The Relationship between Course Evaluation and Academic Achievement of University Students Using Latent Profile Analysis

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Abstract

This study was conducted with the purpose of deriving a heterogeneous potential profile through the results of university lecture evaluation, which is students' perception of class and the product of professor-student interaction in the classroom, and identified the factors that affect it. In addition, the degree of learning flow for each potential profile was investigated and the difference was verified. For the analysis, 83,069 cases were used because of the university A course evaluation organized in the second semester of 2020, and a total of 12,919 subjects were studied. As a result of analyzing the aspects of course evaluation through class plan, content delivery, communication, response, and evaluation system, that were the sub-factors of course evaluation, the miscellaneous material profiles were classified in four. It was named as the upper group. As factors determining the latent profile using physiological data analysis. It was discovered that significant differences existed between student features (grade, major field), professor features (position), and lecture variables (category of accomplishment, lecture size). Students with lesser grades have a greater chance of succeeding quickly in the top group than do those in the humanities and social sciences, science, or engineering professions. The likelihood of being in the upper group in a course assessment as well as the likelihood of being in the upper group with higher course evaluation outcomes for general education lectures as opposed to major lectures and smaller lecture sizes increases with decreasing professor status. The level of academic obligation was then examined by potential profile based on the course evaluation outline, and the results revealed that the greater the course evaluation result, the greater the level of educational obligation. This is a significant study because it examines the variables that affect the outcomes of the university's course evaluations, which are done at the end of every semester, as well as the relationship between the outcomes of the course evaluations and academic commitment. This study established a scientific basis for colleges to prepare measures to improve the quality of education through lecture evaluation and emphasized the importance of preparing concrete measures to improve students' learning outcomes in college education.

Keywords: course evaluation, feedback, interation, learning flow, LPA

1. Introduction

The university's course evaluation system was first implemented in 1088 at the University of Bologna in Italy, and in the 1960s in the United States, it was established as a system to comply student's needs for the expansion of national interest in university education and the public accountability of education (Kim. et al., 2009). In Korea, the need for course evaluation has been raised regarding enhancing the standard of higher education, and since 1982, it has been openly discussed within the university community, after 1989 the system of professors' lecture assessed by students were talk over. Academic-achievement evaluations were implemented by each university in response to the tendency of bolstering the government's university evaluation, which started with the University Comprehensive Evaluations and Recognition System in 1994 (Chae et al., 2015). The publication of lecture-evaluation outcomes and procedure ideas in several university evaluations, including the university arrangement reform, teacher-training organizations, and financial support plans, later developed a vital university evaluation indicator when the Ministry of Education, Science, and Technology applied the "Financial Support Project for Outstanding Colleges for Promotion of

Education Reform" in 1996. Course evaluations have been recognized by a constant enhancement as a fundamental tool for quality management of tertiary learning since they are used (Kim, 2017; Vitaliy and Maryna 2020).

Emery et al. (2001) regard education as an industry and universities as independent enterprises competing with other universities within the industry. The professor is the provider of those services and products, and the student, as a customer, acquires the services and products provided by the professor. Since students as customers express their satisfaction and dissatisfaction with the university and professors through the quality of lectures provided by actual professors, the university will be able to judge that the quality of lectures is the organizational effectiveness (Lee, 2013). From this point of view, universities are implementing the course evaluation system to pursue summative and formative goals. In the former case, course evaluation is performed as a valid indicator necessary for managerial decision-making, and in the latter case, evaluation is conducted with a focus on collecting information to develop the value of lectures. When course evaluation is conducted for formative purposes, it is premised that feedback from course evaluation by students has the effect of enhancing the lectures standards, but improvement is not easily made if the professor does not recognize the problem of lectures. Therefore, it is necessary to conduct various course evaluations, from improvement according to the professor's own self-esteem to improvement through systematic evaluation, and only through various evaluations, the possibility of realizing improvement in the educational field and lectures will increase. In other words, the improvement effect is high, and the quality of education increases only when the course evaluation is done properly.

The efficiency of lectures is mostly determined by course evaluation with guaranteed validity (Marsh, 1984), and to raise the standard of university instruction, it is necessary to prepare improvement measures through periodic course evaluation and to make multifaceted efforts to support becomes (Peterson, et al., 2000). Nevertheless, the use of course evaluation results to develop the quality of education within colleges has been restricted (Choi & Yun, 2019). Overall, the outcome of course evaluation in universities is simply utilized only as a criterion for evaluating the performance of professors or choosing exceptional professors within the school. When the result of the course evaluation is poor, the lecturer or non-full-time professor will be excepted from the course assignment for the succeeding semester. In other words, it is more disadvantageous to lecturers or non-full-time professors than to full-time professors (Kim, 2017). In the case of full-time professors, although they are encouraged to participate in the teaching method program of the Center for Teaching and Learning (CTL), it is not compulsory. For this reason, it has been pointed out that course evaluation is somewhat far from the basic purpose of being part of an effort to expand the quality of university education. Thus, it is needed to analyze the effects of course evaluation conducted each semester from various angles and actively utilize to develop a strategy to enhance the standard of university education (Heffernan, 2022; Lee et al., 2020).

How to properly evaluate lectures? It is not easy to come up with an answer to this question if the characteristics of faculty factors, student factors, and school-level factors that affect the results of course evaluation are not considered. In other words, it is important to consider all these characteristics for proper course evaluation (Cunningham et al., 2021). Looking at the results of several previous studies such as Goldberg and Callahan (1991), it was confirmed that part-time instructors' grades for students were more generous than full-time professors, and accordingly, their course evaluation scores were higher. Questions arise as to whether this is justified or to what extent this result can be trusted (Ryu, Lee, 2005). In this study, lesson design, content delivery, interaction, feedback, and evaluation system were set as observation variables as sub-factors of course evaluation, and course evaluation was undertaken to meet the request for learner-centered university teaching and to enhance the standard of the university. Potential profiles were classified according to the results, and student trait (grade, major), professor trait (rank), and lecture quality (classification of courses, lecture scope) were input as factors affecting the analysis. Furthermore, we tried to find out if there is a dissimilarity in the level of learning flow for every potential profile, and to utilize course evaluation. The purpose of this is to categorize the types of potential profiles and to analyze the features of course evaluation made at the end of every semester from various angles, to set the direction for the improvement of education and knowledge programs to develop the excellence of university education, and to find ways to support knowledge. Earlier research on course evaluation have mainly focused on item development and evaluation methods (Ha, Jung, 2014; Yang, 2014; Park, 2012; Song, Lee, 2020), validity of evaluation items (Kim, Kim, 2008; Yun, 2008; Seol, 2007), weighting methods (Man, Cho, 2014; Yang, Park, 2012), and factors affecting evaluation results (Rhy, Lee, 2005; Lee, Lee, 2005; Ha, Rah, 2017), this study divided possible groups into categories based on the effects of course evaluation and looked at the features to determine a degree of dedication to academics for each group. The following research questions must be taken to fulfill the study's objectives.

