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Learning Style Analysis on an Online Course by Structural Equation Modeling

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Abstract

This study analyzes learning styles for an online course with flipped learning employing structural equation modeling. First, we discuss the definition of learning style in this study and design a structural equation model of the learning style. Next, we obtain data via LMS for 94 students (53 Japanese and 41 International students) attending the machine learning course offered in Japanese and evaluate the validity of the structural equation model. Furthermore, we compare the structural equation models in terms of groups for students' language abilities, prior knowledge of the course, and learning motivation to compare the characteristics of each group.

Keywords: learning style, online lectures, structural equation modeling.

1 Introduction

Online learning has gained new momentum in today's 21st century with the advent of information and communication technologies. The emergence of Open Education Resources (OER) and Massive Online Open Courses (MOOCs) has provided access to education for a broader range of people [1]. In addition, due to the COVID-19 outbreak, many universities attempted to use online learning instead of traditional classrooms to reduce the risk of infection and keep educational activities [2].

In our university, online lectures on COVID-19 were mainly conducted in the following four approaches: A) asynchronous delivery of classroom lectures by lecture archive; B) synchronous delivery of classroom lectures by Cisco Webex meetings [3] and asynchronous delivery by lecture archive; C) synchronous delivery of Webex meetings and asynchronous delivery by Webex recordings; D) Webex synchronous delivery only (no asynchronous delivery).

The total number of such online lectures in our university in FY2020 was 2,751 (more than double that of previous years), and the use of hybrid online lectures (face-to-face and online) is continuing even now that the COVID-19 situation has improved.

Thus, especially in the higher education field, where online course is accelerating and the diversity of learning is increasing, it is necessary to provide suitable instruction according to the learning styles, representing how learners perceive learning, and to increase their motivation and vitality. Therefore, this research analyzes how learning styles affect their learning behavior and outcomes through structural equation modeling to one of our online courses.

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2 Learning Style

Learning styles have been studied for long years. Some focus on the student's intrinsic nature, while others discuss external factors such as curriculum, learning strategies, and assessment methods. Table 1 grouped these learning styles based on the LSRC (Learning Skills Research Centre, UK) classification [4].

Table 1: Families of Learning Style Organized by LSRC [4]

Style	Key Researchers
Constitutionally Base	Gregorc [5], Dunn & Dunn [6]
Cognitive Structure	Riding [7]
Stable Personality Type	Myers Briggs [8], Apter [9]
Flexibly Stable Learning Preferences	Kolb [10], Honey & Mumford [11], Hermann [12], Allison & Hayes [13]
Learning Approaches, Strategies, Orientations, and Conceptions of Learning	Entwistle [14], Vermunt [15], Sternberg [16]

Although various learning styles have been proposed, learning styles in educational institutions should not be considered permanent based on the students' characteristics. In other words, it should be viewed as something that depends on the surrounding environment, such as the learning environment and teaching methods. This is because schools and teachers can improve their students' motivation to learn by devising teaching methods. Therefore, in this study, we define learning styles based on Vermunt's learning styles.

Vermunt [15] conceived learning style definitely "not as an unchangeable personality attribute, but as the result of the temporal interplay between personal and contextual influences." He proposed the following four categories: meaning-directed, reproduction-directed, application-directed, and undirected, based on learning styles according to how students perceive learning. However, the discussion about the relationship between learning styles and their actual performance is limited. In this study, we try to clarify the relationship between the student's perception of the course (comprehension and difficulty), his/her own learning strategy (planning and behavior), and his/her grades as performance. It is expected that learning style-specific behaviors will emerge in online courses based on flipped learning regarding preparation learning, lectures, and review learning.

3 Approaches

3.1 Purpose

In this study, we focus on language ability, prior knowledge, and learning motivation to clarify the tendency of learning styles. We examine the differences between Japanese and international students in terms of language ability, prior knowledge in terms of prior knowledge of the target course and learning motivation in terms of learning motivation based on Vermunt's classification of learning styles.

