

# BAYESIAN MODEL IN THE CONJUGATION OF ARABIC TRILITERAL VERB BY SECOND LANGUAGE LEARNERS

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**Abstract:** *One of accurately assumed model for understanding how native speakers of flective languages use morphological structures is Bayesian model. This model explains that the ability of native speakers to predict other inflective forms of conjugation of Arabic triliteral verb is influenced by their knowledge of other inflective forms, which they are already familiar with, and also by the natural predictability of the inflective form candidates they want to conclude. The objective is to test empirically whether the Bayesian model in that phenomen also applies to Arabic learners in predicting morphological forms of Arabic as L2. As experimental research, we obtained data from answers sheet of respondents in predicting word forms in imperfective verb conjugations. Data analysis utilized Descriptive Analytics and Generalized Linear Mixed Model (GLMM). The results stated that prior information makes it easier for respondents to predict forms derived from unknown roots*

**Keywords:** *Bayesian mode, conjugation of Arabic, Arabic triliteral verb, predicting morphological forms*

## Introduction

One lexeme in several languages expresses many categories, e.g. tense, gender, case, number, aspectual (Holes, 2004). The adequate models which represent those morphological systems are necessary need, to conduct and develop research in applied linguistics, particularly for developing technology for language processing. One of them is Bayesian model. This model is empirically validated to capture native speaker's productivity while predicting the inflective form in their daily communication (Allen, 2016). According to this model, the probability of native speakers generating and inferring inflective forms that they are not familiar with is theoretically influenced by (1) their understanding of the structure of the inflective forms they already know and (2) the predictability of the inflective forms they want to infer.

Empirical support for this claim (Allen, 2016) explains, among other things, that the predictability of native Icelandic speakers guessing inflective forms that are relatively unknown tends to increase when there is additional information about other inflective forms of a word. It was also found that the lexical frequency of different groupings of words plays a major role in influencing the behavior of native speakers in using inflectional structures. The findings of Allen (2016) and Allen & Becker (2016) open opportunities for further research to be carried out, to prove whether the Bayesian framework also applies in capturing the behavior of non-native speakers, for example second language learners, in using the morphological structure of the language they are learning. Therefore, this research will conduct experiments on Arabic language (AL) learners in Indonesia, to empirically prove whether the Bayesian model is able to represent their behavior in using the morphological structure of Arabic or vice versa. The main goal to be generated from the research is to have a new perspective on how the ability of Arabic learners apply morphological operations that is more effective is built.

This study took Arabic as the object of research because Arabic is a flective language based on its morphological structure (Lauder, Muhadjir, & Lucy, 2007). This type of language has complexity in its morphological structure, because one word represents a number of grammatical categories which cannot be identified solely based on the relation of form and meaning (Freynik, Gor, & O'Rourke, 2017). Then, to model it requires an appropriate theoretical framework, that is the Bayesian model.

As previously explained, Allen (2016) had succeeded proving the validity of the Bayesian model paradigm to capture the inference process of Polish and Icelandic native speakers to generate word or flective forms from familiar and unfamiliar lexemes. This study will try to do the same thing, but not on native speakers, but on second language learners, those are Arabic language learners in Indonesia. In other words, this study will empirically prove whether the Bayesian model is able to represent their behavior in using the morphological structure of Arabic to guess Arabic inflective word forms or patterns, especially in triliteral verbs. Then, the problem in this study is how the Bayesian model can be applied to the learning process of learners of Arabic as a second language in predicting Arabic inflective word forms, especially those derived from valid triliteral verbs. We have two questions to solve that problem, those are (1) does giving an inflective form as a clue make it easier for Arabic learners to predict an inflective form being asked? (2) Does a particular inflective form as a clue make it easier for learners of Arabic as a second language to predict an inflective form being asked compared to another inflective form?