1. According to the outcomes of the course assessments for the second semester of 2020 at University A, how many prospective profiles are categorized, and what are the traits of each potential group?

2. According to the outcomes of course evaluations for the second semester of 2020 at University A, what effects do student factors (grade, major), professor features (position), and lecture characteristics (completion category, lecture size), have on determining the potential profiles?

3. What are the differences in the degree of academic dedication amongst possible profiles ranked by the outcomes of University A's 2020 second semester course evaluations?

2. Theoretical Background

2.1 University Course Evaluation

University course evaluation is a value judgment of students about university classes, and it is a means to develop the quality of university teaching (Braskamp & Ory, 1994). Through course evaluation, students have an opportunity to review their learning in the lectures they have taken during the past semester, and professors can check how the lectures designed and provided have affected students through the evaluation results. can Recently, as university education, which had been focused only on quantitative expansion, faces intense competition among universities and social demands for nurturing excellent talent, interest in quality management and course evaluation has increased (Ha & Rah, 2017).

According to the evaluator, course evaluation can be divided into self-evaluation by the professor himself, evaluation by fellow professors, evaluation by students, and evaluation by university administrators or external observers (Lee, 1993; Shin, 2005). The class evaluation method is adopted. The scope of evaluation also differs from school to school, and includes syllabus, lecture content, communication, response, assignments, and evaluation systems including the evaluators. Course evaluation can be said to be the act of mediating the effectiveness of university courses based on a set of guidelines for the entire teaching-learning process from the viewpoint of the consumer from the student (Lee, 2001, Pavlov & Pohrebniuk, 2020).

In addition, course evaluation provides diagnostic feedback on class effectiveness and information related to teaching effectiveness, and course evaluation results are mainly used in the decision-making process for professor promotion or re-appointment. From this point of view, the purpose of course evaluation can be classified into a formative purpose and an overall purpose (Braskamp & Ory, 1994). Lecture evaluation can be done in several ways. Lecture evaluation simply to find out students' class satisfaction can be called formative evaluation. In this regard, the method of utilizing the results of course evaluation can also be divided into a formative purpose and a general purpose. If it is used to develop the quality of the next lecture by delivering the results of the investigated course evaluation to each professor and individual lecturer, this If it is used for formative purposes, to award excellent professors or to manage professors who have received poor course evaluation results, it can be said to be a general purpose (Baek & Shin, 2008; Tian et al., 2022).

Universities require professors to have both research and teaching skills and course evaluation is one of the main measures to evaluate educational capabilities. Although some previous studies raise questions about the evaluation qualities of students who are evaluators of course evaluation (Choi, Kim, 2013), in reality, course evaluation is the most practical and cost-effective way to gauge how well university lectures are delivered. The evaluation tool is individually prepared and used by the university to comprehensively evaluate the student's level of satisfaction with the lectures and class performance, and the evaluation results are used to improve problems in education and to prepare options to develop the standard of education.

Its the most important goal of the university to select excellent students and provide quality education to develop them into world-class talents. From the point of view that the value of learning cannot exceed the quality of teachers, universities must develop the quality and excellence of education. The ability and responsibility of instructors for education should be emphasized, and this should be managed and controlled through course evaluation. Course evaluation is described as a functional relationship between the characteristics of the student, the characteristics of the professor, and the characteristics of the course. This is because students are the main users of the scholastic services contributed by the university, participate directly in the coaching and knowledge process, and can view the lectures most objectively. In other words, the student is the only subject to participate in the professor's class, the most important stakeholder, and the subject that can evaluate the lecture most accurately in that it can directly observe the lecture.

The following problems exist in the method of evaluation of lectures by students. In relation to the validity and reliability of course evaluation, it is a question of the students' response attitudes, that is, whether the students faithfully took part in the evaluation. Yang (2014) noted that most university course evaluations are conducted on the online system, but in order to increase the participation rate, they are implemented in a semi-compulsory manner as a prerequisite for reading grades. It has been pointed out that there is a tendency to give insincere responses due to the difficulty of repeatedly performing evaluations for all classes (Yang, 2014). Conversely, there are prior studies that acknowledge the validity and reliability of course evaluation conducted by students (Peverly et al., 2003). Cohen (1981) analyzed the relationship between students' course evaluation results and academic achievement using a meta-analysis method that integrates existing studies and found a positive relationship among course evaluation results and academic accomplishment. These studies have the meaning that the students who directly participated in the class describe the advantages and disadvantages. of the class on their own, solve the problems of the class, act as the main agent to improve the class effect, and provide feedback to improve the class.

Course evaluation by students is an evaluation of teaching behavior in the entire process of teaching and learning. And it provides a valid and reliable basis for directly judging the quality of teaching activities through students. Therefore, in this study, students' course evaluation for the entire teaching and learning process was judged as a major indicator of teaching efficiency. Although it has not been completely verified whether the results of course evaluation by students are appropriate and valid data for use in improving the quality of university lectures and evaluating the performance of professors, it is judged to be the most useful and effective information for improving and developing current university education did.

2.2 Factors Influencing University Course Evaluation

Variables that affect course evaluation are being discussed at a very diverse level. According to previous studies, course evaluation factors are split into student level, professor level, and course level (Yun, 2008). Thus, this study will describe the influence factors of course evaluation in three scopes: student factors, professor factors, and lecture factors. The main factor manipulating the standard of university education is the traits of the instructor, who is the teacher, but the triats of the students are very important in that lectures are essentially activities that involve interaction with students (Yang, 2014). Most of the preceding studies that revealed the determinants that affect course evaluation through the characteristics of the students present the analysis results by distinguishing between the characteristics of professors and characteristics of students (Marsh, 1984). Studies analyzing the correlation among student-related aspects and the results of course evaluation mainly reflect the student's gender, grade level, major, school year, and other various factors as student characteristics. It has a close impact on education and learning. In that college knowledge is far from the indoctrination and inert knowledge that took place in middle and high school, grade level or major field is highly related to course evaluation (Wachtel, 1998; Klann & Hoff, 1976). Variables such as school year are closely related to the difficulty of the learning content. Although there are very few existing literature studies that have studied the effect of students' age or school year on the results of course evaluation, school year or age is not relevant in subjects requiring high difficulty the higher the number and the higher the level of lecture topics, the higher the course evaluation score. In addition, there are previous studies showing that there is no difference in the results of course evaluation between majors and geneeral education subjects (Sohn & Kim, 2007; Chi & Chang, 2006; Han, 2001).