First, we construct a structural equation model based on the relationship between cognition (comprehension and difficulty), the student's own learning strategies (planning and behavior), and performance. Next, we apply structural equation modeling to each student population to confirm the magnitude of the effects on the factors and observed variables. Finally, we examine the causes of such differences among the populations.

3.2 Structural Equation Model

Structural Equation Modeling (SEM) is a modeling technique that considers the existence of factors and latent variables (not actually observed) behind the actually observed data and models their influence on the observed data and other factors [17]. The measurement model represents the influence of latent variables on observed variables, while the structural model represents the influence between latent and observed variables and the influence of observed variables on latent variables, and the structural equation model is the combination of these two models (Figure 1). The unidirectional arrows represent causal relationships, and the bidirectional arrows represent correlations.

Structural equation models can be set up based on experience or theory and can reveal causal and correlational relationships among variables in the model. By finding parameters so that this theoretical model approaches the covariance structure obtained using actual data (using methods such as maximum likelihood, least squares, etc.), it is possible to calculate the values of the path coefficients and factors of the assumed model. The fitting indicators between the actual data and the model includes the χ-square value, GFI, CFI, RMSEA, and AIC.

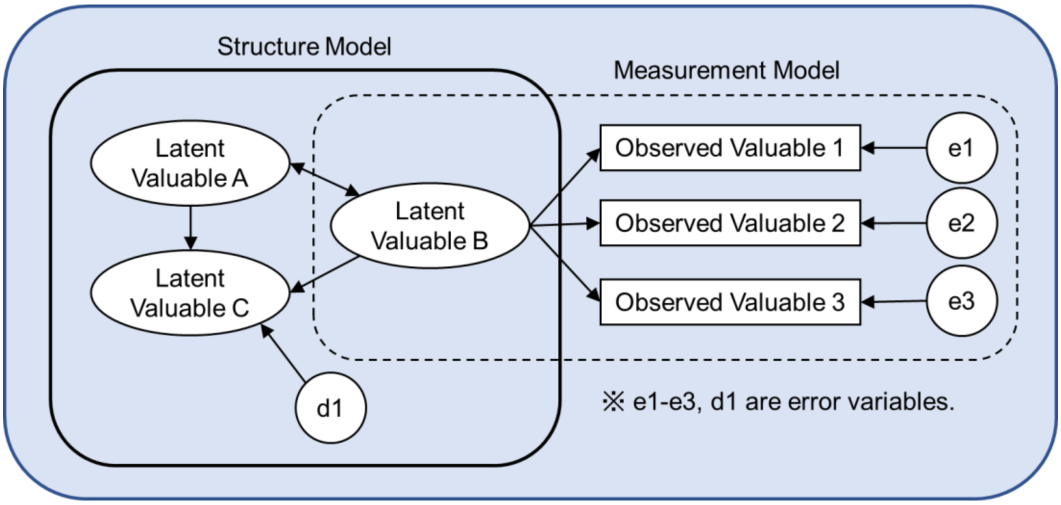

Figure 1: Concept of Structural Equation Modeling (Revised from [17])

There exist various studies to analyze the success factors of learning using SEM in blended learning [18], flipped learning [19], and micro lectures [20]. In these studies, learning styles, learner performance or satisfaction, and other factors are subject to analysis based on learners' demographic data and questionnaires. On the other hand, the unique characteristic of this study is to analyze factors, including the amount of learning and planning of the learning process based on their learning history.

3.3 Target Course

The course analyzed in this study is "I239 Machine Learning," offered in our university's 1-2 terms of the FY2020. Since two faculties instructed the first and second half of the course at different paces/progress, respectively, therefore, this study analyzes only the first half of the course. Table 2 shows the content of the target course. The first lecture is not included in the analysis because it is an introduction to the course. In Tutorial Hours (TH) in this course, students confirmed machine learning implementations using Google Colaboratory [21], which can quickly implement machine learning codes with cloud servers. Attendance at TH was optional, but this data is not excluded from seeing the difference in learning.

