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Analysis of Course Data for Curriculum Review and Improvement

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***Abstract*—Analyzing class data collected by educational institutions is imperative for deriving measures to improve the curriculum. Data analysis can identify students' grades and learning behaviors; on this basis, students' learning effectiveness and satisfaction can be improved by promoting curriculum improvement. In this study, it was possible to derive students' learning patterns, key factors, and process improvement plans necessary for the composition and development of the curriculum. The analysis results according to the type of course taken showed that class interest was highly related to learning content understanding, and class understanding had a weak relationship. In addition, it was found that interest in the class and understanding of the contents were important when learners took the course, and the difficulty of the assignment was found to have no relationship with other factors except for the number of assignments. Cluster analysis based on cross-analysis of the subject showed that the subject's difficulty, importance, and association all play an important role, and actual academic grades do not affect it. Interest in the subject and understanding of the contents of the class were crucial factors, and the number and difficulty of tasks did not have a significant impact. Based on these analysis results, providing a quantitative basis for expanding learners' participation in curriculum improvement is possible. These analyses and improvements must be carried out continuously, and the introduction of new data and technologies enables more effective curriculum improvement by performing more detailed and accurate analyses.**

***Keywords*— Course data analysis; curriculum improvement; cluster analysis; intergroup mean analysis; learning factors; academic achievement.**

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I. INTRODUCTION

The curriculum plays an important role in students' acquisition of major knowledge and skills, growth, and development. Therefore, it should be organized so that students can acquire the skills and knowledge required in the industrial field; furthermore, students should be supported to play a better role in it. Understanding the needs of learners while developing and maintaining an appropriate curriculum accordingly is crucial for developing and maintaining an appropriate curriculum and courses in university education [1]. To this end, learners' learning outcomes should be regularly monitored and analyzed to improve their curricula and courses. To accomplish this, it is necessary to analyze data from these curricula and courses. Data analysis of the curriculum and course may be conducted for several reasons [2], [3].

First, data analytics can help assess course performance and identify areas of improvement, which can increase learners' achievement. Second, data analytics can help identify learner needs and develop new curricula and courses, providing a better learning experience. Third, data analytics can help identify courses that are in high demand and those that are not and allocate resources appropriately; this can increase the efficiency of the resources.

Curriculum data analysis from various perspectives is a very important process and an essential step in improving the curriculum to identify and improve the factors that affect its efficiency and students' learning performance [4]. We identified areas that require improvement and derived improvement measures based on the analysis results. For example, students with low grades and difficulty in a subject may require improvement measures such as supplementing the subject's content or encouraging more appropriate prerequisites.

The derived improvement measures are executed, and their results are analyzed. If the improvement plan is effectively implemented, resulting in improved grades or increased enrollment rates, the improvement of the subject is considered successful. Improving subjects through this analysis can improve students' learning performance and contribute greatly to improving the quality of education at universities. Moreover, if an improved subject becomes more interesting and popular with students, it can improve their satisfaction with college [5].

The analysis of course data to improve the subject involves analyzing the data regarding the subject taken by students and suggesting ways to improve the subject. Universities can improve the quality of education, and students can learn more effectively [6]. Therefore, this study addresses the necessity and purpose of analyzing course data to improve the subject. Course data analysis for subject improvement is necessary to improve students' learning performance. Students learn by performing assignments, tests, and projects on the subjects they have taken.

Hence, the subject's nature, content, difficulty, and teaching methods significantly influence students' learning performance. Students can improve their learning performance by identifying these effects and deriving improvement measures. For example, an analysis of student performance by subject may reveal that a student finds some subjects difficult and tends to obtain low grades. In this case, the faculty of the subject can develop improvement measures, such as supplementing the contents of the lecture or providing auxiliary materials for students to understand.

Additionally, if a learner’s subject appears to impact the subject's understanding and student performance significantly, improvements can be made by identifying what needs to be supplemented or improved in the learner's subject. By preparing such measures, students' learning effectiveness and satisfaction can be improved, which can also improve the curriculum.

