# IEEE Copyright Notice

© 2023 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

# Differential Analysis of Biological Information during the Learning of a Second Language and a Programming Language

Katsuyuki Umezawa Dept. of Informatics Shonan Institute of Technology Fujisawa, Japan umezawa@info.shonan-it.ac.jp Takumi Tajima Dept. of Information Science Shonan Institute of Technology\* Fujisawa, Japan (\*Note: Affiliation at the time of experiment) Makoto Nakazawa Dept. of Industrial Information Science Junior College of Aizu Fukushima, Japan nakazawa@jc.u-aizu.ac.jp

Michiko Nakano Faculty of Education and Integrated Arts and Sciences Waseda University Tokyo, Japan nakanom@waseda.jp Shigeichi Hirasawa Research Institute for Science and Engineering Waseda University Tokyo, Japan hira@waseda.jp

Abstract-In 2016, the "government curriculum guidelines" emphasized the importance of early introduction of English and programming education toward globalization and the internationalization of education. A considerable amount of research has been conducted on the similarities and teaching methods between second languages and programming languages. However, most of these studies are limited to evaluations by questionnaires. In this study, to clarify the difference in biometric information when learning English and programming languages, we defined similar problems for both languages and measured 18 types of biometric information. As a result, no significant difference was observed in the average values of any biometric information for similar problems between English and programming languages (for example, English reading comprehension problem and program reading comprehension problem). Therefore, we can say that there is a possibility that the know-how of English learning, which has a lot of research achievements, can be applied to programming learning.

*Index Terms*—learning analytics, biological information, electroencephalogram, heart rate, facial expression.

## I. INTRODUCTION

Research is being actively conducted on the similarities between second languages and programming languages and their respective educational methods. However, most of the previous studies are limited to evaluation by questionnaire; a quantitative evaluation is yet to be performed based on learner's biological information data, which can be measured directly, such as learner's degree of concentration and tension.

The ultimate goal of this research is to establish a methodology for learning a second language and a programming language. Specifically, in addition to the questionnaire-based evaluation conducted after a learning session, we quantitatively analyzed the learning situation by acquiring more valid biometric information during the learning processes. Then, by using the results, the evaluation method for applying the second language learning method to the programming language learning method would be stricter, thus establishing an effective learning method. In this study, we measured the biometric information during the learning of English and a programming language, and we demonstrate no significant difference in the biometric information for the same-question categories in both languages. Furthermore, we show that the methodology can be applied to the learning of any programming language.

# II. PREVIOUS WORK

A. Relationship between programming languages and other languages

Fredrick and Sun [1] conducted the Second Language Acquisition in a Blended Learning (SLA-aBLe) Project to focus on the similarity between a second language and programming languages. In this project, they focused on the similarities between programming and natural languages and applied successful examples of second language acquisition to programming language education from the viewpoint of teaching methods. The scores the learners obtained were higher when the educational method for second language acquisition was applied. In addition, the intrinsic motivation index (interest, tension, etc.) and the self-evaluation type workload index (effort, frustration, etc.) were used as the evaluation indexes through the questionnaire survey. Another study [2] emphasized the importance of cross-training. In crosstraining, a programming language that has not been mastered is learned by transferring the knowledge of a programming language that has already been mastered. In addition, previous research [3] attempted to clarify the relationship between

the types of second languages (English, Russian, Latin, etc.) and programming languages by asking more questions, such as whether learning a programming language correlates with learning methods.

#### B. Utilization of biometric information for learning

Matsui et al. attempted to estimate the mental state of learners from multifaceted information related to learning by using machine learning techniques [4]. They also stated that a learner's mental state (emotional domain) and comprehension state (cognitive domain) are mutually related. They are currently researching the acquisition and analysis of biometric information to grasp the learning processes of learners, and they aim to construct a model in which one can ultimately estimate the psychological state, realizes appropriate educational and learning support, and finally provide automatic mentoring. In a previous study [5], we measured the biological information (brain waves, heart rates, and facial expressions) while performing programming tasks with different degrees of difficulty. We obtained a significant regression equation by focusing on the difference in the average of the biometric information when performing tasks with different degrees of difficulty. Then, we estimated the values of brain waves  $(\beta/\alpha)$ based on the heart rate and facial expressions and estimated the learning state without wearing an EEG during learning.