Table 2: Lecture Topics in I239 Machine Learning

Lecture	Topics
1	Introduction
2	Version Space
3	Basic Statistics
4	Decision Tree
TH	Python for ML
5	Support Vector Machine
6	Naïve Bayse
TH2	Python for ML
7	Online & Batch Learning

This course adopted a flipped classroom approach in which the content of schoolwork and homework are switched [19]. The lecturer provided course materials and preparation videos for basic knowledge uploaded on the LMS and real-time online lectures for practice, as shown in Figure 2. In other words, students were expected to acquire knowledge at home through the course materials and preparation videos before attending lectures. The real-time online lectures confirmed their knowledge and understanding through practice, problem-solving, and cooperative learning. This was a Japanese course, but the course materials were prepared in English for international students unfamiliar with Japanese. The preparation videos were multiple 10-20 minute videos summarizing the prerequisite knowledge required for the real-time online lectures. The real-time online lectures were conducted using Cisco Webex Meetings [3]. Students can ask questions in the chat function, and the lecturer can ask questions to the students using the survey function, making the lectures interactive.

To familiarize students with the online exam system, the LMS (Moodle) allowed students to answer the practice given in each lecture. There were no time and trial limitations that they could take, and it would not affect students' grades. Students were required to take an exam as a quiz function on the LMS within one week after the end of each real-time online lecture. To ensure fairness of grades, the exam was taken only once, with a time limit for each. Each question in the exam was randomly selected from a set of questions with the same difficulty level but different values and answers. The final grade was 50 points as a total score, based on the sum of the exam scores and the report score (Python machine learning implementation) to be submitted at the end of the course. Students were also asked the questionnaire after each lecture which was no relationship to the grades.

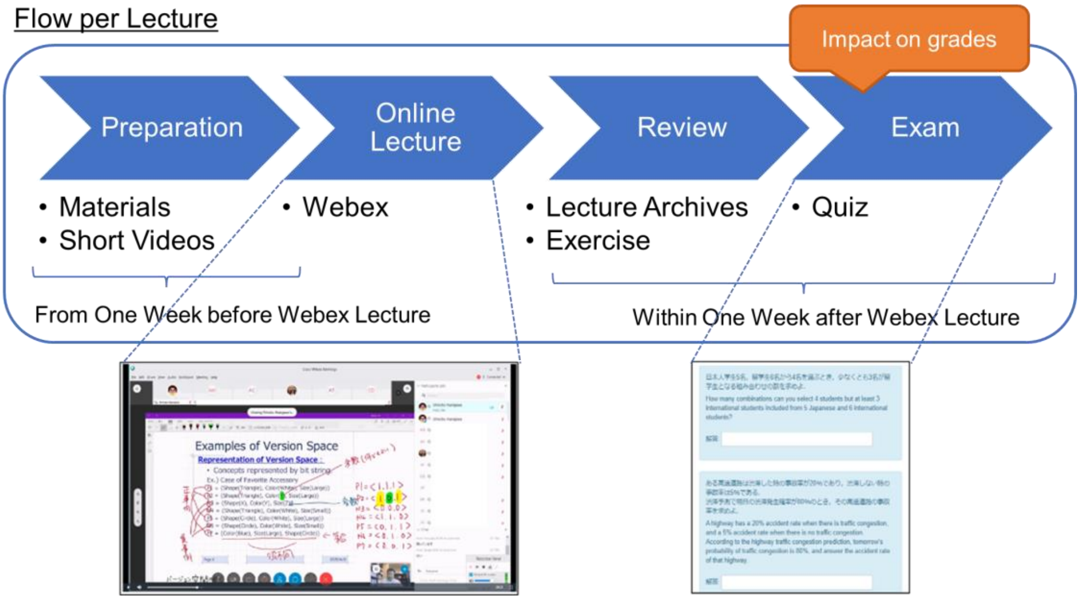

Figure 2: Lecture Format and its Content

3.4 Target Students

The analysis was conducted on students taking the I239 Machine Learning course who responded to the first survey with 94 valid responses. A breakdown of the students' Japanese proficiency, prior knowledge, and student motivation is shown in Table 3. Note that most students were familiar with the online learning style under the COVID-19 situation.