## Literature Review

### Morphology of the Paradigm Cell Filling Problem

There are two types of morphological process in fleective language, i.e. declination and conjugation. Declination is a change in word form caused by a change in gender, number, and case. Meanwhile, conjugation is a change in word form caused by differences in persona, gender, number, aspect, and tense (Ryding, 2005). These two kinds will generate a number of words that come from the same root, and that is called a paradigm. The derivative paradigm is a set of words with a new lexical meaning, which is the result of a morphological change of a root or lexeme. The inflective paradigm is a set of words with a new grammatical meaning which is also the result of a morphological change from a root or lexeme (Holes, 2004). Here are the morphological derivative and inflective of Arabic verb.

**Table 1: Derivative and inflective changes**

| Paradigm     |                | Stem/<br>base | Slot 1 | Slot 2 | Slot 3  | Slot 4   | Slot 5  | Slot 6 | Slot 7  |
|--------------|----------------|---------------|--------|--------|---------|----------|---------|--------|---------|
| Type         |                |               |        |        |         |          |         |        |         |
| a. Derivatif | Template       | fa'ala        | fa'l   | maf'al | fā'il   | maf'ul   | maf'al  | mif'al |         |
|              | Implementasion | daraba        | darb   | maḍrab | dārib   | maḍrūb   | maḍrab  | miḍrab |         |
| b. Inflektif | Template       | fa'ala        | fa'alā | fa'alū | fa'alat | fa'alatā | fa'alna | ...    | fa'alnā |
|              | Implementasion | daraba        | ḍarabā | ḍarabū | ḍarabat | ḍarabatā | ḍarabna | ...    | ḍarabnā |

Arabic learners have a lot of difficulties predicting the form in each slot, even though they have been given information through the template. In fact, these forms are the key in studying the morphological structure of Arabic. In addition, the learner's ability to predict each form in the slot correctly will make it easier for them to search the meaning of the word in the dictionary. To find the meaning of a word from the dictionary, Arabic learners cannot directly look for the entry of the word in question, but should know the root of the word. The root of the word becomes the entry, then look for the word in question from the root entry. This searching process relies heavily on morphological abilities which are closely related to filling each slot with word forms.

### Bayesian Model of Morphological Structures

In today's digital era, the morphological problems associated with these derivative and inflectional changes do not only focus on how to predict the form of words in each slot, but continue on how to capture the phenomenon of the language learner's cognition structure in predicting it. So, there is a learning process in the mind of language learners that can be modeled, to understand the patterns of changing word forms, so that they can generate the right form in each slot. Allen (2016) took this position, which try to present a theoretical framework for understanding and predicting the process of inflection in cognition, especially in native speakers of the fleective language. He studied the inference process that exists in the mind of native speakers when they are about to produce a word form from a root form in an inflective paradigm.

Using the bayesian model framework, Allen studied the behaviour of speakers of native Polish and Icelandic languages in filling in the slots of tenses in the inflective paradigm. He called it "modeling the paradigm cell filling problem" (Allen, 2016). He did this to prove that the inference process for speakers of a language in producing a number of word forms based on the rules that apply in that language, can be captured by probability theory a la Bayesian Model. According to him, the advantage of this theory is that it can model the process of generating new words (novel words) or unattended words in the mind of speakers, which in other models

only maximize the inflection of words that are already familiar to the mind of speakers (Allen, 2016). In this context, models of the paradigm cell-filling problem can build general-purpose models for various inflectional morphological phenomena.

The Bayesian model in morphological structure utilizes Bayesian probability theory from the discipline of probability theory. Bayesian theory states that the probability of an event occurring is proportional to other relevant information and information about the probability that the event occurs naturally (prior probability). This Bayesian principle can be brought into the realm of morphology to portray how speakers of a language can productively infer inflectional or derivational forms. Let  $D$  be a random variable candidate for the derivational form of a lexeme and  $B_1, B_2, \dots, B_k$  is another well-known collection of inflectional form random variables. According to the Bayesian principle, the probability that the speaker will infer that candidate  $D = d$ ---when the speaker has knowledge that the derivational forms  $B_1 = b_1, B_2 = b_2, \dots, B_k = b_k$ ---will be proportional to the speaker's ability to predict collections  $B_1, B_2, \dots, B_k$  and the natural probability distribution of generating of the derivational form  $D$ , or

$$P(D = d_1 | B_1 = b_1, B_2 = b_2, \dots, B_k = b_k) \propto P(B_1 = b_1, B_2 = b_2, \dots, B_k = b_k | D = d)P(D = d)$$

