## UMAR MUHAMMAD-GOMBE, PETER FRENCH, ELEANOR CHODROFF

# A Comparative Analysis of Nigerian Linguistically-Naïve Native Speakers and Nigerian Linguist Native Speakers Categorising Four Accents of Nigerian English

In the field of LAAP (Language Analysis in the Asylum Process), there has been debate over who should undertake the task of inferring a speaker's country and region of socialisation from their language and dialect. This chapter investigates whether native speaker linguists perform more accurately than native speaker non-linguists in determining the first language of Nigerian speakers of English. Eighty non-linguist and 25 linguist speakers of Hausa, Igbo, Kanuri and Yoruba were recruited. They listened to 30-second recordings of Nigerianaccented English, and assigned each to an L1 (Hausa, Igbo, Kanuri, Yoruba or non-Nigerian). Listeners of both groups were most accurate in classifying accents of their own L1. Linguists did not differ significantly from non-linguist in accuracy. The results provide empirical support for having educated non-linguist native speakers involved in LAAP casework.

*Keywords*: Accent classification, Linguist native speakers, Language analysis, Asylum seekers, National origin

### 1. Introduction

In the field of LAAP<sup>1</sup> (Language Analysis in the Asylum Process), there has been debate over who should undertake the task of inferring a speaker's country and region of socialisation based on their language and dialect: academic or professional linguists with detailed knowledge of the languages/varieties that may be at issue (see LNOG, 2004; Fraser, 2009, 2011; Patrick, 2010, 2012, 2016, 2019), or linguistically-naïve native speakers of those languages/varieties, or a combination of both (see Cambier-Langeveld, 2010b; 2012; Cambier-Langeveld, 2007, cited in Cambier-Langeveld, 2016; Fraser, 2011; Foulkes, French & Wilson, 2019; Wilson, 2009). Opposing positions within this debate have largely been argued on principle alone, without support from empirical studies. Contributing to this debate, this chapter concerns research which was designed to determine whether native speaker linguists perform more accurately than native speaker non-linguists in determining the first language (L1) of Nigerian speakers of English.

Previous work in this area has largely been based on intuition; however, a few studies have attempted an empirical approach. One pioneering instance of this

<sup>&</sup>lt;sup>1</sup> This area was formerly termed 'LADO'— Language Analysis in the Determination of Origin. This term is still used by some authors; LAAP is used throughout this chapter.

comes from Wilson (2009). This work attempted to determine the most reliable method for identifying people's nationality or region of socialisation from Ghanaian English. Wilson (2009) has four groups: (1) native speakers of Ghanaian English, (2) non-native academic and postgraduate linguists (3) undergraduates of linguistics and (4) LADO/LAAP professionals. Both groups (2) and (3) were provided with working material on features of Ghanaian English in advance of the experiments. Wilson observed that native speakers of Ghanaian English were the best performing group despite their lack of linguistic expertise. Though Wilson (2009) had indeed included linguists as a test group in the experiment, these individuals were not native speakers of Ghanaian English. As mentioned earlier, these participants mainly encountered the tested English variety through the working material given to them in advance of the experiment.

A thorough investigation is necessary to determine whether native speaker linguists outperform native speaker non-linguists (as tested in Wilson, 2009) in language analysis. With this paradigm, one would be able to infer the potential influence of linguistic knowledge on performance in a more clear and exact manner as the two groups have the same language background but differ in linguistic expertise. Determining whether such a difference exists and is statistically significant is of utmost value to the debate concerning who should conduct the task of analysing a speaker's language in the asylum process.

Having identified the need for comparing naïve and linguist native speakers of the same accent group, two research questions were used to guide this research: (1) How and by whom in a LAAP (Language Analysis in the Asylum Procedure) context should the analysis of spoken English be analysed? Is it native speaker linguists? Or are native speaker non-linguists equally accurate? (2) If linguistic training is found to be effective, which specific linguistic expertise will be required?