II. Materials and Method

Recently, in education, it has become necessary to improve and modify curricula to increase their effectiveness and efficiency. In particular, the curricula of universities play a crucial role in the country's development and the strengthening of the professional capacity of the people. Accordingly, one way to improve the quality and efficiency of university education is to improve the curriculum through class data analysis [7].

Course data analysis collects and analyzes data on students' educational activities, such as course records, academic achievement, evaluation, feedback, and attendance. This can improve students' educational experiences and help them efficiently manage the school's educational programs. Course data analysis uses data analysis techniques to collect and analyze data on students' educational activities, such as academic achievement and attendance status. This allows schools and teachers to understand student attendance and provide a more customized learning environment for individual students [8].

Learning analysis aims to improve students' learning outcomes and learning processes by collecting and analyzing the data generated during the learning process. This allows students to learn more effectively and teachers and schools to improve their learning processes. Educational evaluation is evaluating a curriculum, its goals, and students' learning outcomes. In course data analysis, educational evaluation aims to evaluate student learning outcomes and modify the curriculum accordingly.

Course data analysis is important in improving students' learning performance by understanding their learning process and outcomes and providing a customized learning environment for individual students. Prerequisite verification is the process of checking whether a student has the necessary learners' knowledge to study, which can increase their chances of learning success. An analysis method that measures learners' behavior and learning activities and analyzes them to identify individual learners' learning situations and determines appropriate countermeasures accordingly. Improving the curriculum and recommending classes by analyzing the curriculum and learners' course histories [7], [8].

Recently, many studies have been conducted to improve the curriculum and student performance through class data analysis. It aims to use machine learning algorithms to predict student success and improve the curriculum. Course data is analyzed to predict a student's success based on information such as student attendance, grades, and assignment submissions; this can help improve the curriculum and student performance [9].

One study developed a curriculum recommendation system that allows students to be recommended lectures that suit their interests and achievements and analyzes students' records and grades to identify students' interests and achievements [10]. This study collects and visualizes student enrollment, attendance, and assignment submission data to develop a dashboard that analyzes students' learning activity data to help the faculty improve the curriculum [11].

In a study that reviewed the possibility of using data mining using predictive analysis techniques in the field of education, the prediction of students' chances of success was examined by analyzing their grades, attendance, and learning patterns based on course data [12]. In a study that explored how to improve students' academic performance and instructional design using learning analysis, a model that predicts students' success was developed using learning analysis; the results of this study may improve instructional design using that model [13].

Some studies have suggested a participatory approach to curriculum improvement using a data analysis framework, suggesting that it is possible to evaluate and improve curricula through data analysis [14]. Student feedback and academic performance data were used to analyze methods for continuous class improvement. The research results showed that it is possible to improve class design and students’ learning performance using student feedback and academic performance data [15].

As shown by a case study of data-based curriculum review, it is possible to review and improve the curriculum using data analysis. Some studies have presented research results that can improve students' learning outcomes and employment opportunities [16]. A case study of the curriculum review of engineering programs using data analysis has shown that it is possible to use data analysis to improve the curriculum as well as students' learning outcomes and employment opportunities [17].

It is possible to seek ways to improve the curriculum using learning data from MOOC, large-scale online courses [18]. Furthermore, large-scale courses such as MOOCs have the advantage of collecting learning data for various students because they have few time and place restrictions; such data collection may be difficult to conduct in the case of typical university education as they use a different educational method from these courses [18]. One study suggested a data collection and analysis methodology while confirming the possibility of improving university curricula using data analysis techniques [19]. However, this study is limited in that the results can only be applied to certain universities.

Educational data mining technology can be used to identify learners' learning outcomes and preferences to help them improve their curriculum, which results in providing customized educational services to learners [20]. It addresses the problem that it is difficult for students to choose an appropriate course to achieve better academic performance [21]. To solve this problem, researchers constructed a curriculum knowledge graph and used it to propose a framework for recommending an appropriate course [21]. The greatest advantage of this study is that it makes it possible to build a better recommendation system using a curriculum knowledge graph [21]. Unlike previous studies, this study provides course recommendations while considering additional information such as prior courses and student preferences.