Among various factors influencing the results of course evaluation, studies on the effect of factors linked to teaching are relatively few compared to studies analyzing the effect of factors linked to the characteristics of lectures and the characteristics of students as evaluators. As factors affecting course evaluation, the characteristics of professors are mainly the professor's position, quantity of lecture hours, and age, and these factors directly or indirectly affect course evaluation (Kim, et al., 2009). Existing literature that identifies the link among the demographic characteristics of professors and the results of course evaluation points out that the professor's position is a major determinant influencing the results of course evaluation. Lueck et al. (1993) classified a research example into senior professors, junior professors, and part-time professors to investigate whether the professor's position is a variable that affects the course evaluation results. Lueck, et al., (1993) analyzed the difference, and Holtfreter (1991) confirmed that there is a weak but positive correlation between the professor's position and the course evaluation result, indicating that the professor's position has a strong influence on the course evaluation (Feldman, 1987; Marsh, 1987; Ting, 2000; Civian & Brennan, 1996). In some studies, associate professors or full professors tend to receive higher course evaluation scores than assistant professors, whereas in some studies, the younger the professor's age and lower rank, the higher the course evaluation score (Kim, et al., 2009; Villano, 1975). Summarizing the results of previous studies, the professor's position acts as a major factor influencing course evaluation in that it is the core competency of the professor reflecting the professor's intellectual ability, class management ability, and communication skills, and Centra (1993) As pointed out by (Centra, 1993), although the influence of the professor's position on the results of course e evaluation is very limited in that it is mainly a result of lateral research, it has been confirmed that it has a major influence on course evaluation (Centra, 1993). Course characteristics can be a lecture size, course division (main subjects, general education subjects, teaching profession subjects), class first hours (daytime, nighttime), and lecture linguistic (Korean, English, etc.), the size of the talk has the greatest effect on the course evaluation (Scheck, et al., 2010; Feldman 1984). In other words, in a large lecture, it is difficult for a professor to satisfy all students because there is a high possibility that students with different competencies, experiences, and interests are mixed. Previous research also analyzed the outcome of lecture size on course evaluation. In the case of compulsory subject rather than elective subjects, and in the case of elective subjects rather than compulsory subjects, the course evaluation results were higher (Ting, 2000; Cranton & Smith, 1990; Murray, 1990). This study classifies factors affecting the course evaluation results into student characteristics, professor characteristics, and lecture characteristics through careful consideration of previous studies, and grade and major field as student characteristics. Classification as a characteristic of the professor, classification as a characteristic of a lecture, and class size as a variable were assumed as variables and put into the study.

2.3 Use of A University Course Evaluations

As of the second semester of 2020, the number of undergraduate students at University A located in Seoul, Korea was 15,109 and 1,311 teachers (591 permanent faculty, 720 non-permanent faculty), and the number of students per permanent faculty was 25.6. University A, reflecting the characteristics of the university, composed a total of six course evaluation measurement tools, including course planning, content delivery, interaction, feedback, evaluation system, and learning flow in detail. The course evaluation by the professor is conducted during the grade reading period after the end of the program, and the student is obliged to participate in the grade reading.

University A utilizes the outcomes of course evaluation in two scopes. First, course evaluation score for every subject is delivered to the professor and provided as a reference to make a way to develop a standard lesson. The second is used as an evaluation index for the performance evaluation of lecturers. In the case of full-time faculty, it is reflected in promotion and personnel evaluation, and for non-full-time faculty, the result of course evaluation is applied to the evaluation criteria for reappointment. However, the current course evaluation is limited to a formal evaluation, and it is being pointed out that the evaluation result cannot be fed back to the educational field. Therefore, to develop the standard of university education, it is essential to find a way to utilize the course evaluation outcomes.

Therefore, this study conducted a latent profile using physiological data analysis agreeing to the lecture plan, content delivery, interaction, response, and evaluation system, that are sub-factors of the 2020 second semester course evaluation of University A, classifies the group, and evaluates the lecture by potential group. Influencing factors were analyzed, and an analysis of differences by the group on learning flow, the goal of university lectures, was attempted. Through the analysis results, we intend to explore a sustainable course evaluation feedback method to develop the quality of university learning.

3. Research Method

3.1 Research Model

This study explores the potential profile according to course evaluation by setting the lesson plan, content delivery, interaction, response, and evaluation system of university lectures as observation variables, and examines student characteristics, professor characteristics, and lecture characteristics as factors that affect them. was put in. Furthermore, it was investigated whether there was a dissimilarity in the student's academic obligation level by profile. The research model is shown in Figure 1.