### Empirical Support for the Bayesian Model

Actually what Allen did is one of a number of studies that explain how language speakers utilize the grammatical knowledge they have in their mind very well, to produce wellformed utterances (novel utterances)(Allen, 2016). In this digital era, an explanation of this phenomenon leads to the development of models for the benefit of formulating algorithms in programming, especially in NLP (natural language processing).

Previously, (Ackerman, Blevins, & Malouf, 2009) and (Malouf & Ackerman, 2010) had conducted studies such as using the entropy paradigm to measure morphological simplicity. Allen adopted the two studies to model the inference process of speakers of languages in producing word forms derived from unfamiliar lexemes. Moreover, Cotterell et al (2017) had already conducted neural-bayesian network for morphological paradigm, and Perrone et al. (2021) also utilized dynamic Bayesian mixture model to observe the dynamics of changes in meaning caused by changes in form.

Theoretically and empirically, modeling of the behavior of language speakers in inferring morphological paradigms had been widely carried out in the past, among others started by (Chomsky & Halle, 1968) and (Chomsky, 1956, 1957). The two scientific works asserted a type of linguistic behavior which become important focus of the study; that was the inferences that are processed in the mind of native speakers when generating linguistic units in their language. This inference was also studied by (McCarthy, J.J. & Prince, 2001) and (Prince & Smolensky, 2008) with their flagship theoretical framework, i. e. Optimality Theory (OT). In 1957, Chomsky also announced his minimalist syntax theory, to model the inference behavior.

Other studies that have also enlivened the modeling arena for the benefit of NLP, particularly on morphological paradigms, both derivative and inflectional, have been conducted by (Pater & Tessier, 2003) on the learning process of morphology in a first language; by (Hayes & Wilson, 2008), (Coleman & Pierrehumbert, 1997) about judging wellformedness. It is certain that the modeling studies that have existed on the inference process in the mind of speakers of a language are still being carried out for the first language. In other words, the researches in this

area are still spotlighted on native speaker. For that reason, we try to investigate it with divergent center of attention, that is the second language learners.

In his dissertation, Allen, who relied on the Bayesian Model, also examined the behavior of Icelandic and Polish native speakers in generating word forms in the inflective paradigm. The results of empirical experiments on the behavior of native speakers (Allen & Becker, 2016) explained that the predictability of native Icelandic speakers in guessing relatively unknown inflective forms tends to increase when there is additional information about other inflective forms of a word. It was also found that the lexical frequency of different groupings of words plays a major role in influencing the behavior of native speakers in using inflectional structures. In this study, we try to prove the validity of the Bayesian probability model in capturing the behavior of learners of Arabic as a second language in Indonesia, when they make inferences to generate a form of a word in BA.

### Research Design

This research is an experimental study. We Applied a split plot design (SPD) with several replications and several treatments. Split Randomized Plot Design (SRPD) is an experimental design that uses two factors which focus on investigating the main effect of one of the factors and the interaction of the two factors which are considered more important to study, rather than the influence of the other factors (Jones & Nachtesheim, 2017).

The respondents of this research were Indonesian students who learn Arabic as a second language. They are students of Department of Arabic Language and Culture from University of Al-Azhar Indonesia (UAI) and Univeristy of Indonesia (UI), who have at least in the fourth semester or taken courses in Arabic Grammar, Theoretical Linguistics, Applied Linguistics, and Language Proficiency. The entrollment or entry year is treated as the variable of study, and we call it batch. From each batch, 20 students will be selected to take part in the trial. In experimental design terms, these 20 students represent the number of replicates of the experiment. With an average number of students per batch of around 35 people, the sample size that was studied in each batch represents approximately 60% of the population size. We consider this number is relatively sufficient to represent the characteristics of the population.