In response to question (1), we first hypothesised that native speakers of any of the following four Nigerian languages – Hausa, Igbo, Kanuri and Yoruba – would outperform the respective non-native speakers of those four Nigerian languages in identifying the speaker's L1 from their accented English. In addition, we hypothesised that native speaker linguists would outperform their native speaker non-linguist counterparts in identifying fellow speakers of their own native accent. In response to question (2), we hypothesised that native speaker linguists who were also phoneticians would outperform non-phonetician linguists.

We investigated the following questions as a baseline assessment of the accent performance task:

- 1. Are native speakers indeed more accurate at classifying their own L1 from the accented English samples relative to non-native speakers?
- 2. Are some languages simply more difficult to classify than others?
- 3. Is the relationship between confidence and accuracy significant?

In addition, we statistically assessed the following research questions:

1. Are linguists better than non-linguists at accent identification among the four Nigerian languages?

2. Are native speakers specifically with a linguistic background in phonetics better at accent identification than other native speakers?

An accent classification experiment was conducted to address these research questions. The experiment included native speakers of Hausa, Igbo, Kanuri and Yoruba who either did not have linguistic training (non-linguists) or did have linguistics training (linguists). The stimuli were recordings of spoken English from native speakers of these four languages along with two foil languages. The following sections review the methods and results, which include a comparison of the relevant participant groups (non-linguist versus linguist and non-phonetician linguists versus phoneticians). This is then followed by a discussion and conclusion.

### 2. Methods

#### 2.1 Participants

The native speaker non-linguist group comprised 80 linguistically naïve, educated, native speakers of Hausa, Igbo, Kanuri, and Yoruba. The group was predominantly composed of university students and administrative staff. All participants were recruited at universities in the cities of Kano, Nsukka, Maiduguri and Ibadan. The dominant language of each of these cities corresponds to a relevant L1 test language: Hausa, Igbo, Kanuri, and Yoruba, respectively. Each non-linguist L1 group was represented by 20 speakers, and their ages ranged from 18 to 70 years (mean age = 28, SD = 9). The full native speaker linguist group comprised 25 academic linguists with various specialisations in e.g., phonetics, phonology, syntax, semantics and sociolinguistics of their Nigerian L1. The original plan was to recruit only sociophoneticians in the linguistics group, but their scarcity resulted in the need to draw participants from a broader range of linguistics specialisations. Linguists who self-classified as a phonetician or phonologist were grouped together in the present study to represent experts in the physical sounds or sound patterns of language. In subsequent sections, we refer to this group as the broad "phonetician" group. The linguists were recruited at Bayero University in Kano (6 L1 Hausa linguists including 1 phonetician), the University of Nigeria in Nsukka (9 L1 Igbo linguists including 1 phonologist), the University of Maiduguri (5 L1 Kanuri linguists including 1 phonologist), and the University of Ibadan (5 L1 Yoruba linguists including 1 phonetician and 1 phonologist).

#### 2.2 Stimuli

The experiment employed eighteen recordings of accented English that were approximately 30 seconds in duration. The recordings comprised bits of "The Rainbow Passage" and spontaneous speech in which the speaker narrated aspects of their life experience. Sixteen recordings of L1 speakers of Hausa, Igbo, Kanuri and Yoruba speaking in English were selected. These represented four speakers from each of the four language groups: Hausa, Igbo, Kanuri and Yoruba. These recordings were made during a fieldwork visit to Nigeria. Additionally, two foil recordings (Ghanaian and Guinean English speakers) were added for a total of 18 recordings. These latter recordings were made by Ghanaian and Guinean English speakers who were pursuing their Masters degree at the University of York. They were recorded in a studio in the Department of Language and Linguistic Science.

# 2.3 Procedure

Using Qualtrics Survey Software, each participant was asked to listen to the recordings and assign each of the recordings to an L1 accent (Hausa, Igbo, Kanuri, Yoruba or non-Nigerian). Following classification, each participant was asked to report their confidence in their decision on a scale from 0 to 100.