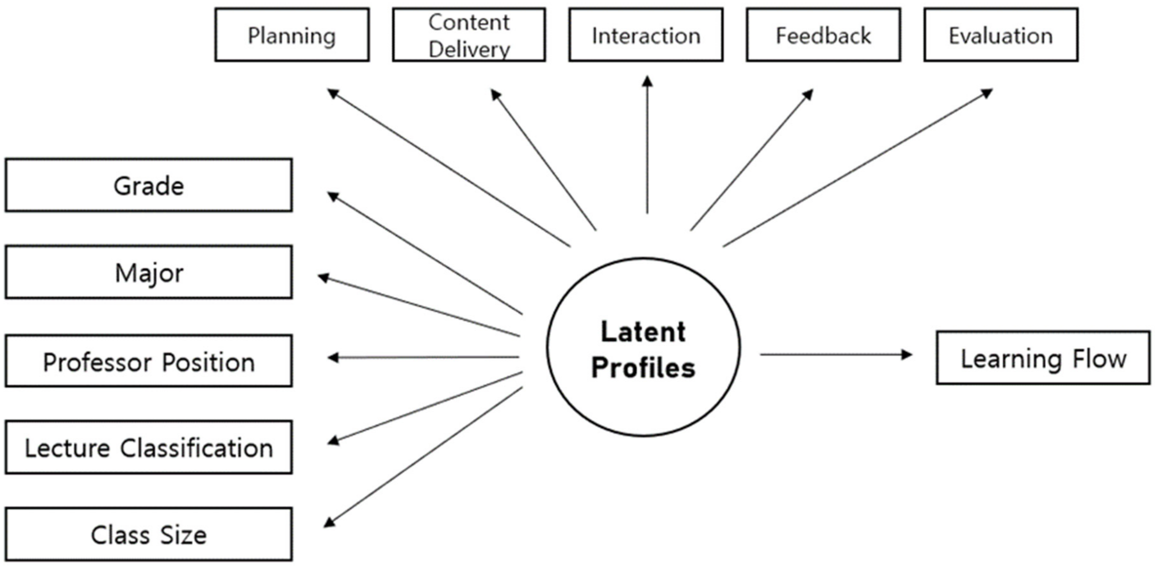


Figure 1. Research Model

3.2 Research Subject

The participants in this study were 12,919 university students from A University in Seoul who participated in classes and evaluated lectures in the 2nd semester of 2020. The survey was conducted from December 10th to 17th after the 2020 2nd semester classes ended. Excluding insincere answers, the results of student course evaluations on 83,069 subjects were finally collected as data and used for analysis. Table 1 shows general characteristics of participants.

Table 1. General Characteristics

(n=12,919)

		N	%
	Freshmen	20,839	25.1
Grade	Sophomore	22,018	26.5
	Junior	21,436	25.8
	Senior	18,776	22.6
Major	Humanities and Social Sciences	37,207	44.8
	Science and Engineering	30,940	37.2
	Arts and Physical Education	14,922	18.0
	Total	83,069	100.0

3.3 Research Tools

To assess university students' perception of lectures, Choi Yeon-ok (1995)'s lecture evaluation measurement tool was referenced, modified, and supplemented according to the lecture evaluation environment of University A (Marsh, 1987). This tool contains of 6 items, but only 5 items were used except for the student's self-directed knowledge evaluation items. The five problems are the teaching management plan, current content delivery, several interactions, professor response, and the evaluation system. The detailed questions are 'The class was properly planned and operated according to the online lecture format', 'The professor can effectively manage the class content.', 'I had interactions with the professor through various channels during the semester.', 'Professor gave feedback on the results of assignments and class activities.' I would like to recommend that you take this class.' All items were evaluated using a 5-point Likert scale, and the Cronbach's alpha reliability test result was 0.958.

3.4 Analysis Procedure and Method

In this study, Latent Profile using physiological data analysis was performed to classify the types of lecture evaluation by college students, and for this purpose, the Mplus 8 program was used. Latent profile analysis using physiological data analysis is an individual-centered analysis, not a variable-oriented analysis like regression analysis, and assumes that there is a heterogeneous distribution in the distribution of variables. Therefore, it is not a method to look at the overall trend of response results, but rather to analyze and assume that the pattern of lecture evaluation can vary depending on the individual. Like this, there is a cluster analysis, but the latent profile using physiological data analysis is different from the cluster analysis in that it undergoes a statistical verification procedure. To determine the number of potential layers and check the practical usefulness, it is necessary to compare the relative fit between competing models, which will be explained in more detail below. Since the data collected in this study are continuous variables rather than categorical variables as students' lecture evaluation data, a latent profile analysis using physiological data analysis was performed rather than a latent class analysis (LCA).

First, Latent profile analysis using physiological data analysis (LPA) was conducted to confirm the potential class in the course evaluation results. Latent profile analysis using physiological data analysis is based on a person-oriented approach that categorizes people, unlike the variable-oriented method, and based on the multivariate distribution of constant variables, people with similar characteristics according to the similarity of response patterns are classified as invisible potential subordinates. It is a statistical technique that classifies groups into groups (Bergman & Magnusson, 1997). When the dependent variable consists of continuous items, latent profile analysis using physiological data analysis is applied. When determining the latent profiles, the groups is increased while comparing models based on the information index, model comparison confirmation, and classification quality, and choose a matching final model. LPA a mixture modeling that searches for groups with heterogeneous characteristics through the item response patterns of individuals in the population, reveals the heterogeneous characteristics of potential variables in the population for each potential group, and finds the probability to each course. It is a method of typifying (Schmiege et al., 2012). This is a method of explaining the relationship by assuming that there are potential classification elements that are not directly observed by grouping subjects with similar response patterns into the same group when the population is composed of invisible latent variables. Unlike Latent Class Analysis (LCA), which uses a categorical variable as a dependent variable, latent profile analysis using physiological data analysis uses the dependent variable as a continuous variable and assumes that the distribution of the continuous variable observed by the analysis is normally distributed. Each profile does not have a single probability distribution, but each potential group has its own probability distribution.

Based on this analysis method, this study examines the results of course evaluation (class operation plan, effective content delivery, several interactions, professor response, evaluation system) conducted for students who participated in lectures opened in the second semester of 2020. To classify the latent layers, the information fit index AIC (Akaike Information Criteria), BIC (Baysian Information Criteria), SSABIC (Sample-size Adjusted BIC), numerical importance, and entropy index were referred to. For numerical importance test, LRT (likelihood ratio test) and BLRT (bootstrap likelihood ratio test) were utilized (Mc Lachlan et al., 2002; Masyn, 2013), and to recognize the number of potential profiles, interpretability and practical meaning based on the results of statistical criteria were utilized. Finally, the model that clarifies how groups are classified were chosen by comprehensively considering such factors (Lubke & Muthén, 2005). The classification ratio within the group is an additional consideration. In many previous studies, the latent profiles are selected as an appropriate latent profile when the classification ratio of latent profiles is at least 5%. It was considered that comparison was possible (Hill et al., 2000; Jung & Wickrama, 2008; Nooner, 2008). In this study, the standard of the minimum group ratio was set to 1% or more and the analysis results were examined.

After classifying the latent profile, a three-step approach was used to verify the influence of related variables. The three-step approach proposed by Asparouhov & Muthen (2014) is a method to independently evaluate the relationship between latent profile variables and influencing factors. In the first stage of the three stages, the basic model with only displays for the categorization of the latent profile is evaluated, and in the second stage, the latent profile to which specific belongs is estimated based on the posterior group membership probability (Asparouhov & Muthén, 2014). Step 3 verifies the effects of independent variables or dependent variables that affect profile classification while considering classification errors. To this end, multinomial logistic regression was done, and the correlation among covariates and profiles was examined through logit coefficients.