Each student will be given a number of questions that they have to answer within a certain time period. The questions given to students were related to the inflectional forms of Arabic triliteral verbs, which students had to guess. There are three types of question formats that will be tested. Each type of question format represents a level of complexity in processing and generating Arabic triliteral verbs. There are inflectional forms that students must guess, in the condition that no information is provided about other inflectional forms of the verb. Another question format tests students' ability to guess the inflectional form of Arabic triliteral verbs, when given information about other inflectional forms of the verb to be tested. In total there are three types of treatment, in the form of three different question formats, which will be tested on students.

The experiment was carried out online using Google Form as an instrument to test student responses to various questions. The experimental mechanism followed the experigen framework (Becker, Nevins, & Levine, 2012). The types of questions tested in each type of test are different. The first type of test questions asks test takers to guess certain inflectional forms (for example the third form) of Arabic triliteral verbs, without being provided with other information about other inflectional forms of the verb. The next type of test question asks test takers to guess certain inflectional forms (for example the fourth form) of Arabic triliteral verbs,

if the information about other inflectional forms of the verb is provided. The last type is asking students to infer the inflection form in a certain slot with the support of the inflection form in another particular slot. We provide the last type of question twice, using disparate particular slot clue.

Each question tested is an Arabic lexeme which is generally relatively unknown to students. Each student will be exposed to one or more inflectional forms of the new lexeme in one or several sentences. The student's next task is to choose one of the four answer options regarding other inflectional forms (which can express tense, aspect, location, actor, etc.). The order in which the options for inflectional forms are presented is random. Respondents' choices for the inflectional forms in question will be recorded as a basis for analyzing their predictability in generating inflectional forms under various conditions.

**Table 2. Type of Tests**

| Type of the given tests                                                |                                                                      |                                                                                                             |                                                                                                            |
|------------------------------------------------------------------------|----------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|
| 1                                                                      | 2                                                                    | 3a                                                                                                          | 3b                                                                                                         |
| Inferring the inflectional form if no other inflectional form is given | Inferring the inflectional form when given another inflectional form | Inferring the inflectional forms when given another inflective form in a certain slot (for example, slot 3) | Inferring the inflectional form if given another inflective form in a different slot (for example, slot 6) |

In this research, two types of analysis will be used. First, descriptive analysis. At this stage, the characteristics of the object under study will be presented. Apart from that, the statistical profile of the results of trials processing triliteral verb inflectional forms on a number of students will also be presented. Several basic statistical measures, such as mean, median, mode, variance, proportion, and frequency distribution, will be used to describe the statistical profile of the experimental results.

In the second stage, inferential analysis will be carried out. At this stage, the significance of the treatment and observation unit groups will be estimated and tested statistically, in explaining students' ability to guess inflectional forms of triliteral verbs. We will estimate the generalized linear mixed model (GLMM) regarding students' ability to process the inflectional forms of Arabic triliteral verbs using 3 types of treatment. Several types of tests will be applied, such as the t test, ANOVA test on the effect of group, ANOVA test on the effect of treatment, and ANOVA test on the effect of group and treatment. The test results will be used as material to analyze and conclude student behavior, as second language learners, in processing the inflectional forms of Arabic triliteral verbs.

## Result And Discussion

### Predictability with Clue

The Bayesian hypothesis states that second language learners' predictability in guessing inflectional forms will be better when they are provided at least one type of information about other inflectional forms, compared to without being provided with information about other inflectional forms. To test this empirically, first an F test (or Anova test) is carried out. This test is used to examine if null hypothesis  $H_0$  (the average score on type I and type II questions is not different) is rejected under a given significance level. If  $H_0$  is rejected, then we accept the alternative hypothesis  $H_1$ , which is the average score on type I and type II questions is different. The results of the F test at a significance level of 5% are as follows:

**Table 3. ANOVA test for the difference in average test scores for type I and type II questions**

| ANOVA               |             |     |          |        |         |        |
|---------------------|-------------|-----|----------|--------|---------|--------|
| Source of Variation | SS          | df  | MS       | F      | P-value | F crit |
| Between Groups      | 2912,121    | 1   | 2912,121 | 11,398 | 0,001   | 3,914  |
| Within Groups       | 33214,394   | 130 | 255,495  |        |         |        |
| Total               | 36126,51515 | 131 |          |        |         |        |

The Anova test results explain that the p-value of the test results is 0.001. This value is much smaller than the significance level of 0.05. These results indicate that the null hypothesis (the average score on type I and type II questions is not different) is rejected. In other words, sample data further supports the situation that the average scores for type I questions and type II questions are significantly different. This empirical fact is also supported by the F-stat value of 11.39, which is still much greater than the critical F value, namely 3.91 (table 3). These results demonstrate that empirically the predictability in guessing the Arabic inflectional form can be different when language learners are provided by one of another form and when they are not provided with one of another form.

Because the average scores on Type I and Type II exams are empirically considered to be different, a test was then carried out to test whether the average score on Type II exams was greater than the score on Type I exams. For this purpose, we applied the *t* test for the average of the difference in score of paired observations, which is the average of difference between exam score when students are given one of inflectional form and when they are not provided by another inflectional form. If this hypothesis is supported by sample data, it means that the Bayesian hypothesis is considered valid in representing the process of answering inflectional forms of second language learners.

The results of the *t* test at a significance level of 5% are presented in Table 4 The results of this test indicate that the one-tail p-value is close to zero. The value is lower than the 5% significance level. The t-stat value (10.83) is also greater than the critical t value (1.67). Thus, in general it can be concluded that the null hypothesis (the average difference between type II and type I scores is equal to zero) is rejected. The sample further supports the situation that the average difference between type II and type I scores is greater than zero. In other words, the sample data better represents the situation that students on average have better scores from type II exams than from type I exams. This suggests that providing one of Arabic inflection form on average will improve the ability of learners in guessing another inflectional form.

**Table 4. Average t-test results difference between type I and type II test scores**

|                              | <i>Skor Tipe I</i> | <i>Skor Tipe II</i> |
|------------------------------|--------------------|---------------------|
| Mean                         | 68,41              | 77,80               |
| Variance                     | 266,28             | 244,71              |
| Observations                 | 66,00              | 66,00               |
| Pearson Correlation          | 0,90               |                     |
| Hypothesized Mean Difference | -                  |                     |
| df                           | 65,00              |                     |
| t Stat                       | - 10,83            |                     |
| P(T<=t) one-tail             | 0,00               |                     |
| t Critical one-tail          | 1,67               |                     |
| P(T<=t) two-tail             | 0,00               |                     |
| t Critical two-tail          | 2,00               |                     |

Based on the results of the t-test, it can be said that, in general, providing information about an inflectional form of a verb, helps learners of Arabic as a second language, in improving their ability to guess other inflectional forms, which are asked in the question. This indicates that Bayesian patterns tend to be applied in guessing the inflectional forms of trilateral Arabic verbs. In other words, learners of Arabic as a second language are more helped in inferring inflectional forms, if they are provided with information on other inflectional forms.

Next, we will analyze the predictability of the trilateral verb inflection process, based on batch status (entry year) and background of high school. We applied linear regression of the difference between type II and type I scores as a function of high school background (HSB) and class status or batch of 2018 (B2018), 2019 (B2019), and 2020 (B2020). The estimation results are presented in table 5 indicates that high school background and batch status are considered statistically irrelevant in explaining the variation in score differences between type I and type II questions. Regardless of the irrelevance of these variables in the regression model, from an interpretation perspective it can be explained that respondents from Madrasah Aliyah (MA) tend to have better abilities on average in predicting the inflectional form of trilateral verbs using clue information compared to their peers, which are their colleagues who are not from MA.