# 3. Results

To address the research questions, we provide a descriptive and inferential analysis of accuracy in identifying both speakers of native and non-native accents for each of the relevant subgroups: non-linguists versus linguists (section 3.1), and nonphonetician linguists versus phoneticians (section 3.2). For the inferential analysis, we implemented two logistic mixed-effects models to investigate variation in accuracy. Both models assessed the baseline questions of accent performance. The first model specifically targeted whether native speaker linguists were better than native speaker non-linguists at accent identification. The second targeted the question of whether native speaker phoneticians specifically were better than other native speaker non-phonetician linguists at accent identification. In addition, individual performances were also investigated in an exploratory analysis.

# 3.1 Non-linguists versus linguists

# 3.1.1 Descriptive statistics

Overall, non-linguist and linguist listeners were substantially more accurate at identifying the L1 accent of a recording when it matched their own L1 (Figure 1 and Table 1). This was reasonably consistent across L1 backgrounds, with the one exception of the Kanuri linguist group (Tables 2 and 3). For the non-linguist L1 groups, accuracies at identifying their own L1 accent ranged from 71% to 81% (Table 2), and for the linguist L1 groups, accuracies ranged from 75% to almost 92%, with the exception of Kanuri (Table 3). The Kanuri linguist group had a lower accuracy of 35%. Overall, non-linguists and linguists had highly comparable accuracy rates in identifying fellow speakers of their accents (76.6% and 76.0%, respectively; Table 4). The Hausa, Igbo and Yoruba linguists were numerically more accurate than their non-linguist counterparts in identifying accents of their own L1, but this did not hold for the Kanuri listeners.

Accuracies generally dropped for classification of Nigerian accents that did not match the L1 of the listener (Figure 1). Linguists numerically outperformed their non-linguist counterparts in classifying other L1 Nigerian accents that were not their own, though the results were somewhat more mixed for classification of non-Nigerian accents (Table 1). For non-linguist L1 groups, these accuracies ranged from 37.5% to 50.0% for other Nigerian L1 accents and from 12.5% to 27.5% for non-Nigerian L1 accents. For linguist L1 groups, these accuracies ranged from 45.0% to 56.9% for other Nigerian L1 accents from 8.3% to 44.4% for non-Nigerian L1 accents.

Figure 1 - Accuracy of classifying the accent of own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from non-linguists and linguists in each L1 group. Error bars reflect ± one standard error of the proportion

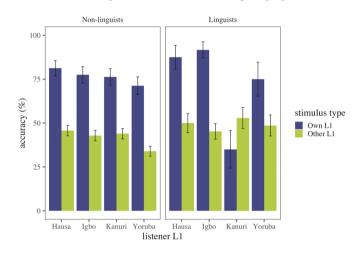


Table 1 - Accuracy of classifying the accent of each stimulus type from non-linguists and linguists

Stimulus Set	Non-linguists	Linguists
Own L1	76.6% (245/320)	76.0% (76/100)
Other Nigerian L1s	45.1% (433/960)	52.0% (156/300)
Non-Nigerian L1s	20.6% (33/160)	28.0% (14/50)
Overall	49.4% (711/1440)	54.7% (246/450)

Table 2 - Accuracy of classifying the accent of each stimulus type from non-linguists in each L1

		Non-linguists		
L1 Group	Own L1	Other Nigerian L1s	Non-Nigerian L1s	Overall
Hausa	81.2% (65/80)	50.0% (120/240)	20.0% (8/40)	53.6% (193/360)
Igbo	77.5% (62/80)	46.2% (111/240)	22.5% (9/40)	50.6% (182/360)
Kanuri	76.2% (61/80)	46.7% (112/240)	27.5% (11/40)	51.1% (184/360)
Yoruba	71.2% (57/80)	37.5% (90/240)	12.5% (5/40)	42.2% (152/360)