4. Results

4.1 Descriptive Statistics and Correlation Analysis

Descriptive statistical analysis and correlation analysis on the research variables were carried out prior to the potential profile being implemented in the second semester of 2020 in accordance with the class plan, content delivery, interaction, response, and evaluation system composed of sub-factors of course evaluation. First, the regular score for lesson plan was the maximum with 4.414, followed by content delivery (4.385), interaction (4.332), feedback (4,329), and assessment system (4.305), according to descriptive statistical analysis of the variables employed. In addition, because of calculating skewness and kurtosis to check whether the variables satisfy the assumption of normality, the variables used in this study all met the assumption of normality as the complete value of skewness were fewer than 3 and the total value of kurtosis was fewer than 10.

Statistically significant positive correlations were discovered for all variables in the range of r=.574 to r=.667 because of the correlation study between the primary variables. The correlations among variables were: lesson plan and content delivery (r = .667, p <.01), content delivery and evaluation system (r = .654, p <.01), interaction and feedback (r = .641, p) <.01), content delivery and interaction (r = .636, p <.01), lesson plan and evaluation system (r = .623, p <.01), interaction and evaluation system (r = .620, p<.01) was the highest.

Table 2. Descriptive Statistics and Correlation Analysis

(n=12,919)

Variables	Course Planning	Content Delivery	Interaction	Feedback	Evaluations Method
Course Planning	-				
Content delivery	.667**	-			
Interaction	.614**	.636**	-		
Feedback	.574**	.593**	.641**	-	
Evaluations Method	.623**	.654**	.620**	.611**	1
Mean	4.414	4.385	4.332	4.329	4.305
SD	.821	.870	.905	.924	.953
Skewness	-1.468	-1.472	-1.339	-1.372	-1.413
Kurtosis	2.131	1.950	1.410	1.457	1.620

**p<.01

4.2 Latent Profile Analysis Using Physiological Data Analysis: Numbers of Profiles

Since the number of latent layers cannot be determined in advance in latent profile analysis using physiological data analysis, the number of latent profiles that best match the information is formed by linking the results obtained by accumulative number of latent layers one by one through the observed data. Therefore, to identify the optimal number of potential layers, the number of potential groups is increased sequentially from 1 to meet statistical criteria such as information fit index, classification quality, model comparison and verification, cases to be classified, and the potential groups. The possibility of interpretation should be evaluated comprehensively (Asparouhov & Muthén, 2014).

The fitness index includes Akaike's Information Criterion (AIC), Baysian Information Criterion (BIC), and Sample-size Adjusted BIC (SA-BIC). AIC and BIC are the most used fitness indices among information-based fitness indices, and among them, BIC is evaluated as the most reliable index for calculating the number of groups. However, BIC has the disadvantage that the accuracy increases as the sample size increases. Next, entropy is an index indicating the quality of how accurately the latent group is classified, and it is used to judge the usefulness of the latent hierarchical analysis to find out whether a specific set of indicators is good at grouping in a sample. The formula to calculate entropy is as follows. Where P is the expected conditional possibility of individual, I be in to group k, n is the sample size, and K is the number of groups. A value with an entropy index closes to zero indicates that the latent layers are not sufficiently distinguished from the estimated layers. When there is a saturated model that completely describes the data including all unknowns as many as the number of data and a nested model that includes some unknowns in the saturated model, LR has two different parameter limits. This method is used to select the more suitable model among the models.

However, the comparison of latent group models does not satisfy the assumption of normality that must be satisfied for the log-likelihood ratio difference test by distribution. Therefore, Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LRT) and Parametric Bootstrapped Likelihood Ration Test (BLRT) are used (Asparouhov & Muthén, 2014). Similarly, LMR-LRT is verified with the adjusted difference as a method of comparing whether a statistically important development in fit is achieved as the number of latent layers is greater than before. BLRT also verifies the optimal number of potential groups by estimating the log maximum likelihood difference distribution through bootstrap sampling. Taken together, the smaller the fitness index value, the closer the Entropy index is to 1, and the more significant the LMR-LRT verification is, the better the type classification. In addition, when judging the suitability of group classification, the number of groups with high explanatory power can be selected as the final model if the ratio of the number of cases per group and interpretability are considered together (McCrae et al., 2006).

To this end, in this study, to detemine the number of latent profiles, the number of classification groups were sequentially augmented from two groups to one by one and looked up to six groups. When this method determines the latent profile type, the smaller the information fit index AIC and BIC. The comparison indices LMR-LRT (Lo-Mendell-Rubin adjusted Likelihood Ratio Test) and BLRT (Parametric Bootstrapped Likelihood Ratio Test), which are comparative indices between the models to compare and verify when the number of latent profiles is k and k-1, are the p-value (statistical Significance) is important, select a model with k number of latent profiles instead of k-1. Entropy, an index indicating the degree of classification, which ranges from 0 to 1, and the closer the value to 1, the appropriate classification (Jung & Wickrama, 2007).

Accordingly, to identify the number of latent profiles based on the results of university student course evaluation, an unconditional model without predictor variables was first analyzed, and then a qualified model that included variables likely to affect latent class classification as covariates was developed. A three-step approach to the analysis was utilized (Asparouhov & Muthen, 2014; Vermunt, 2010). To recognize the number of latent layers, in adding one more layer, the information quality index, verification, and categorization were examined. The analyses' findings are shown in Table 3.

Table 3. Criteria for Asessing of Latent Profiles

Category		Numbers of Latent Profile				
		2	3	4	5	6
Information Index	Loglikelihood	-400369.887	-309589.881	-239127.956	-224765.341	-214247.709
	AIC	800771.774	619223.761	478311.913	449598.682	428575.418
	BIC	800921.013	619428.964	478573.081	449915.815	428948.515
	SABIC	800870.164	619359.048	478484.096	449807.762	428821.394
χ^2(p)	LMR-LRT	0.0000	0.0000	0.0000	0.0000	0.0000
	BLRT	0.0000	0.0000	0.0000	0.0000	0.0000
Quality of classification	Entropy	0.952	0.978	1.000	0.993	0.987
%	Profiles 1	61.1	57.2	58.6	3.1	55.3
	Profiles 2	38.9	13.7	12.0	55.5	3.3
	Profiles 3		29.1	3.5	25.9	22.4
	Profiles 4			25.9	3.5	12.0
	Profiles 5				12.0	3.5
	Profiles 6					3.5

AIC, BIC, and SABIC, which are statistics significance indices, were examined as the second criterion for judgment. According to Figure 2, all three information relevance indices decrease until the number of layers increases to 4, and after 5, the decrease becomes gradual and there is little change. This can be seen as a phenomenon in which the AIC, BIC, and SABIC indices decrease more as the model becomes further complex when the sample size is very huge

(Jedidi, 1997). With this, the number of latent layers can be identified in the same way as determining the number of factors in the section where the slope becomes gentle by examining the scree chart in factor analysis. Therefore, this study judged that the model with the number of latent layers were the most appropriate.