**Table 5. Results of linear regression estimation of the difference between type II and type I scores as a function of high school background, Class Status of 2018, 2019, and 2020.**

| <i>Regression Statistics</i> |                     |                     |               |                |                       |                  |
|------------------------------|---------------------|---------------------|---------------|----------------|-----------------------|------------------|
| Multiple R                   | 0,284               |                     |               |                |                       |                  |
| R Square                     | 0,081               |                     |               |                |                       |                  |
| Adjusted R Square            | 0,020               |                     |               |                |                       |                  |
| Standard Error               | 6,972               |                     |               |                |                       |                  |
| Observations                 | 66                  |                     |               |                |                       |                  |
| ANOVA                        |                     |                     |               |                |                       |                  |
|                              | <i>df</i>           | <i>SS</i>           | <i>MS</i>     | <i>F</i>       | <i>Significance F</i> |                  |
| Regression                   | 4                   | 260,295             | 65,074        | 1,339          | 0,266                 |                  |
| Residual                     | 61                  | 2.965,462           | 48,614        |                |                       |                  |
| Total                        | 65                  | 3.225,758           |               |                |                       |                  |
|                              | <i>Coefficients</i> | <i>tandard Erro</i> | <i>t Stat</i> | <i>P-value</i> | <i>Lower 95%</i>      | <i>Upper 95%</i> |
| Intercept                    | 12,805              | 2,358               | 5,429         | 0,000          | 8,089                 | 17,521           |
| HSB                          | 0,793               | 1,844               | 0,430         | 0,669          | - 2,894               | 4,479            |
| B2018                        | - 3,598             | 4,542               | - 0,792       | 0,431          | - 12,681              | 5,486            |
| B2019                        | - 3,465             | 3,500               | - 0,990       | 0,326          | - 10,464              | 3,533            |
| B2020                        | - 5,058             | 2,269               | - 2,230       | 0,029          | - 9,595               | - 0,522          |

Furthermore, a regression model for type II question scores was also estimated as a function of high school background and the year of entry. The results of this regression estimate are presented in table 6. The regression estimation results show that High School background is the only predictor variable that is considered relevant to explain the variation in type 2 scores. The p-value of the High School background coefficient is close to 0 (much lower than the 5% significance level). Batch status or year of entry were considered by the sample to be irrelevant for explaining variation in type II scores. This is shown by the p-value of the coefficient for each class status, which is much greater than the specified significance level, namely 5%.

The Senior High School background coefficient is positive 13.40. Meanwhile, Senior High School Background is worth 1 if the student comes from MA. With a regression coefficient of 13.40, it can be indicated that students who come from MA are thought to have a higher average score of approximately 13.40 points compared to their peers who do not come from MA, regardless of their batch status.

**Table 6. Type 2 score regression estimation results as a function of High School background and Class batch**

| Regression Statistics |                     |                       |               |                |                       |                  |
|-----------------------|---------------------|-----------------------|---------------|----------------|-----------------------|------------------|
| Multiple R            | 0,461               |                       |               |                |                       |                  |
| R Square              | 0,213               |                       |               |                |                       |                  |
| Adjusted R Square     | 0,161               |                       |               |                |                       |                  |
| Standard Error        | 15,925              |                       |               |                |                       |                  |
| Observations          | 66                  |                       |               |                |                       |                  |
| ANOVA                 |                     |                       |               |                |                       |                  |
|                       | <i>df</i>           | <i>SS</i>             | <i>MS</i>     | <i>F</i>       | <i>Significance F</i> |                  |
| Regression            | 4                   | 4.179,375             | 1.044,844     | 4,120          | 0,005                 |                  |
| Residual              | 61                  | 15.470,625            | 253,617       |                |                       |                  |
| Total                 | 65                  | 19.650,000            |               |                |                       |                  |
|                       |                     |                       |               |                |                       |                  |
|                       | <i>Coefficients</i> | <i>Standard Error</i> | <i>t Stat</i> | <i>P-value</i> | <i>Lower 95%</i>      | <i>Upper 95%</i> |
| Intercept             | 68,981              | 5,387                 | 12,806        | 0,000          | 58,210                | 79,753           |
| HSB                   | 13,403              | 4,211                 | 3,183         | 0,002          | 4,982                 | 21,824           |
| B2018                 | - 4,051             | 10,375                | - 0,390       | 0,698          | - 24,798              | 16,695           |
| B2019                 | - 5,151             | 7,994                 | - 0,644       | 0,522          | - 21,135              | 10,834           |
| B2020                 | - 10,356            | 5,182                 | - 1,999       | 0,050          | - 20,718              | 0,005            |