		Linguists		
L1 Group	Own L1	Other Nigerian L1s	Non-Nigerian L1s	Overall
Hausa	87.5% (21/24)	56.9% (41/72)	8.3% (1/12)	58.3% (63/108)
Igbo	91.7% (33/36)	45.4% (49/108)	44.4% (8/18)	55.6% (90/162)
Kanuri	35.0% (7/20)	55.0% (33/60)	40.0% (4/10)	48.9% (44/90)
Yoruba	75.0% (15/20)	55.0% (33/60)	10% (1/10)	54.4% (49/90)

Table 3 - Accuracy of classifying the accent of each stimulus type from linguists in each L1 group

 Table 4 - Accuracy of classifying the accent of own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from non-linguists and linguists in each L1 group

	Own L1		Other L1s	
L1 Group	Non-linguists	Linguists	Non-linguists	Linguists
Hausa	81.2%	87.5%	45.7%	50%
Igbo	77.5%	91.6%	42.9%	45.2%
Kanuri	76.2%	35.0%	43.9%	52.9%
Yoruba	71.2%	75.0%	37.5%	48.6%

The above findings strongly indicate that listeners were much more accurate when classifying their own L1 accent than when classifying others. In addition, Table 5 presents the confusion matrix among the stimuli accents. L1 accents were not uniformly confusable: a Kanuri accent was most often mistaken for a Hausa accent, whereas a Yoruba accent was most often mistaken for an Igbo accent and vice versa.

				Stimulus acce	nt	
		Hausa	Igbo	Kanuri	Yoruba	Non-Nigerian
e	Hausa	273	4	198	14	23
Response	Igbo	26	252	22	130	63
Resj	Kanuri	88	21	151	16	37
	Yoruba	11	113	19	234	40
	Non-Nigerian	22	30	30	26	47

 Table 5 - Confusion matrix of accent responses against stimulus accents for all participants in the study

In the following analysis, we investigated the errors surrounding the classification of accents that do indeed *match* the L1 of the listener. Although the task was a fiveway forced choice classification, we can calculate the responses based on whether a native speaker correctly matched the accent in the recording to their own L1 (true positive), whether they incorrectly matched the accent in the recording to their own L1 (false positive), whether they correctly rejected another L1 accent as not the same as their own L1 (true negative), or whether they incorrectly identified another L1 accent as their own L1 (false negative). Table 6 shows the false negative and false positive rates for each L1 group. The false negative rate is calculated as the number of false negatives divided by the total number of false negatives and true positives: when the accent was indeed the listener's L1, how many times did the listener fail to classify it as the L1? The false positive rate is calculated as the number of false positives divided by the total number of false positives and true negatives: when the accent was indeed not the listener's L1, how many times did the listener classify it as the L1?

With respect to the false negative rate, the linguist groups had slightly lower false negative rates than their non-linguist counterparts, except for the Kanuri group. This suggests that the Hausa, Igbo, and Yoruba linguists were numerically more precise in identifying accents of their own L1 when presented with them than the non-linguists. For Kanuri, this pattern was reversed. With respect to the false positives, the linguist groups again had slightly lower false positive rates than their non-linguist counterparts except for the Igbo group. Overall, linguists were slightly less likely to accept a non-member of their L1 group as a fellow member based on their spoken English.

	False negatives		False positives	
L1 Group	Non-linguists	Linguists	Non-linguists	Linguists
Hausa	18.8%	12.5%	18.9%	15.5%
Igbo	22.5%	8.3%	13.6%	17.5%
Kanuri	23.8%	65.0%	11.1%	4.3%
Yoruba	28.7%	25.0%	16.1%	8.6%

Table 6 - False negative and false positive rates for non-linguists and linguists in each L1 group

As stated in the methods section above, the listener provided a self-confidence rating on a scale from 0 to 100 after classifying each audio clip. This was to determine how confident the participant was in their classification decision. Figure 2 shows the average z-scored self-confidence ratings by response accuracy across participants in the non-linguist and linguist groups for each of the L1 backgrounds, and when categorising their own L1 and other L1s. For accents that matched the L1 of the participant, confidence was generally higher for correct than incorrect responses. This same general pattern was mostly observed for other L1 accents, particularly for linguists. The two exceptions were the non-linguist Hausa and Igbo non-linguist groups. Further exploration of individual patterns is provided in section 3.3.