However, this study has a disadvantage in that it takes a lot of effort and time to build a curriculum knowledge graph. In addition, it is difficult to grasp student preferences accurately. These problems limit the applications of this research [21, 22, 23]. These recent studies examine how to improve the curriculum using learning analytics and data analysis techniques and show that data analysis can improve students' learning outcomes and job opportunities.

III. Result and Discussion

It is crucial to evaluate and analyze a curriculum to improve its quality [24, 25]. Various research methods can be used to evaluate and analyze curricula [26, 27]. Class data analysis is useful for reviewing and improving curricula [28, 29]. By reviewing data such as class evaluations, student performance, and course trends, educators can identify areas that need improvement in the curriculum and adjust them to better meet students' needs [30], [31]. Fig. 1 shows the schematic results of the research process used in this study. The following steps can be taken to review the curriculum and analyze class data for improvement [6], [9], [16], [20]

1) Data collection and organization: The first step is to collect relevant data, such as class evaluations, student grade data, and course trends. These data can be organized using spreadsheets or data analysis software.

2) Problem identification: Once data are collected and organized, educators can identify problems such as consistently low-class evaluation scores, high dropout rates, or poor student performance.

3) Data Analysis: Statistical tools such as regression, analysis of variance (ANOVA), or factor analysis allow educators to identify patterns or relationships between variables such as student performance and class difficulty.

4) Solution Development: Educators can develop solutions for these problems based on data analysis results. For example, if a student's performance is consistently poor in a particular class, one can adjust the curriculum or provide them with additional resources.

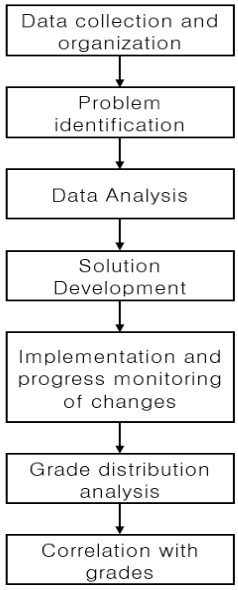


Fig. 1 Schema of research process

5) Implementation and progress monitoring of changes: After developing and implementing solutions, educators should monitor the students' progress to determine the solutions' impact on student outcomes; this could mean collecting additional data, such as class assessments or student grade data, to assess the effectiveness of the changes. The representative methods used to conduct the data analysis to improve the curriculum are as follows. Student grade data and course trend analyses provide important information for improving the curriculum, enabling the students to perform well in class. Student grade data analysis can be performed as follows.

6) Grade distribution analysis: The mean, median, minimum, maximum, and other grades can be calculated by checking the distribution of student scores; this allows educators to determine whether the distribution of grades is constant, whether some students score lower than others, and the level of students with high grades.

7) Correlation with grades: The correlation between student grades and other variables can be analyzed. For example, the correlation between student attendance, assignment performance, discussion participation, and class participation can be analyzed. In addition, one can compare distributions based on gender to identify differences between groups. For example, there may be cases in which the distribution of grades varies depending on gender, grade, major, and other factors.

Course trend analysis can be performed in the following ways.

1) Analysis of the number of students: The trends concerning the number of students may be analyzed. If the number of students increases or decreases, the cause may be identified.