Entropy, the third criterion, measures the accuracy of categorization based on posterior probabilities discovered by latent profile analysis of physiological data. Its value ranges from 0 to 1, with 0 being the lowermost and 1 being the uppermost. The better the model, the higher the entropy value, which, in general, should be 0.8 or above, can be deemed a satisfactory classification (Muthén & Muthén, 2007). The research revealed that the entropy index gradually rose until there were 4 latent layers, then reached 1, and then declined from 5 to 1. In every instance, LMR-LRT and BLRT were statistically significant.

Next, to match the fit of the model according to the system, it was confirmed that the latent profile was classified into four layers through the results of the college student course evaluation. Can be looked at. As for the posterior hierarchical membership probability, the classification can be more accurately made when the number is at least 0.7 and is closest to 1, it can be judged that the classification is at an acceptable level (Nagin, 2005). Table 4 shows the posterior hierarchical affiliation probability analysis results of the hierarchical model according to each group.

Looking at the posterior hierarchical membership probability table for the four latent layers presented in Table 4, as shown in the main diagonal of the matrix, the correct hierarchical classification probability is 97.0% for tier 1, 95.3% for profile 2, and 94.8% for profile 3, profile 4 was 97.1%. According to the analysis result, the probability to each course was 0.9 or greater, which greatly exceeded the reference value of 0.7, and it was judged that all five classes showed acceptable accuracy in classifying the classes. Accordingly, this study was judged to be the most optimal model to explain heterogeneity of latent profiles when the number of latent profiles were 4 based on the course evaluation result by synthesizing the interpretation possibilities along with the criteria of various information indexes.

Table 4. Probability of Each Latent Profile

Category	Profile 1	Profile 2	Profile 3	Profile 4
Profile 1	0.970	0.028	0.002	0.001
Profile 2	0.013	0.953	0.034	0.000
Profile 3	0.000	0.042	0.948	0.009
Profile 4	0.000	0.000	0.029	0.971

4.3 Characteristics of the Latent Profile of Course Evaluations

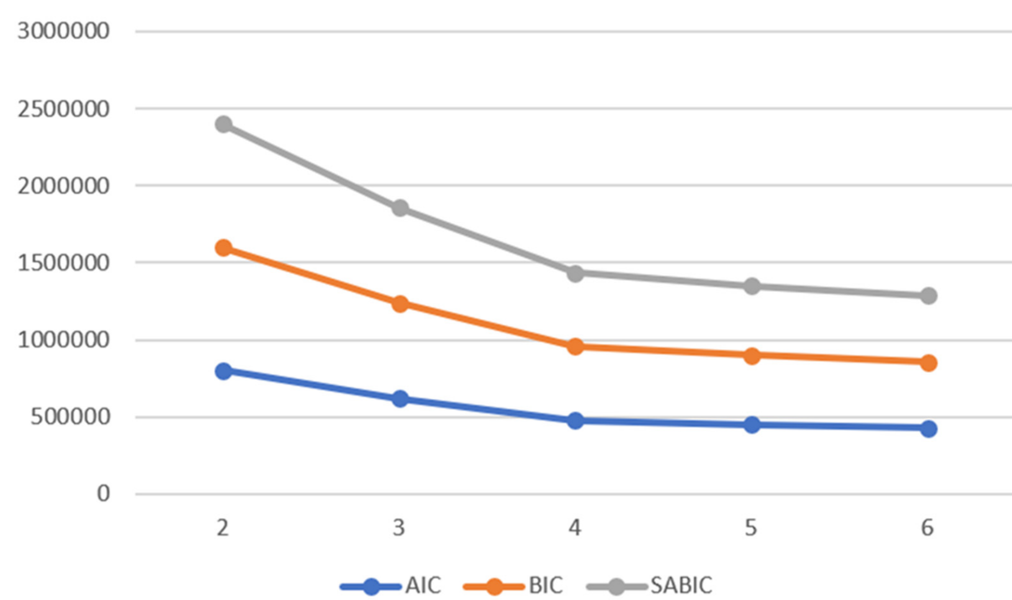
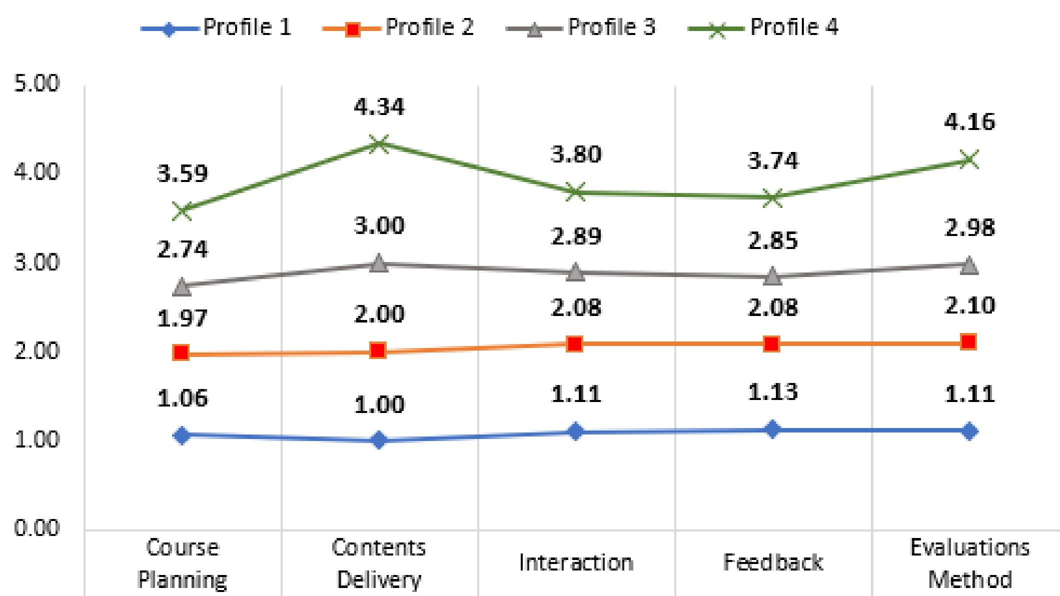


Figure 2. Changes in AIC, BIC, and SABIC and Number of Latent Profiles

The possible classes were divided into four categories based on the effects of the course evaluation, with profile 1 representing the upper group, profile 2 the upper middle group, profile 3 the middle lower group, and profile 4 the lower group for each class. Descriptive data are displayed in Table 5, and the form of the latent layer extracted in accordance with the lesson plan, content delivery, interaction, response, and evaluation system—all of which are sub-factors of course evaluation—is depicted in Figure 2.

