IY1)</td><td>rep('IY1','i i')</td></tr>
<tr><td>4</td><td>if eWrd eswt('OR') & ePhon eswt('ER')</td><td>rep('ER','ọ')</td></tr>
<tr><td>5</td><td>if eWrd eswt('LE') & ePhon eswt('AH0 L'|'AH1 L'|'AH2 L')</td><td>rep('AH L', 'u') rep('AH L', 'u')</td></tr>
<tr><td>6</td><td>if eWrd eswt('IH1'+C) & C!=['H'|'R'|'Y']</td><td>rep('IH1','i i')</td></tr>
<tr><td>7</td><td>if eWrd eswt('AO1'+C) & C!=['H'|'R'|'Y']</td><td>rep('IH1','ọ ọ')</td></tr>
<tr><td>8</td><td>if eWrd lik(*+('OW2'|'OW1'|'OW0')+C) & C!= ['H'|'R'|'Y']</td><td>rep('OW','o o')</td></tr>
<tr><td>9</td><td>if eWrd lik(*+('UW2'|'UW1'|'UW0')+C) & C!= ['H'|'R'|'Y']</td><td>rep('UW','u u')</td></tr>
<tr><td>10</td><td>if eWrd eswt('US') & not preceded by V & eWrd!=['BUS'|*+'BUS']</td><td>map('US','u')</td></tr>
</table>

Notation:

i. the acronyms 'eWrd' and 'ePhon' stand for English Word and its phonetic transcription respectively.

ii. similary, 'sswt', 'eswt', 'btw' and 'lik' stand for 'startswith', 'endswith', 'between' and 'like' respectively

iii. +, & and | stand for concatenation, logical AND, and logical OR operators

*iv. V, C, N, * set of English and Yorùbá vowels, set of English and Yorùbá consonants, nasals, and any number of characters (phonemes or graphemes) respectively.*

Table A6: Algorithm2 for Transliteration Rules for Resolving Phoneme AH0

<table>
<tr><th>No</th><th>Conditions</th><th>Action to take</th></tr>
<tr><td>1</td><td>if eWrd lik(*+'ANT'+*) & ePhon lik('AH0 N T')</td><td>rep('AH0 N T','a n t')</td></tr>
<tr><td>2</td><td>if eWrd lik(*+'ENT'+*) & ePhon lik('AH0 N T')</td><td>rep('AH0 N T','e n t')</td></tr>
<tr><td>3</td><td>if eWrd lik(*+'EST'+*) & ePhon lik('AH0 S T')</td><td>rep('AH0 S T','e s t')</td></tr>
<tr><td>4</td><td>if eWrd lik(*+'IST'+*) & ePhon lik('AH0 S T')</td><td>rep('AH0 S T','i s t')</td></tr>
<tr><td>5</td><td>if eWrd lik(*+'TION'+*) & ePhon lik('SH AH0 N')</td><td>rep('SH AH0 N','ṣ ọ n')</td></tr>
<tr><td>6</td><td>if eWrd lik(*+'BOD'+*) & ePhon lik('B AH0 D')</td><td>rep('B AH0 D','b ọ d')</td></tr>
<tr><td>7</td><td>if eWrd lik(*+'BUD'+*) & ePhon lik('B AH0 D')</td><td>rep('B AH0 D','b ọ d')</td></tr>
<tr><td>8</td><td>if eWrd lik(*+'BAD'+*) & ePhon lik('B AH0 D')</td><td>rep('B AH0 D','b a d')</td></tr>
<tr><td>9</td><td>if eWrd lik(*+'BED'+*) & ePhon lik('B AH0 D')</td><td>rep('B AH0 D','b ẹ d')</td></tr>
<tr><td>10</td><td>if eWrd lik(*+'BID'+*) & ePhon lik('B AH0 D')</td><td>rep('B AH0 D','b i d')</td></tr>
<tr><td>11</td><td>if eWrd lik(*+'NIO'+*) & ePhon lik('N Y AH0')</td><td>rep('N Y AH0','n i ọ')</td></tr>
<tr><td>12</td><td>if eWrd lik(*+'NU'+*) & ePhon lik('N Y AH0')</td><td>rep('N Y AH0','n u')</td></tr>
<tr><td>13</td><td>if eWrd lik(*+'NIE'+*) & ePhon lik('N Y AH0')</td><td>rep('N Y AH0','n i ẹ')</td></tr>
<tr><td>14</td><td>if eWrd lik(*+'NIA'+*) & ePhon lik('N Y AH0')</td><td>rep('N Y AH0','n i a')</td></tr>
<tr><td>15</td><td>if eWrd sswt('ESS') & ePhon sswt('AH0 S')</td><td>rep('AH0 S','ẹ s')</td></tr>
<tr><td>16</td><td>if eWrd sswt('OUS') & ePhon sswt('AH0 S')</td><td>rep('AH0 S','ọ s')</td></tr>
<tr><td>17</td><td>if eWrd sswt('A') & ePhon sswt('AH0')</td><td>rep('AH0','a')</td></tr>
<tr><td>18</td><td>if eWrd sswt('O') & ePhon sswt('AH0')</td><td>rep('AH0','ọ')</td></tr>
<tr><td>19</td><td>if ePhon endswt('AH0'|'AH1'|'AH2')</td><td>rep('AH','a')</td></tr>
<tr><td>20</td><td>if ePhon lik(*+'Y UW1 AH0 T'+*)</td><td>rep('Y UW1 AH0 T','uwit')</td></tr>
<tr><td>21</td><td>if ePhon lik(*+'ER0 AH0 T'+*)</td><td>rep('ER0 AH0 T','aret')</td></tr>
<tr><td>22</td><td>if 'AH0' btw('JH','G')</td><td>rep('AH0','u')</td></tr>
<tr><td>23</td><td>if 'AH0' btw('K','M')|('K','N')|('F','M')|('F','N')|('M','N')|('D','K')|('D','M')|('L','JH')|('JH','JH')</td><td>rep('AH0','ọ')</td></tr>
<tr><td>24</td><td>if 'AH0' btw('JH','P')|('V','D')|('R','M')|('F','D'|'T')|('T','N')|('TH','M'|'N')|('L','M'|'T')|('N','P'|'V'|'F'|'S'|'R')|('N','T')|('V','T')|('S','T'|'P'|'K')</td><td>rep('AH0','i')</td></tr>
</table>