### Predictability with Specific Clue

The test results on the average difference between type II and type I question scores indicate that providing information on one inflectional form (clue) will improve students' ability to answer other inflectional forms correctly. In type II questions, two types of inflectional forms are used as information to answer the other forms. The inflectional forms for which information is provided are inflectional form 3 (*yaf'aluna*) and inflectional form 6 (*yaf'alna*).

In the next analysis, we will test the hypothesis that students rely on certain inflectional forms that are easy to understand, to answer other inflectional forms correctly. In this case, do students rely more on inflectional form 6 or 3 in answering other inflectional forms correctly? To answer this hypothesis, we test whether inflectional forms 3 or 6 were relied on more by students, to answer other inflectional forms. Testing is carried out by testing the average difference in scores between the correct answers if given information in inflectional form 6 and if given information in inflective form 3. The null hypothesis that we propose is that the average difference in scores between correct answers when the provided information is inflective form 6 and when the provided information is the inflective form 3 is equal to zero. Meanwhile, the alternative hypothesis that we tested was that the average difference in scores between the correct answers if given information on inflectional form 6 and if given information on inflectional form 3 was greater than zero.

**Tabel 7. t-test results for the average difference in correct answer scores using inflective form information 6 compared to using inflective form information 3.**

|                              | <i>Klu 6</i> | <i>Klu 3</i> |
|------------------------------|--------------|--------------|
| Mean                         | 77,222       | 58,056       |
| Variance                     | 569,206      | 290,397      |
| Observations                 | 36,000       | 36,000       |
| Pearson Correlation          | 0,471        |              |
| Hypothesized Mean Difference | 0,000        |              |
| df                           | 35,000       |              |
| t Stat                       | 5,269        |              |
| P(T<=t) one-tail             | 0,000        |              |
| t Critical one-tail          | 1,690        |              |
| P(T<=t) two-tail             | 0,000        |              |
| t Critical two-tail          | 2,030        |              |

The test results using the t-test for the average difference in values from paired observations, using a significance level of 5%, are presented in Table 7. The t-test results explain that the t-stat value of the sample is 5.269. Meanwhile, the t-critical value at 35 degrees of freedom and a significance level of 5% is 1.690. Because the t-stat value is greater than t-critical, the null hypothesis is rejected. In other words, the sample better represents the conditions stated in the alternative hypothesis that the average difference in scores between the correct answers if given information on inflectional form 6 and if given information on inflectional form 3 is greater than zero. These results indicate that on average it is easier for students to rely on inflectional form 6 to answer other inflectional forms correctly, rather than using inflectional form 3 as additional information in answering trilateral inflectional forms. At least this is represented by some student samples.

## Conclusion

This research aims to test the existence of a Bayesian framework in learners of Arabic as a second language, in predicting an inflectional form of trilateral verbs. To test this, an experiment was carried out in the form of asking students to answer a number of questions divided into two types of questions. The first type of question asks students to predict an inflectional form without additional information about another inflectional form. Meanwhile, the second type of question asks the same thing, but provides information on another inflectional form.

By applying several types of statistical tests, such as the F test and t test, the results of experiments on 66 UAI and UI students explain that providing information about an inflectional form is more helpful for students of Arabic as a second language, in predicting the inflectional form in question. The test results also indicate that the inflectional form that is more often used as a basis for information to improve the ability to correctly predict other inflectional forms is the sixth inflectional form. Both of these results indicate that the Bayesian framework was generally supported by the sample.