3.5 Hypothetical Model

In this study, we used the learning logs from the preparation study, the Webex online lectures, the review study, the first half of grades, and the results of the questionnaires from the LMS. In addition, we randomly assigned IDs to each dataset so that individuals could not be identified and then processed the data. Based on the learning styles described in Section 2, this study designed a structural equation model shown in Figure 3.

The latent variables include "lecture quality," "lecture difficulty," "lecture comprehension," "planning," "amount of learning," and "grades." "Lecture quality," "lecture difficulty," and "lecture comprehension" consist of observed variables based on the average of the questionnaire results from the second to the seventh lectures. The "planning" means observed variables averaged learning starting days and taking exam days in the second to seventh lectures. The "amount of learning" and "grades" are based on the observed variables of the ratio of answer time in the exams, the scores of the exams in the second to seventh lectures, and the score of the report in the TH.

Table 3: Student Language, Prior Knowledge, and Learning Motivation

Students			Student Motivation: Application	Student Motivation: Significance	Student Motivation: Etc.	Total
Japanese Students	Prior Knowledge	Yes	14	11	2	27
		No	13	13	-	26
	Total		27	24	2	53
International Students	Prior Knowledge	Yes	4	2	-	6
		No	14	18	3	35
	Total		18	20	3	41
Total	Prior Knowledge	Yes	18	13	2	33
		No	27	31	3	61
	Total		45	44	5	94

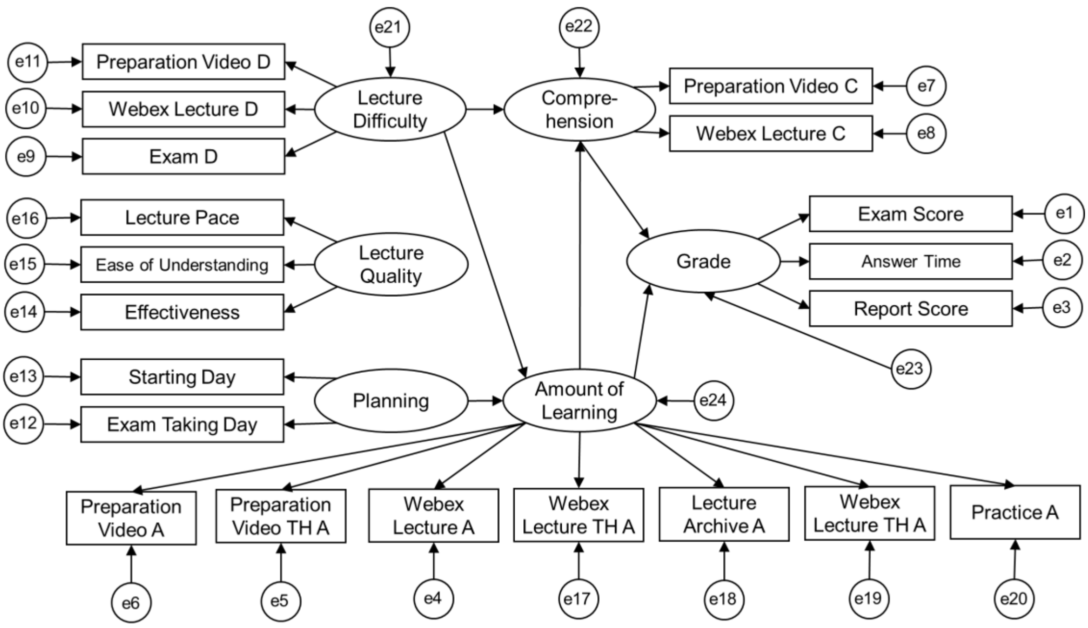

Figure 3: Hypothetical Model of Learning Styles

4 Results and Discussion

4.1 Learning Styles of All Learners

Figure 4 shows the results of applying the hypothesized model to all learners. The goodness of fit was checked: $\chi2$=442.3 (163 degrees of freedom) p=0.00, RMSEA=0.136, GFI=0.703, and CFI=0.780. The p-value of the $\chi2$ test is 0 (<0.05), which means that the null hypothesis (hypothesized learning style model = actual data) is rejected. RMSEA is generally considered a good-fitting model when it is less than 0.05, GFI is greater than 0.9, and CFI is greater than 0.95. So, we cannot say it is a good fit.