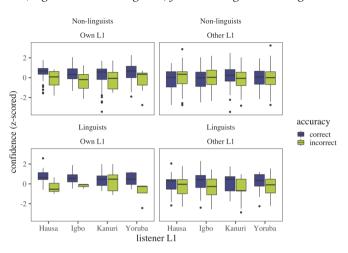


Figure 2 - Confidence ratings (z-scored) for each response accuracy when classifying own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from non-linguists and linguists

#### 3.1.2 Inferential statistics

To test whether Nigerian linguists significantly outperformed their Nigerian non-linguist counterparts, the full dataset containing both Nigerian linguists and Nigerian non-linguists was used. Accent identification accuracy was analysed as a binary dependent variable (1 = correct, 0 = incorrect) with a logistic mixed-effects model using the lme4 R package (Bates et al., 2015; RStudio Team, 2020). The model included fixed effects of native speaker match, linguist status ("linguist"), stimulus language, confidence rating, the interaction between linguist and confidence rating, as well as a random intercept for participant. Models with more complex random effect structures failed to converge.

Native speaker match had two levels: whether the L1 of the participant (the listener) matched the L1 of the recorded speaker or not. This variable was sum-coded with no-match as the held-out level. Linguist had two levels: whether the participant was a linguist or non-linguist. This factor was sum-coded with non-linguist as the held-out level. The factor for stimulus language had five levels: Hausa, Igbo, Kanuri, Yoruba or non-Nigerian. This factor was sum-coded with non-Nigerian as the held-out level. As mentioned in the methodology section, the experiment included self-rating confidence levels using a sliding scale from 0–100. These confidence levels were converted to z-score confidence values for each participant. The interaction between linguist and confidence was included to check the presence or absence of a significant correlation between Nigerian linguists' confidence and accuracy in classifying the English accents. The alpha level for determining significance was set to 0.05: predictors with a p-value less then 0.05 were considered significant.

The expectation was for a significant and positive effect of native speaker match, indicating a higher accuracy when the listener's native language matched the language of the stimulus. Another expectation was for a significant effect of linguist status, indicating higher overall accuracy for linguists than non-linguists. The effect of stimulus language was included to determine whether some languages were more difficult to identify than others.

As predicted, native speaker match was significant, indicating that listeners exposed to stimuli of their L1 were approximately two times as likely to be accurate than when exposed to stimuli of other L1s ( $\beta_{match} = 0.70, p < 0.001$ ). The result of stimulus language showed that accuracy differed significantly depending on the presented accent, but in different directions. Listeners were significantly more accurate for Hausa, Igbo, and Yoruba classification ( $\beta_{Hausa} = 0.74, p < 0.001;$  $\beta_{Igbo} = 0.48, p < 0.001; \beta_{Yoruba} = 0.29 p < 0.01$ ), but significantly less accurate for Kanuri classification ( $\beta_{Kanuri} = -0.59, p < 0.001$ ).

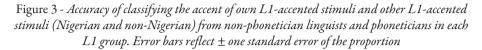
The effect of linguist was not significant ( $\beta_{linguist} = 0.14$ , p = 0.12), indicating that native linguist speakers did not perform more or less accurately than their non-linguist counterparts. A significant positive relationship was also observed between confidence and accuracy for all listeners ( $\beta_{zconf} = 0.25$ , p < 0.01), indicating that listeners were more confident when accurate. This correlation was even stronger for native linguists than non-linguists ( $\beta_{linguist:zconf} = 0.15$ , p < 0.05).

#### 3.2 Non-phonetician linguists versus phoneticians

#### 3.2.1 Descriptive statistics

This section compares the performance of the Nigerian native speaker phoneticians against that of the non-phonetician linguists. We preface these analyses with a reminder that the sample size of the linguist group was smaller than the non-linguist group (25 linguist listeners total), and particularly the number of representative phoneticians (20 non-phonetician linguists; 5 phoneticians: 1 Hausa speaker, 1 Igbo, 1 Kanuri, and 2 Yoruba). Ideally, future research would be able to access a larger sample size for more stable inferential conclusions. We present a high-level overview of observed patterns in the data, and provide a preliminary analysis of whether native speaker phoneticians indeed outperform other native speaker, non-phonetician linguists.