# III. PROPOSAL

In this study, focusing on the differences in difficulty, we use the analytical method (focus on the difference in difficulty) proposed in our previous study [5] to verify the relationship between English and programming languages and estimate a learner's comprehension states based on biological information and experimental questionnaires.

# A. Question categories of English and a programming language

This study was aimed at acquiring the biometric information of learners when learning English and programming languages and simultaneously estimating the degree of comprehension and discovering common features. In learning English and programming languages, we assumed a correspondence between the two, as shown in Table I. In this experiment, biological information is measured when solving eight types of problems, four types of English (E1 to E4) and programming languages (P1 to P4), as shown in Table I.

 TABLE I

 Correspondence chart of English and programming languages

English	Programming		
E1 (English words)	P1 (Reserved words)		
E2 (English grammar)	P2 (Syntax)		
E3 (English reading	P3 (Program reading		
comprehension)	comprehension)		
E4 (English composition)	P4 (Programming)		

## B. Experimental questions to the learners

In this experiment, we decided to solve four questions each with three levels of difficulty (easy, fair, and hard) for a total of eight types of problems (four types each of English and programming).

Programming language questions were created with reference to Paiza learning [6] and *Java2ndedition* [7]. Paiza learning has many questions with different difficulty levels. We also created questions based on the difficulty level by referring to the first half, middle part, and second half of the book [7]. For English, we created the questions by referring to the teaching materials for the EIKEN Test in Practical English Proficiency Grade 4, Grade 3, Grade Pre-2, and Grade 2.

To compare English and programming languages, we tried to align the question format based on the correspondence shown in Table I. Figure 1 illustrates a simple question with E3 (English reading comprehension) and P3 (Program reading comprehension).



Fig. 1. Examples of E3 (English reading comprehension) and P3 (Program reading comprehension) questions (difficulty: easy)

#### C. Experimental method

A total of eight applicants participated in the experiment. We divided the participants into two groups: a group of 4 people who started with English questions (Group A) and a group of 4 people who started with programming language questions (Group B). Figure 2 shows the overall flow of the experiment.

After finishing the E4 (English composition), Group A took a 10-min break and then solved programming questions starting with P1 (Reserved words). On the other hand, Group B, after completing P4 (Programming), proceeded to answer E1 (English words). Measurement of biological information (EEG, heart rate, and facial expression) was started at the beginning of each category (squares in Figure 2) and stopped at the end of a task. Participants solved questions in succession in the order of difficulty (easy, fair, and hard) in each category. The biological information was then measured continuously, and the biological information when solving the problems for each difficulty level was recorded and saved after the experiment.



% EEG, Heart rate measurement, facial expression recording

Fig. 2. Experimental flow

#### D. Measuring equipment for biological information

In this study, we employed Neuro Sky's Mind Wave Mobile 2 for measuring the EEG signals, Garmin's VENU 2 SERIES for monitoring of heart rate, and the Kokoro Sensor by CAC Co., Ltd. for the evaluation of facial expressions.

For the EEG analysis, we used five distinct  $\beta/\alpha$  combinations, namely  $\beta_l/\alpha_l$ ,  $\beta_h/\alpha_l$ ,  $\beta_l/\alpha_h$ ,  $\beta_h/\alpha_h$ , and  $(\beta_l + \beta_h)/(\alpha_l + \alpha_h)$ , denoted as  $\beta_{l+h}/\alpha_{l+h}$ , where  $(\beta_l + \beta_h)/(\alpha_l + \alpha_h)$  represents the averaged value of the low and high frequencies. One specific type of heart rate data was employed for the heart rate monitoring. Regarding facial expression analysis, we quantified 12 emotional states, including anger, contempt, disgust, fear, joy, sadness, surprise, sentimentality, confusion, neutral, engagement, and valence.