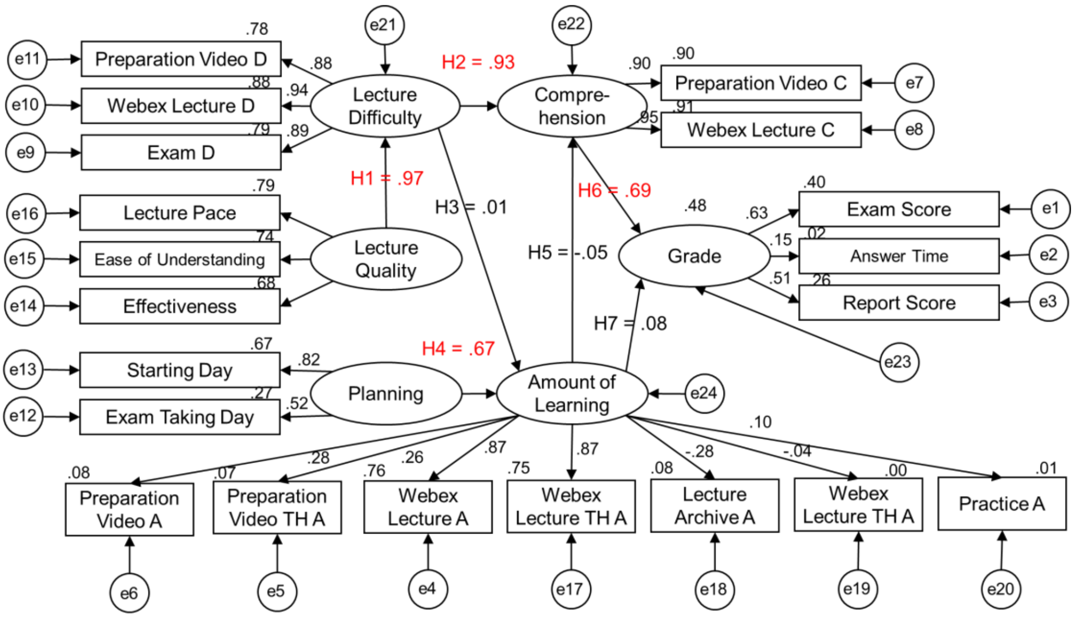

Figure 4: Learning Style Model for All Learners

However, a high correlation was found between "lecture quality" and "lecture difficulty," between "lecture difficulty" and "comprehension," and between "comprehension" and "grades." These results suggest that early detection of students who find the lectures difficult through questionnaires may supports their learning. As from "planning" to "amount of learning," most students who watched the preparation videos before the day of the Webex lectures and who accessed the preparation videos within four days after the Webex lectures participated in more than 60% of the Webex lectures. On the other hand, the number of students who started to study the preparation videos after four days of the Webex lectures increased to less than 50% of the Webex lectures. This may be because some students cannot keep up with the lectures and are behind in their overall learning or do not actively participate in the Webex lectures but use the preparation videos to learn just before the exam.

There may be other essential variables that define learning styles that are not included in the observed variables. For example, in this study, we defined the total amount of time spent on each lecture as the "amount of learning," but other indicators such as how the lecture was watched may be necessary. Specifically, indicators such as the number of watched and the watching points could be considered.

Another reason for these results is that different groups of students tend to learn differently. Therefore, the following sections present the results for the characteristics of the groups. We compare the values of the standardized coefficients (path coefficients), which indicate the degree of influence on each factor and observed variable, and present the results for paths in which one standardized coefficient is 0.7 or higher and a difference is observed between the two populations (a test of the difference in standardized coefficients yields a significance level of 10% or higher). Furthermore, when there is a significant difference in the paths between factors (latent variables), we compare them using correlation coefficients with Wilcoxon rank sum tests (nonparametric tests on observed data).