As shown in Figure 3 and Table 7, phoneticians marginally outperformed nonphonetician linguists in overall accuracy, but the performances were otherwise highly comparable. In classifying accents that matched their own L1, nonphonetician linguists had a numerically higher accuracy at 76.2% against the phonetician accuracy of 75.0%. Phoneticians had numerically higher accuracies than non-phonetician linguists in classifying other Nigerian L1s and non-Nigerian L1 accents.



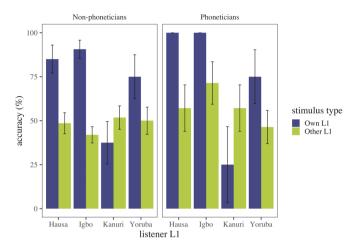
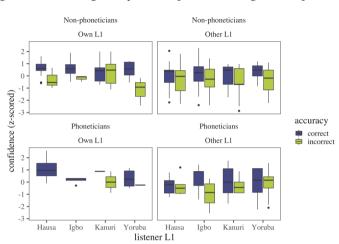


 Table 7 - Accuracy of classifying the accent of each stimulus type from non-phonetician linguists

 and phoneticians in each L1 group

Stimulus Set	Non-phoneticians	Phoneticians
Own L1	76.2% (61/80)	75.0% (15/20)
Other Nigerian L1s	50.0% (120/240)	60.0% (36/60)
Non-Nigerian L1s	27.5% (11/40)	30.0% (3/10)
Overall	53.3% (192/360)	60.0% (54/90)

Figure 4 shows the average z-scored self-confidence ratings by response accuracy across participants in the non-phonetician and phonetician groups for each of the L1 backgrounds, and when categorising their own L1 and other L1s. In the previous section, we found that at a group level, linguists had higher confidence for correct than incorrect responses. In cases when correct and incorrect responses are observed, this pattern also held for each of the non-phonetician and phonetician subgroups. No major observable differences were observed between these two subgroups in the confidence ratings.



### Figure 4 - Confidence ratings (z-scored) for each response accuracy when classifying own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from non-phonetician linguists and phoneticians

#### 3.2.2 Inferential statistics

To test whether native speaker phoneticians significantly outperformed their nonphonetician linguist counterparts, the same model as described above in section 3.1.2 was run, but using only the linguist data and replacing the two-level factor of "linguist" with the two-level factor of "phonetician". The two levels of phonetician were: native speaker phonetician and native speaker non-phonetician linguist. The variable was sum-coded with native speaker non-phonetician linguist as the held-out level.

As in the previous model, native speaker match was significant, indicating that the linguist subgroup was also better at identifying their own L1 accent than other accents ( $\beta_{match} = 0.48$ , p < 0.01). As before, stimulus language also had a significant influence on accuracy: Nigerian linguists regardless of specialty were significantly more accurate with Hausa and Igbo ( $\beta_{Hausa} = 0.84$ , p < 0.01;  $\beta_{Igbo} = 0.$ , p < 0.01), and significantly less accurate with Kanuri ( $\beta_{Kanuri} = -1.11$ , p < 0.001); accuracy on Yoruba did not differ from the average accuracy in the task ( $\beta_{Yoruba} = 0.12$ , p = 0.55).

Though phoneticians were numerically slightly more accurate than nonphonetician linguists, the effect of phonetician was not significant, indicating that Nigerian phoneticians were not significantly better than other linguists ( $\beta_{phonetician} = 0.17, p = 0.32$ ). In addition, the overall relationship between confidence and accuracy was significant ( $\beta_{zconf} = 0.39, p < 0.01$ ); however, no significant difference was observed in the effect of confidence between phonetician and nonphonetician linguists ( $\beta_{phonetician: zconf} = -0.04, p = 0.78$ ).