# IV. QUESTIONNAIRE ITEMS FOR DIFFICULTY EVALUATION

To confirm the difficulty level of the experimental questions, we distributed a questionnaire among the eight participants. Based on the results, we confirmed whether the difficulty level of the created problem is appropriate from the viewpoint of the participants. Table II shows the results of the questionnaire answered at five levels: 1 (very easy), 2 (easy), 3 (fair), 4 (hard), and 5 (very hard). The numbers in Table II show the median values of the questionnaire results.

The results of the questionnaire show that with the increase in the difficulty level, the participants find it more difficult to solve the questions. In addition, when comparing English and programming languages, the difficulty level was almost the same for both languages. However, a difference was observed in the difficulty level between P2 (syntax) and E2 (English grammar). Nevertheless, no big difference was observed between the two languages in terms of the difficulty level.

#### V. EXPERIMENTAL RESULTS AND EVALUATION

#### A. Experimental Results

In our experiment, we acquired time-series data for 2 min (1 min, depending on the problem). However, in this analysis, we will focus on the average value of those data and evaluate from

TABLE II QUESTIONNAIRE RESULTS IN TERMS OF DIFFICULTY LEVEL (MEDIAN OF 8 PEOPLE)

	P1	P2	P3	P4
	(Reserved words)	(Syntax)	(Program reading comprehension)	(Programming)
Easy	2	2	1.5	3
Fair	4	3.5	3	4
Hard	5	4.5	5	5
	E1	E2	E3	E4
	(English	(English	(English reading	(English
	words)	grammar)	comprehension)	composition)
Easy	2	4	3	4
Fair	3	5	4	5
Hard	4.5	5	5	5

the viewpoint of whether a change is observed in the average value. As an example, Figure 3 shows the average values of the heart rate during the experiment for E1 (English word) and P1 (reserved word) of the eight participants. One plot in the figure is the mean value of the time series data of heart rate during the experiment. Some participants showed similar trends in E1 and P1, while others showed different trends. Owing to space limitations, only heart rate data for E1 and P1 are shown, but data for E2 to E4 and P2 to P4 were obtained in the same manner. We also acquired biological information (5 types of brain waves and 12 types of facial expressions) other than the heart rate in this study. In the following sections, we verify whether En and Pm  $(1 \le n \le 4, 1 \le m \le 4)$  show the same trend when n = m. Additionally, we will verify what happens when  $n \ne m$ .



Fig. 3. Comparison of the average heart rate during the experiment between E1 (English words: solid line) and P1 (Reserved words: dotted line)

#### B. Evaluation

We tested whether or not the mean values change. This research was aimed at determining whether a difference exists among the mean values between the same category problems in English and programming languages, for example, E1 (English words) and P1 (Reserved words). In addition, we investigated the relationship among problems other than the same category. For example, we analyzed whether the mean value of P1 (Reserved words) differs from the average values of four types of English questions (E1 (English words), E2 (English grammar), E3 (English reading comprehension), and E4 (English composition)). In addition, as with P1(Reserved words), we analyzed whether the mean values of P2(Syntax), P3(Program reading comprehension), and P4(Programming) differ from those of the four types of English questions, i.e., E1 (English words), E2 (English grammar), E3 (English reading comprehension), and E4 (English composition). The overall analysis results are shown in Table III.

TABLE IIIRESULTS OF THE MEAN DIFFERENCE TEST (t-TEST)

			-	
	E1	E2	E3	E4
	(English	(English	(English	(English
	words)	grammar)	reading	compo-
			compre-	sition)
			hension)	
P1	No	heart rate	No	heart rate
(Reserved	significant	(P1 <e2)< td=""><td>significant</td><td>(P1<e4)< td=""></e4)<></td></e2)<>	significant	(P1 <e4)< td=""></e4)<>
words)	difference	p = 0.0068	difference	p = 0.0044
P2	No	No	No	No
(Syntax)	significant	significant	significant	significant
	difference	difference	difference	difference
P3				anger
(Program	No	No	No	(P3 <e4)< td=""></e4)<>
reading	significant	significant	significant	p = 0.0081
compre-	difference	difference	difference	engagement
hension)				(P3 <e4)< td=""></e4)<>
				p = 0.0089
P4	No	No	anger	No
(Program-	significant	significant	(P4 <e3)< td=""><td>significant</td></e3)<>	significant
ming)	difference	difference	p = 0.0117	difference