4.1 Learning Styles of Japanese and International Students

The standardized coefficients for the "amount of learning" to "preparation video" were 0.26 for Japanese students and 0.94 for foreign students (5% significant difference). The Wilcoxon rank-sum test shows that p=0.009, rejecting the null hypothesis that the distribution of amount of preparation video is equal for Japanese and international students. On the other hand, the standardized coefficients for the "amount of learning" to "Webex lecture" were 0.93 for Japanese students and 0.27 for international students (5% significant difference). The Wilcoxon rank sum test shows that p=0.237, which supports the null hypothesis that the distribution of the amount of Webex lectures studied by Japanese and international students is equal. In addition, the standardized coefficients for the "amount of learning" to "amount of TH learning" were 0.91 for Japanese students and 0.36 for international students (5% significant difference). The result of the Wilcoxon rank sum test shows that p=0.863, which supports the null hypothesis that the distribution of the amount of TH learning by Japanese and international students is equal. In the "amount of learning," many international students did not watch the preparation videos. Japanese students tended to watch the preparation videos but did not participate in Webex lectures, while international students tended to watch less preparation videos but actively participated in Webex lectures. But there was no statistically significant difference between Japanese students and international students in the "amount of learning" to "amount of TH learning."

The standardized coefficients of "comprehension" to "grade" were 0.88 for Japanese students and 0.29 for international students (1% significant difference). The correlation coefficients between Japanese students and international students were r=0.740 and r=0.256, respectively. A test of the difference between the correlation coefficients showed a significant difference at 1%, p=0.0014. These results show there was a strong correlation among Japanese students, but among students with high comprehension, there was a polarization between those who obtained a high score (around 90%) and obtained only about 60% in the exam. The percentage of grades for international students varied from 100% to 60%, even if they had a high level of comprehension. This indicates that Japanese students' subjective and objective comprehension (actual grades) tended to be relatively consistent, while international students' subjective and objective comprehension did not necessarily coincide. Since this course was given in Japanese, it might have been difficult for the students to understand the detailed nuances in the lectures, which may have resulted in such a difference.

4.2 Learning Styles based on Differences in Learning Motivation

The standardized coefficients from "grade" to "report score" were 0.71 for significance-oriented students who are interested in machine learning and 0.28 for application-oriented students who want to apply what they have learned to their research or work (10% significance difference). The Wilcoxon rank sum test result was p=0.655, which supports the null hypothesis that the report scores of the significance-oriented and application-oriented students are equal.

4.3 Learning Styles based on Differences with and without Prior Knowledge

The standardized coefficients for "comprehension" and "grade" were 0.86 with prior knowledge of machine learning and 0.59 without prior knowledge (5% significant difference). The correlation coefficients between students with and without prior knowledge were r=0.801 and r=0.333, respectively. A test of the difference in correlation coefficients revealed a significant difference at 1%, p=0.0008. Students with prior knowledge showed a strong correlation between comprehension and grade, while students without prior knowledge showed a weak correlation. This shows students with prior knowledge could objectively judge their own level of understanding, whereas students without prior knowledge thought that they understanded the material.

5 Conclusion

In this study, to clarify the characteristics of each group in terms of language ability, prior knowledge, and learning motivation in online lectures based on flipped classrooms, we created a structural equation model of the reference learning style, compared standardized coefficients that indicate how much each observed variable and latent variable affects the model, and discussed the differences. The results showed that the fitness of the learning style modeling for all learners was not good, so the analysis was conducted again to reveal significant differences among specific student groups. This time, no significant difference was found in the learning motivation. This is because most of the students in this course have high motivation for learning, such as the desire to apply what they have learned to their research or work or an interest in machine learning. In terms of language differences, there was a difference between Japanese and international students in the "amount of learning," but further investigation is needed to determine why this difference has occurred.

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