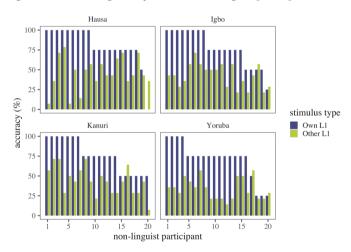
#### 3.3 Exploration of individual participant accuracy

The above results show the overall accuracies of the participants at the group and sub-group levels. This, however, may not precisely indicate consistency across all

individual participants in the experiments. We additionally explored the consistency in the identification task across the individual Nigerian linguists. Figure 5 shows the range of accuracies across the non-linguist listeners in classifying accents of their own L1 against accents of other L1s. Figure 6 shows the equivalent data for the linguist listeners.

A full 74 out of 80 non-linguist participants were numerically better at classifying the L1s of their own accent than they were at their classifying other accents; only 6 out of 80 non-linguist participants showed the opposite pattern. Among linguists, 20 out of 25 participants were numerically better at classifying their own accent than other accents; just 5 out of 25 participants showed the opposite pattern. Overall accuracy of classifying all accents for non-linguists ranged from 16.7% to 83.3% (median = 50.0%, mean = 49.4%). Overall accuracy of classifying all accents for linguists ranged from 27.8% to 77.8% (median = 55.6%, mean = 54.7%). Individual overall performance from non-linguists reached overall higher accuracies than individual linguists; however, the range of non-linguist individual accuracies was much higher and reached overall lower accuracies as well.

Figure 5 - Accuracy of classifying the accent of own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from each non-linguist participant in each L1 group



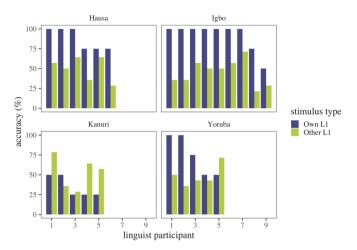
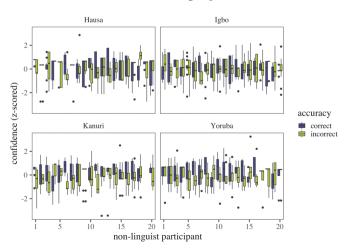


Figure 6 - Accuracy of classifying the accent of own L1-accented stimuli and other L1-accented stimuli (Nigerian and non-Nigerian) from each linguist participant in each L1 group

Figure 7 shows the relationship between confidence and accuracy for each individual non-linguist participant. Figure 8 shows the equivalent data, but for linguist participants. The relationship between confidence and accuracy was somewhat variable among non-linguists. In line with the model results in which confidence positively correlated with accuracy, 47 out of 80 non-linguist participants were on average more confident on correct than incorrect responses. However, 33 out of 80 participants were on average more confident on incorrect than correct responses. This relationship between confidence and accuracy was much more consistent among linguists, which reflects the model results. 21 out of 25 linguists were on average more confident on correct than incorrect than incorrect than showed the opposite ranking.

Figure 7 - Confidence ratings (z-scored) for each response accuracy from non-linguist participants in each L1 group



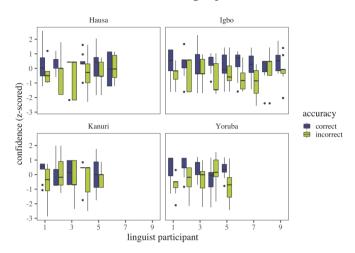


Figure 8 - Confidence ratings (z-scored) for each response accuracy from linguist participants in each L1 group

#### 4. Discussion

Overall, Nigerian native speakers from all four L1 backgrounds, irrespective of linguistic expertise, performed well above chance level. A mixed-effects logistic regression model of accuracy revealed a significant influence of native speaker match, indicating that listeners classifying accents of their own L1 were significantly more likely to be accurate than when classifying accents of other languages. The linguists, however, were only slightly better than the non-linguists on a numerical basis; the difference was not significant and applied to only 3 of the 4 L1 groups.