Notation

i. the acronyms 'eWrd' and 'ePhon' stand for English Word and its phonetic tran- scription respectively.

ii. similary, 'sswt', 'eswt', 'btw' and 'lik' stand for 'startswith', 'endswith', 'between' and 'like' respectively

iii. +, & and | stand for concatenation, logical AND, and logical OR operators

*iv. V, C, N, * set of English and Yorùbá vowels, set of English and Yorùbá consonants, nasals, and any number of characters (phonemes or graphemes) respectively.*

Table A7 Algorithm 3 for Final Mapping Transliteration Rules

No	Conditions	Action to take
1	if ePhon lik(V | C *+'Y U'+*)	rep('Y UH', 'u')
2	if ePhon lik(V | C *+'Y U'+*)	rep('Y UW', 'u')
3	if ePhon lik(*+C+'Y AH'+*) & C in ['b']	rep('B Y AH', 'b u')
4	if ePhon lik(*+C+'Y AH'+*) & C in ['g']	rep('G Y AH', 'g u')
5	if ePhon lik(*+C+'Y AH'+*) & C in ['k']	rep('K Y AH', 'k u')
6	if ePhon lik(*+C+'Y AH'+*) & C in ['m']	rep('M Y AH', 'm u')
7	if ePhon lik(*+C+'Y AH'+*) & C in ['p']	rep('P Y AH', 'p u')
8	if 'AH' in ePhon	rep('AH', 'ọ')
9	if ePhon lik(*+C1+'AA'+C2+*) & C2 !in ['h', 'r', 'y'] }	rep('AA', 'ọ')
10	if ePhon lik(*+C1+'AA'+C2+*) & C2 in ['h', 'r', 'y'] }	rep('AA', 'a')
11	if ePhon lik(*+'AW'+V+*)	rep('AW', 'a w')
12	if ePhon lik(*+'AW'+*)	rep('AW', 'a o')
13	if ePhon lik(*+'AY'+V+*) & V != i	rep('AY', 'a y')
14	if ePhon lik(*+'AY'+V+*) & V = i	rep('AY', 'a')
15	if ePhon lik(*+'AY'+*)	rep('AY', 'a i')
16	if ePhon lik(*+'ER'+V+*)	rep('ER', 'ẹ r')
17	if ePhon lik(*+'ER'+*)	rep('ER', 'a')
18	if ePhon lik(*+'EY'+V+*)	rep('EY', 'e y')
19	if ePhon lik(*+'EY'+*)	rep('EY', 'e')
20	if ePhon lik(*+'OW'+V+*)	rep('OW', 'o w')
21	if ePhon lik(*+'OW'+*)	rep('OW', 'o')
22	if ePhon lik(*+'OY'+V+*)	rep('OY', 'ọ y')
23	if ePhon lik(*+'OY'+*)	rep('OY', 'ọ i')
24	if ePhon lik(*+'UW'+V+*)	rep('UW', 'u w')
25	if ePhon lik(*+'UW'+*)	rep('UW', 'u')
26	if ePhon lik('A R'+C+*) & C != y	rep('A R', 'a')
27	if ePhon lik('O R'+C+*) & C != y	rep('O R', 'ọ')
28	if ePhon endswith ('a a r')	rep('a a r', 'a a')
29	if ePhon endswith ('ọ ọ r')	rep('ọ ọ r', 'ọ ọ')
30	if ePhon endswith ('o o r')	rep('o o r', 'o o')
31	if ePhon lik(*+'ọ r'+C+*) & C != y	rep('ọ r', 'ọ ọ')
32	if ePhon lik(*+'o r'+C+*) & C != y	rep('o r', 'o o')
33	if ePhon lik(*+'a r'+C+*) & C != y	rep('a r', 'a a')
34	if ePhon lik(*+'ẹ r'+C+*) & C != y	rep('ẹ r', 'ẹ ẹ')
35	if ePhon eswt('i r')	rep('i r', 'i a')

Notation: same as for Appendix 5

Table A8: Sample: Test Data Showing Single and Multiple references

English	Reference-1	Reference-2	Reference-3
America	Amẹrika		
Bank	Banki		
Consonant	Kọnsonanti		
Doctor	Dọkita		
Flour	Fulawa		
Grammar	Girama		
Nurse	Nọọsi		
Photocopy	Fotokọpi		
Theory	Tiọri		
Vowel	Faweli		
Alum	Alọọmu	Aalọmu	
Class	Kilaasi	Kilasi	
Dictionary	Dikisọnẹri	Dikisọnari	
Office	Ọfiisi	Ọfisi	
Google	Gọgu	Gugu	
Glass	Gilaasi	Gilasi	
Paper	Pepa	Beba	
Pharmacy	Famesi	Famasi	
School	Sukulu	Sukuu	Suku
Electric	Ẹlẹntiriiki	Ẹlentiriki	Ẹlẹtiriiki