Two-Dimensional Analysis of Indigenous Language Learning Effectiveness: Proficiency Advancement and Within-Level Mastery

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Abstract:

Taiwan is an inclusive maritime nation characterized by rich linguistic and cultural diversity. Its Indigenous languages constitute the Austronesian language family. This study evaluates the learning effectiveness of an AI-based learning platform for Indigenous learners in Taiwan. Longitudinal learning data were extracted from Indigenous users from the Indigenous Language Audio Challenge platform. Utilizing quantitative methods, this research analyzed Indigenous learners' assessment records stored within the system database. Logistic regression and Ordinary Least Squares (OLS) regression were employed to examine learning effectiveness through two lenses: proficiency advancement and within-level mastery. The findings suggest potential avenues for language education, cultural preservation, and technological innovation. The primary results indicate: (1) prior ability exhibits a stable effect on sustained Indigenous language learning; (2) advancement thresholds and performance disparities manifest across ethnic groups; and (3) school environments exert structural interference on learners' mastery of Indigenous languages.

Keywords: Indigenous language, Indigenous peoples, learning effectiveness

1. Introduction

Taiwan is a maritime nation characterized by extensive linguistic and cultural diversity. Its Indigenous languages of Taiwan belong to the Austronesian language family. Blust (2013) posits Taiwan as the homeland of the Austronesian languages. These languages represent critical cultural assets but face intergenerational disruption and the risk of extinction due to modernization, many Indigenous languages in Taiwan are facing intergenerational disruption and the risk of disappearance. The preservation and revitalization of Indigenous languages and cultures have therefore become urgent tasks.

Recent advances in digital technology have accelerated the development of Artificial Intelligence (AI). Natural Language Processing (NLP) and machine learning techniques facilitate the processing of large unstructured datasets, allowing computers to interpret human language. Accordingly, research in text analysis, Machine Translation (MT) (Tan et al., 2020), and Automatic Speech Recognition (ASR) (Malik et al., 2021) has made substantial progress.

Centering on Taiwan's Indigenous peoples, this study adopts AI-based Natural Language Processing (AI-NLP) as its technological core. It aims to develop an AI adaptive testing and self-learning service system for Indigenous language literacy. This platform supports individualized learning and serves as an integration of technology and cultural education. By promoting effective and sustainable models, the platform has the potential to further opportunities for language education, foster and technological innovation.

2. Literature Review

The AI-based technology platform for Indigenous language education consists of two main websites: the Indigenous Language Literacy Self-Learning Service System and the Indigenous Language Audio Challenge (Shih et al., 2024).

The former provides learners with individualized online learning tailored to learners' motivation. Modules include Interactive Listening and Speaking Literacy, Indigenous Language–Mandarin Translation, Human–Machine Dialogue, AI Indigenous Writing, Indigenous Board Games, Indigenous Singing Instruction, Indigenous Self-Learning Path Planning, and Digital Animation. The pedagogical foundation rests on the ARCS Model of Motivation (Keller, 2010), focusing on Attention, Relevance, Confidence, and Satisfaction.

The Indigenous Language Audio Challenge is a personalized online self-challenge platform, covering eight thermotic domains, which are life experience, interpersonal interaction, language and humanities, leisure and entertainment, social institutions, technology and health, nature and the universe, and values and beliefs, and 13 levels of difficulty. Its construction utilizes Item Response Theory (IRT), precisely measure ability and item characteristics through the Item Characteristic Curve (ICC). Unlike traditional methods, IRT improves assessment reliability and validity within computer-based environments (Chen, 2006).

3. Research Methodology

3.1 Participants

The research data were drawn from the Indigenous Language Audio Challenge using a longitudinal matched-sample design. Users with multiple records were selected, comparing the initial challenge with the chronologically most distant final challenge. Participants included Indigenous learners from the Tsou, Truku, and Pinuyumayan groups. Descriptive statistics are presented in Tables 1 and 2.

Table 1. Descriptive Statistics of Background Variables (N = 142)

Independent Variable	Category	Count	Percentage	Number Advanced	Proportion
Gender	Female	42	29.58	31	73.81
	Male	100	70.42	74	74.00
School Type	Elementary school	112	78.87	93	83.04
	Junior high school	30	21.13	12	40.00
Ethnicity	Tsou	100	70.42	87	87.00
	Truku	28	19.72	10	35.71
	Pinuyumayan	14	9.86	8	57.14
Home Language Environment	No	29	20.42	17	58.62
	Yes	113	79.58	88	77.88
Advancement Status	Yes	105	73.94	-	-
	No	37	26.06	-	-

Table 2. Descriptive Statistics of Continuous Variables

Variable	Minimum	Q1	Median	Q3	Maximum	Mean	SD
Initial score	0	50	67	83	100	64.54	26.18
Final-stage score	0	38	63	75	100	55.25	27.59
Number of level advancements	0	0	1	1	4	1.03	0.86

3.2 Research models

All categorical variables were converted into dummy variables, and the first category of each variable was selected as the reference group, including Tsou, female, and no Indigenous language use at home. Two analytical models were employed to address the two research questions.

3.2.1 Proficiency advancement model: binary logistic regression

The first model examined whether a learner advanced to a higher level as the binary dependent variable (1 = advanced; 0 = did not advance). Ethnicity, initial score, gender, and home language environment were included as predictors to examine the extent to which these factors affected learners' ability to progress beyond their current level of difficulty. In the sample, 105 learners (73.94%) advanced, whereas 37 learners (26.06%) did not.