This study also estimates and tests a regression model for test scores or changes in test scores as a linear function of high school background and student entry year class status. The test results indicated that second language learners' ability to predict inflectional forms correctly was only significantly explained by their high school background. The student's entry year status is considered statistically irrelevant in this context. These results suggest that the ability

of Arabic as a second language learners to process inflectional forms correctly is also determined by their individual characteristics.

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### References

- Ackerman, F., Blevins, J. P., & Malouf, R. (2009). Parts and wholes: Patterns of relatedness in complex morphological systems and why they matter. In *Analogy in grammar: Form and acquisition* (pp. 54–82). Oxford: Oxford University Press.
- Allen, B. (2016). *Bayesian Model of Learning and Generating Inflectional Morphology*. University of British Columbia.
- Allen, B., & Becker, M. (2016). Learning Alternations From Surface Forms With Sublexical Phonology. *Proceeding of International Conference Phonology 2014, the 89<sup>th</sup> LSA, NYU and UMD*.
- Becker, M., Nevins, A., & Levine, J. (2012). Asymmetries in generalizing alternations to and from initial syllables. *Language*, (88), 231–268.
- Chomsky, N. (1956). Three Models for the Description of Language. *IRE Transactions on Information Theory* 2, 113–124.
- Chomsky, N. (1957). *Syntactic structures*. The Hague/Paris: Mouton.
- Chomsky, N., & Halle, M. (1968). *The sound pattern of English*. New York: Harper & Row.
- Coleman, J., & Pierrehumbert, J. (1997). Stochastic Phonological Grammars and Acceptability. *Computation and Language Journal*.
- Cotterell, Ryan., John Sylak-Glassman, dan Christo Kirov. (2017) Neural Graphical Models over Strings for Principal Parts Morphological Paradigm Completion, *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics (EACL 2017), Volume 2*
- Freyrik, S., Gor, K., & O'Rourke, P. (2017). L2 processing of Arabic derivational morphology. *The Mental Lexicon*, 12(1), 21–50. <https://doi.org/10.1075/ml.12.1.02fre>
- Hayes, B., & Wilson. (2008). A Maximum Entropy Model Of Phonotactics And Phonotactic Learning. *Linguistic Inquiry*, (39), 379–440.
- Holes, C. (2004). *Modern Arabic: Structures, Function and Varieties*. Georgetown: GUP.
- Jones, B., & Nachtesheim, C. J. (2017). Split-Plot Design: What, Why, and How. *Journal of Quality Technology*, (41 (4)).
- Lauder, M. R., Muhadjir, & Lucy, R. M. (2007). *Tipologi Bahasa dan Bahasa-bahasa Dunia, dalam Kushartanti, Untung Yuwono, Multamia RMT Lauder, Pesona Bahasa, Langkah Awal Memahami Linguistik*. Jakarta: Gramedia.
- Malouf, R., & Ackerman, F. (2010). Paradigm entropy as a measure of morphological simplicity. *Proceedings from the Workshop on Morphological Complexity*. Harvard University Press.
- Mc Carthy, J.J. & Prince, A. (2001). *Prosodic morphology I: Constraint Interaction And Satisfaction*. New Brunswick: Rutgers University.

- Pater, J., & Tessier, A.-M. (2003). Phonotactic knowledge and the acquisition of alternations. *Proceedings of the 15th International Congress on Phonetic Sciences, Barcelona*. Universitat Autònoma de Barcelona.
- Perrone, Valerio., Simon Simon Hengchen, Marco Palma, Alessandro Vatri, Jim Q. Smith, dan Barbara McGillivray. (2021). Lexical Semantic Change for Ancient Greek and Latin. Chapter in *Computational Approaches to Semantic Change*, eds by Nina Tahmasebi, Lars Borin, Adam Jatowt, Yang Xu, dan Simon Hengchen. Berlin: Language Science Press
- Prince, A., & Smolensky, P. (2008). *Optimality Theory: Constraint Interaction in generative grammar*. Hoboken: Wiley-Blackwell.
- Ryding, K. C. (2005). A reference Grammar of modern standard Arabic. In *A Reference Grammar of Modern Standard Arabic*. <https://doi.org/10.1017/CBO9780511486975>