Table 5. Mean and Standard Deviations of Variables for Each Latent Profile

Category	Lower Group (58.6%)		Lower-middle Group (25.9%)		Upper-middle Group (12.0%)		Upper Group (3.5%)		F	η^2	Pos hoc
	M	SD	M	SD	M	SD	M	SD			
Lecture Planning	1.06	0.27	1.97	0.27	2.74	0.60	3.59	1.10	79935.00	0.74	d>c>b>a
Contents Delivery	1.00	0.21	2.00	0.12	3.00	0.22	4.34	0.47	2641417.52	0.99	d>c>b>a
Interaction	1.11	0.39	2.08	0.55	2.89	0.61	3.80	1.07	63054.64	0.70	d>c>b>a
Feedback	1.13	0.44	2.08	0.62	2.85	0.70	3.74	1.16	45999.47	0.62	d>c>b>a
Evaluations Method	1.11	0.39	2.10	0.58	2.98	0.64	4.16	0.90	72026.28	0.72	d>c>b>a



	Course Planning	Contents Delivery	Interaction	Feedback	Evaluations Method
Profile 1	1.06	1.00	1.11	1.13	1.11
Profile 2	1.97	2.00	2.08	2.08	2.10
Profile 3	2.74	3.00	2.89	2.85	2.98
Profile 4	3.59	4.34	3.80	3.74	4.16

Figure 3. Characteristics of Sub-Factors of Course Evaluation by Latent Profiles

4.4 Verification of Factors Influencing Course Evaluation

Examining the features of every group in detail, the course evaluation subgroup shows low scores in lesson plan, content delivery, interaction, response, and evaluation system. In particular, the average of content delivery was the lowest at 1.00 and the feedback was the highest at 1.13. The subgroup accounted for 58.6% of the total respondents. About 25.9% of the respondents were incorporated in the mid-subgroup, and all the sub-factor scores of course evaluation was higher than in the subgroup. The average of the evaluation system was the maximum at 2.10, followed by interaction, feedback, content delivery, and lesson plan. 12.0% of the total respondents belonged to the upper-middle group, and it is characterized by a higher score for the sub-factors of course evaluation than the middle-lower group. The average of content delivery was the highest at 3.00, followed by evaluation system, interaction, feedback, and lesson plan. Finally, 3.5% of the overall respondents be in the upper group, and the score for the sub-factors of course evaluation was greater than that of the upper middle group. The sub-factor with the maximum average is content delivery (4.34), followed by evaluation system, interaction, feedback, and lesson plan in order of high average.

4.5 Verification of Factors Influencing Course Evaluation

By including independent variables in the model that served as the basis for the four latent profiles, multinomial logistic regression analysis was carried out to validate the impact on latent profile categorization. With this, each group was set as a reference group and compared with the rest of the group. First, the course evaluation subgroup was set as the reference group, and then the middle subgroup and upper middle group were orderly set. Table 6 prsented the effects of examining the factors affecting the course evaluation by setting the major field of arts and physical education as the reference group and the main lecture as the reference group.

Table 6. Validation of Latent Profiles Influence Factors according to Course Evaluation

Category			Criteria: Lower Group					
			Middle Lower Group		Middle Upper Group		Upper Group	
			b	SE	b	SE	b	SE
Student Characteristics	Grade (school year)		-.001	.020	-.051**	.018	-.020	.018
	Major	Humanities and Social Sciences	.055	.060	.149**	.056	.107*	.054
		Science and Engineering	.094	.063	.169**	.059	.041	.057
Professor Characteristics	Position of Professor		.030	.018	-.011	.017	-.041*	.017
Lecture Characteristics	Classification of Subject	General education	.417***	.056	.471***	.053	.542***	.051
		Teaching profession	-.256	.310	-.040	.280	-.006	.268
	Lecture Size		.030	.033	-.020	.031	-.129***	.030
Category			Criteria: Middle Lower Group				Criteria: Middle Upper Group	
			Middle Lower Group		Middle Upper Group		Upper Group	
			b	SE	b	SE	b	SE
Student Characteristics	Grade (school year)		-.050***	.011	-.019	.010	.031***	.008
	Major	Humanities and Social Sciences	.094**	.035	.052	.032	-.042	.024
		Science and Engineering	.075*	.036	-.053	.033	-.128***	.025
Professor Characteristics	Position of Professor		-.042***	.011	-.071***	.010	-.030***	.007
Lecture Characteristics	Classification of Subject	General education	.054	.030	.125***	.027	.071***	.020
		Teaching profession	.216	.200	.250	182	.035	.125
	Lecture Size		-.049**	.019	-.158***	.017	-.109***	.013

***p<.05, **p<.01, ***p<.001**

First, all student attributes (grade, major), professor attributes (rank), and lecture attibutes (classification of courses, lecture size) were statistically important aspects when the subgroup of course evaluation was used as the reference group and comparisons were made among groups. It seems that the likelihood of being in the upper-middle group increased with lower grade (b=-.051, p.01). Science and engineering have a high likelihood of falling into the upper-middle group (b=.169, p.01) or the upper group (b=.107, p.05). The likelihood in the upper group over the lower group increased with decreasing professor rank (b=-.041, p.05), and general education lectures as opposed to major lectures were likely to be in the lower-level group than the lower-level group (b=.417, p). b=.471, p.001), upper middle class (b=.471), and higher class (b=.542, p..001). Also, the likelihood of being included in the course evaluation for the upper class is a bit higher in the lecture size (b=-.129, p.001).

Next, the lower the grade, the more likely it belongs to the upper-middle group when the low-middle group of course evaluation is used as the reference group and associated with the upper-middle and upper groups (b=-.050, p.001). When the humanities and social sciences or science and engineering areas occur, the field of major is more likely to fall into the upper-middle-class category than the arts/physical education field (b=.094, p.01). It was analyzed that the lower the professor's position, the greater the chance to be included in the upper-middle group (b=-.042, p<.001) or upper group (b=-.071, p<.001) than in the lower-middle group. It was more likely to be in the top group when it was a general education lecture as opposed to a major lecture (b=.125, p.001), and the minor the lecture size, the greater the middle class as opposed to the upper group (b=-.049, p.01) or lower group (b=-.158, p.001).