As anticipated, most native speaker listeners significantly outperformed other listeners when exposed to stimuli of fellow speakers of their native accent. Even Kanuri linguists – who were less accurate compared to other groups – were more accurate than non-native Kanuri listeners in identifying Kanuri-English stimuli. Although most of the linguists outperformed the non-linguists in identifying fellow speakers of their accent, this difference was not statistically significant. Numerically, this finding supports the expectation that linguists would outperform their nonlinguist counterparts; some phoneticians even reached 100% accuracy. However, the difference in accuracy between the linguist and non-linguist group failed to reach statistical significance. Thus, this investigation finds general native speaker status as the most reliable variable for significantly boosting accent identification accuracies. Some pieces of past research have reported similar findings to support the value of native speaker expertise, as discussed below.

Hedegard's (2015) study also found that native speakers linguists did not significantly differ from native speakers non-linguists in classifying a Japanese dialect from a spoken audio sample of Japanese. All native speakers were, however, significantly more accurate than non-native linguists with familiarity of Japanese linguistics. Jenkins's (2016) study indicates that native Scottish listeners were the best in identifying and distinguishing genuine Scottish-accent speakers from nongenuine accent mimics. However, there was no difference between linguists and nonlinguist listener groups in making correct judgements. Nolan (2012) argued that native speakers' knowledge of their language differed from the expertise of linguists with special interest in the language in question. He also argued that native speakers' intuition of detecting the speech of a fellow speaker cannot be fully represented by capturing precise behaviour of speech organs in descriptive linguistics using notations of transcription. Hoskin's (2018) study further supports the value of native speaker involvement in LAAP. He argued that non-linguist native speakers of Kurmanji have demonstrated their awareness of heterogeneity, linguistic accommodation and language mixing by identifying further heterogeneity and complexities in spoken Kurmanji, and such features were not included in the available Kurmanji literature.

In the present study, individual accuracies of the two native speaker non-linguist and linguist groups demonstrate that some non-linguists outperformed their linguist counterparts in the classification task, and maximum overall accuracy rates were achieved by individual non-linguist listeners. Considering this finding, we hold the view that success in carrying out language analysis is dependent on the talent and experience of the individual analyst rather than a linguistic qualification alone. Wilson (2009) argued, based on the marginal difference between linguist groups' accuracy and performance, that in-depth linguistic expertise may not be more significant than a short training for a reliable language analysis. This view supports the position already taken by Foulkes, French & Wilson (2019) and Cambier-Langeveld (2010).

### 5. Conclusion

Native speaker linguists were only slightly more accurate than native speaker nonlinguists in identifying the L1 accent in spoken English; however, the difference between these two groups was not significant. These findings thus offer empirical support for having educated native speakers involved in LAAP casework, even without linguistic training. Further, the findings of the current study as well as other past studies (such as those mentioned above) have discovered the success rates of native speakers in identifying their own speaker group. It could therefore be argued that the involvement of native speakers in LAAP casework is of utmost significance, and such involvement may only serve as one of the several steps taken in the complex procedure of asylum applications and decisions.

Further research could consider the role of explicit, accent-specific training in language analysis, and whether linguists and non-linguists can employ this training to significantly improve accuracy. Given the above findings, native speakers who receive good training and demonstrate a strong potential when tested may be suitable for the task of language analysis. However, being a native speaker alone does not automatically qualify a person to conduct every forensic speech task. Nonlinguist native speakers should receive appropriate training for language analysis and only work in a team under the supervision of a linguist. Our findings do suggest that native speaker linguists will have less variability in performance than native speaker non-linguists; however, individual native speaker non-linguists can also perform with high accuracy. In addition, it may also be beneficial to have asylum speakers perform an accent classification task as well given the strong role of native language match on accent classification performance. As recommended by Wilson (2016), we also recommend that relevant authorities consider this additional testing method by asking asylum seekers to distinguish speech samples spoken by fellow speakers of their native accent from several other samples.

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