Logistic regression expresses the effect of each variable in terms of odds ratios (ORs) and is appropriate for the analysis of binary outcome variables. Model fit was assessed using McFadden's Pseudo-R² and the Akaike Information Criterion (AIC).

$$ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1(\text{Truku})_i + \beta_2(\text{Pinuyumayan})_i + \beta_3(Score\_Early)_i + \beta_4(\text{Male})_i + \beta_5(\text{Home language environment})_i$$

3.2.2 Within-level mastery model: ordinary least squares regression

The second model utilized the final test score (i.e., the final-stage test score) as the dependent variable, controlling for the final level reached as a control variable to ensure that learners' performance was compared under equivalent levels of difficulty.

$$Score\_Late_i = \alpha_0 + \alpha_1(Stage\_Late)_i + \alpha_2(Score\_Early)_i + \alpha_3(\text{Truku})_i + \alpha_4(\text{Pinuyumayan})_i + \alpha_5(\text{Male})_i + \alpha_6(\text{Home language environment})_i + \alpha_7(\text{school})_i$$

4. Results

The statistical results of the two models are presented in Tables 3 and 4.

Table 3. Results of Model 1

Variable	Estimate	Standard Error	Test Statistic	p-value	Significance
Intercept	-1.38	1.11	-1.24	.216	
Truku	-2.73	0.75	-3.64	< .001	***
Pinuyumayan	-0.75	0.81	-0.93	.351	
Initial score	0.07	0.01	4.82	< .001	***
Male	0.16	0.63	0.26	.796	
Home language environment (Yes)	-0.98	0.82	-1.20	.230	

Note. The reference group was Tsou, female, and no Indigenous language use at home.
* $p < .05$. ** $p < .01$. *** $p < .001$.

The results show that the initial score had a significant positive effect. Specifically, each 1-point increase in the initial score was associated with an approximately 7% increase in the odds of advancement. Put differently, a 10-point increase in the initial score nearly doubled the odds of advancement. Prior ability was the most stable and influential predictor in this model. Even after controlling for ethnicity, gender, and home language environment, its effect remained highly significant, consistent with previous findings on the cumulative effect of prior knowledge in heritage language learning (Montrul, 2010).

With regard to ethnicity, the Truku group showed a significant negative effect. Its odds of advancement were only about 7% of those of the Tsou group, indicating a gap of more than fourteenfold. This was the largest ethnicity-related effect observed in the model. In other words, when learners had the same initial score, Truku learners were significantly less likely than Tsou learners to advance to a higher level. This difference was both statistically and substantively meaningful.

Neither gender nor home language environment reached statistical significance. These findings may have been affected by sample variation or unobserved confounding variables and should therefore be interpreted with caution.

Regarding overall model performance, McFadden's Pseudo-R^2 was .42, substantially exceeding the commonly accepted benchmark of approximately .20 for a well-performing model in social science research. This suggests that the model had strong discriminatory power in predicting advancement outcomes. The AIC was 106.99, which may serve as a useful benchmark for subsequent model comparisons.

Table 4. Results of Model 2

Variable	Estimate	Standard Error	Test Statistic	p-value	Significance
Intercept	38.64	9.97	3.88	< .001	***
Truku	-6.63	7.20	-0.92	.357	
Pinuyumayan	0.67	8.38	0.08	.936	
Initial score	0.27	0.11	2.47	.014	*
Male	-2.12	5.28	-0.40	.688	
Home language environment (Yes)	7.58	7.19	1.05	.292	
Final level	-3.90	2.71	-1.44	.149	

Note. The school-type variable was removed because of severe collinearity with Truku ethnicity (VIF > 10). * $p < .05$. ** $p < .01$. *** $p < .001$.

The final level reached showed a negative effect, indicating that for each additional increase in difficulty level, the average score decreased by approximately 3.9 points, which is consistent with expectations.

The initial score again showed a significant positive effect. Specifically, for each 1-point increase in the initial score, the final score increased by an average of 0.27 points, after controlling for the other variables. This finding is consistent with the results of Model 1 and further supports the conclusion that prior ability has a robust positive influence on learning performance.

The home language environment showed a positive coefficient, but the effect was not statistically significant. Gender was likewise non-significant.

With respect to ethnicity, neither Truku nor Pinuyumayan showed a statistically significant effect. This finding has important diagnostic implications. In the original model, Truku ethnicity had shown a significant negative effect; however, that coefficient was influenced by severe multicollinearity. After the removal of the highly collinear school-type variable, the effect disappeared, suggesting that the earlier result may have reflected statistical distortion. Accordingly, the present data do not support an independent effect of ethnicity on within-level score performance.

In terms of overall explanatory power, the model yielded an adjusted R^2 of .061, indicating that it explained only about 6.1% of the variance in final scores. It should be noted that the R^2 used in Model 2 and the McFadden Pseudo-R^2 used in Model 1 are different types of fit indices and therefore should not be directly compared numerically. The former reflects the proportion of explained variance in a continuous dependent variable, whereas the latter captures the improvement in model likelihood relative to a null model.

5. Conclusion

This study yields three main conclusions:

First, prior ability is a robust predictor of sustained Indigenous language learning, which is consistent with the cumulative effect of prior knowledge identified in heritage language learning research.

Second, advancement thresholds vary by ethnic groups potentially due to structural factors. Whether Indigenous learners can progress from their current level of difficulty to a higher one is not determined solely by their initial level of ability; it may also be influenced by structural factors associated with ethnic background.

Third, school environments exert structural interference on learners' mastery of Indigenous languages than ethnic background itself. In the analysis of final-stage scores, ethnic differences disappeared after controlling for school type. This statistical pattern suggests that, under the same level of difficulty, learners' mastery may be shaped more strongly by the school environment than by ethnic language background itself. Therefore, evaluations of Indigenous language learning effectiveness should take institutional learning environments into account, rather than attributing systematic environmental differences solely to ethnic-group ability.

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