Cells described as "no significant difference" represent cells with p-value > 0.05/4 because of the t-test, i.e., the mean values cannot be said to have a difference. All the same category questions, i.e., the diagonal cells in Table III (e.g. P1 and E1, P2 and E2, etc.) showed no/insignificant difference in the mean values. In other words, when solving the same category problem in both English and programming language, similar biological information can be observed owing to the difference in difficulty levels. In other words, it can be said that the English learning method can be applied to programming learning for the same category problem. In addition, in some cells shown in Table III, the mean values for heart rate, angry facial expressions, and engagement of facial expressions were significantly higher in English learning. This can be attributed to various factors, such as the quality and difficulty of the questions and perceived weakness in English. With further analysis, we will use these results to improve the learning methods of both languages.

#### VI. CONCLUSION AND FUTURE WORK

In this study, we measured 18 types of biological information (5 types of brain waves, 1 type of heart rate, and 12 types of facial expressions) while learning English and a programming language. To determine whether biometric information at the time of learning differs, depending on the difficulty level of English and programming language, we focused on the difference between each difficulty level and analyzed the data. The results showed no significant difference in the average values of any biometric information for the same category problems between English and programming languages (for example, English and program reading comprehension problems). Therefore, we can say that there is a possibility that the know-how of English learning, which has a lot of research achievements, can be applied to programming learning for the same category problems for both language types. In addition, significant differences were observed in angry facial expressions for problems that were not in the same category; (for example, program reading comprehension and English composition, programming and English reading comprehension, etc.). In addition, significant differences were measured in the heart rate and the engagement of facial expressions between several problem types. In the future, we would like to proceed with the analysis so that we can propose a learning method suitable for programming by focusing on such differences.

#### **RESEARCH ETHICS**

All experiments were approved by the Research Ethics Committee of Anonymous. We also received written informed consent from the participants and parents or guardians.

#### ACKNOWLEDGMENTS

Part of the work reported here was carried out as a part of the research project "Research on e-learning for nextgeneration" of Waseda Research Institute for Science and Engineering, Waseda University. Part of this work was supported by JSPS KAKENHI Grant Numbers JP22H01055, JP21K18535, and JP20K03082. Research leading to this paper was partially supported by the grant as a research working group "ICT and Education" of JASMIN.

#### REFERENCES

- Christina M. Frederick and Lulu Sun. Work in progress: Using second language acquisition techniques to teach programming - results from a two-year project. *American Society for Engineering Education, ASEE Annual Conference*, pp. 18825 1–13, 2017.
- [2] Nick B. Pandža. Computer programming as a second language. In: Nicholson, D. (eds) Advances in Human Factors in Cybersecurity. Advances in Intelligent Systems and Computing, Vol. 501, pp. 439–445, 2016.
- [3] Jutshi Agarwal, Gregory Warren Bucks, Kathleen A. Ossman, Teri J. Murphy, and Cijy Elizabeth Sunny. Learning a second language and learning a programming language: An exploration. *American Society for Engineering Education*, p. #34240, 2021.
- [4] Tatsunori Matsui. Estimation of learners' physiological information and learners? mental states by machine learning and its application for learning support. *Transactions of Japanese Society for Information and Systems in Education*, Vol. 36, No. 2, pp. 76–83, 2019.
- [5] Katsuyuki Umezawa, Makoto Nakazawa, Michiko Nakano, and Shigeichi Hirasawa. About the relationship between brain waves, heart rate and facial expressions during programming learning. *The Institute of Electronics, Information and Communication Engineers (IEICE) Technical report*, pp. 14–19, 2022.
- [6] Paiza learning. https://paiza.jp/works. Accessed: 18 December 2022.
- [7] Jun Mitani. Java 2nd edition: Introduction, programming from zero. SHOEISHA, 2017.