When the upper-middle class of the course evaluation was set as the reference group and comparison with the upper group was conducted, as school year increased (b=.031, p<.001), the student's main field are science and engineering (b) rather than arts and physical education (b =-.128, p<.001), the lesser the professor's position (b=-.030, p<.001), the more genenal education lectures rather than major lectures (b=.071, p<.001), it was discovered that the chance of being in the upper-middle class was higher than the upper-middle class the lesser the lecture size (b=-.109, p.001).

Lastly, a comparison of each probable profile's levels of student academic dedication was made, and the results are shown in Table 7 below. The differences between groups by potential profile were confirmed for the analysis, which used student educational obligation as the final effect variable of the latent profiles resulting by the lesson plan, content delivery, interaction, response, and evaluation system, which are sub-factors of course evaluation. This study revealed that academic dedication was strong in the upper class (4.83), upper middle group (4.01), lower middle group (3.44), and lower group (3.29) of course evaluation, in that order.

Table 7. Students' Academic Achievement According to Latent Profile

Category	M	SD	F	p	η^2	Scheffe's test
Lower Group[a]	3.29	1.23	250903.08	.000	0.48	d>c>b>a
Middle Lower Group[b]	3.44	0.75				
Middle Upper Group[c]	4.01	0.55				
Upper Group[d]	4.83	0.47				

5. Discussion

To classify the sub-factors of university course evaluation through the latent profile analysis using physiological data analysis technique, recognize the characteristics of every latent course, and identify the influence issues is the purpose of this research. 83,069 course evaluation results of 12,919 students enrolled in the second semester of 2020, participating in lectures, and evaluating lectures while attending university A were used for analysis.

First, by analyzing the data obtained from college students, 4 disparate latent classes were classified, and the characteristics of each latent class were identified. Through this, it was confirmed that the instructor's delivery of lecture plans in advance in college classes, delivery of clear contents, obtaining student responses through interaction, and an objective evaluation system have a significant impact on immersion in learning, this supports a number of previous studies (Im & Jeong, 1999; Yoon, 2018; Kim, 2017; Song, 2018). In order to verify the significant influencing factors for potential classes classified as follows, multinomial logistic regression analysis was performed by inputting student's grade and major field, professor's attribute ranking, subject classification, and lecture size as independent variables. As a result, first, among student characteristics, the lower the grade, the better. In addition, the probability of falling into the lower middle, upper middle, and upper classes is higher in the humanities, social studies, and science and engineering fields than in the lower classes. This is contrary to the results of previous studies that reported that the higher the grade and the older the student, the higher the course evaluation score (Kim et al, 2009; Ting, 2000; Gage, 1961). This is because all lectures in the 2nd semester of 2020 were online lectures conducted in the context of the spread of the corona virus. Through this, it is necessary for schools to make flexible efforts to increase student educational performance in consideration of various variables that affect school classes (Han, 2001; Lee & Nam, 2018).

Second, it was judged that the higher the rank, which is the characteristic of professors, the higher the subject evaluation. These results are contrary to previous studies (Lee & Nam, 2018; Marsh & Roche, 1997; Cashin, 1995) that professor characteristics do not have a significant effect on course evaluation, or previous studies that the higher the position, the higher the ranking. The higher the professor's evaluation of the lecture, the larger it is (Baek & Shin, 2008). Through the analysis of this study, the lower the professor's rank, the higher the course evaluation result, which is almost related to the fact that the lecture evaluation effect acts as a key indicator in determining promotion or reappointment in the next semester. Therefore, professors with lower ranks respond more sensitively to subject evaluation than professors with higher ranks, which can be judged to be the result of their efforts to receive course evaluations (Kim et al., 2009).

Third, the lecture size is almost related to the lecture evaluation result, and the larger the lecture size, the lower the lecture evaluation result. These results revealed that the class size according to the number of students is a key factor in determining the course evaluation results because it is a very important factor in determining the level of interaction with students during class, feedback on assignments, or test results. . Therefore, the selection of an appropriate training method. In previous studies, there is an important correlation between lecture size and lecture evaluation scores (the smaller the score, the higher the score), and the difficulty of communication and feedback with instructors is important in large-scale lectures (Cho, 2013). In addition, it was confirmed that there were differences in the course evaluation results according to the classification of completion (major, liberal arts, teaching profession). It is difficult to apply these results identically because each university has different classifications of completion, but it is in the same context as previous studies in which course evaluation results vary according to credits. (Baek & Shin, 2008).

6. Conclusion

The conclusions of this study are as follows. First, this study is meaningful in that it looked at how much the factors of each lecture that university students participated in during one semester affect their learning flow while an in-depth understanding of course evaluation in universities is required. Second, from a methodological point of view, individual differences in each sub-factor of course evaluation, which determine the quality of university lectures, were reflected in the analysis. classified. In addition, the class plan, content delivery, interaction, response, and evaluation system, which determine the quality of university education, are sub-elements of course evaluation, and influence factors are examined in various contexts, and the characteristics of course evaluation by potential profile are analyzed in relation to academic commitment by doing so, we sought ways to improve the quality of university education.

The limitations and recommendations for additional research are listed below. First, generalizing and applying the research results to all universities in that the study range was based on the results of the course evaluation done at the University A. Therefore, in future study, it is expected that the results of course evaluation done at various universities will be included in the research to derive richer analysis results, and it is expected that various universities will refer to them and reflect them in operation. In addition, if it is possible to conduct interviews with professors and students and analyze the collected qualitative data together, it will be possible to express the perceptions of university society members about course evaluation abundantly. Second, in that this study conducted a cross-sectional study through the course evaluation results of the second semester of 2020, the results of this analysis have limitations in examining the efforts and effects of universities to develop the quality of teaching in the mid- to long-term. Therefore, the follow-up study analyzes the course evaluation results collected over several semesters through a longitudinal study and analyzes the changes in course evaluation results and the education and knowledge improvement program arranged by schools to develop the standard of university education. It is hoped that the effects can be viewed comprehensively. Lastly, in the follow-up study, through the application and effect analysis of the improvement measures presented, the importance of the course evaluation system in the university society is shared, and opinions of various stakeholders related to course evaluation are shared. It is expected that an environment can be created in which efforts to be actively reflected in the major decision-making and policy-making processes within the university can be made together by converging and analyzing the data more broadly.

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