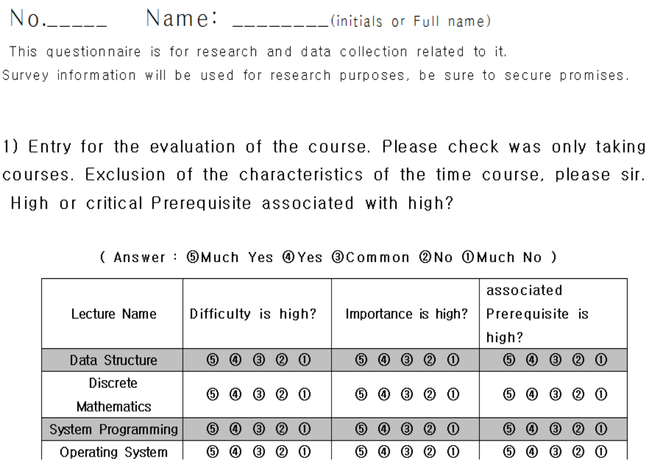
2) Class Analysis: The percentage of students who wish to take the course and have completed the course registration can be calculated; this allows students to express their interest in the class.

3) Analysis of learners' subject relevance: The suitability of the learners' subject can be evaluated by comparing the learners' subject for the class with the student's completion.

4) Instructional Method Analysis: By comparing the teaching method of the class (lecture, discussion, practice, etc.) with whether students apply for classes, one can check the change in course rates according to the teaching method.

5) Evaluation and Feedback Analysis: Students' evaluations and feedback can be analyzed to derive improvements. The parts of the class the students felt were difficult and the parts needed improvement can be revealed.

In this study, a survey of students' class difficulty, importance, and learners' subject linkage was conducted on a 5-point scale. In addition, for cross-analysis and cluster analysis through an average analysis between groups, data on credits were collected along with interest in professors, task quantity, task difficulty, textbook preference, and subject understanding. Fig. 2 shows the survey sheets containing their opinions [32].


No._____ Name: ________(initials or Full name)

This questionnaire is for research and data collection related to it.
Survey information will be used for research purposes, be sure to secure promises.

1) Entry for the evaluation of the course. Please check was only taking courses. Exclusion of the characteristics of the time course, please sir. High or critical Prerequisite associated with high?

(Answer : ⑤Much Yes ④Yes ③Common ②No ①Much No)

Lecture Name	Difficulty is high?	Importance is high?	associated Prerequisite is high?
Data Structure	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①
Discrete Mathematics	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①
System Programming	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①
Operating System	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①	⑤ ④ ③ ② ①

Fig. 2 Survey sheet for the opinions of students

This analysis may be used to improve the curriculum. For example, if the distribution of students' grades is checked and some students' grades are poor, they can be provided with separate guidance to help them improve their grades or the teaching methods can be improved to improve their understanding. If the number of students decreases through class trend analysis, the content or method of the class can be improved to attract students' attention.

In addition, the suitability of the prerequisite course can be evaluated and improved through class trend analysis. For example, if students who have not completed the learner's course experience difficulty in the class, they can improve the learner's course to improve their understanding of the class. Thus, improving the curriculum by actively utilizing the analysis results is important. Group-specific grade analysis classifies students according to specific criteria and analyzes their grades; accordingly, this helps students understand their grades in more detail and respond individually.

Table 1 shows the results of analyzing the correlation between difficulty, importance, prerequisite subjects, and grade factors.

TABLE I
FACTOR CORRELATION ANALYSIS RESULTS

	Difficulty	Importance	Prerequisite subject	Grade
Difficulty	1			
Importance	.339**	1		
Prerequisite subject	.274**	.331**	1	
Grade	.000	-.040	-.031	1

**. The correlation coefficient is significant at the 0.01 level (both sides).

Difficulty, importance, and prerequisite subjects were found to be correlated, and grades were found to be unrelated to other factors. Table 2 shows the results of the distributed analysis of the participants through group performance analysis.

TABLE II
RESULTS OF ANOVA BY GROUP CLUSTER

Item	Cluster		Error		F	p
	Mean Square	df	Mean Square	df		
Difficulty	178.54	1	.62	991	288.86	.000
Importance	332.07	1	.70	991	476.34	.000
Prerequisite subject	661.16	1	.66	991	1001.24	.000
Grade	1.56	1	.52	991	3.02	.083

Table 3 shows the results of the cluster analysis for group (1) that successfully completed the curriculum and group (2) that did not complete the curriculum.

TABLE III
CLUSTER-CENTERED ANALYSIS RESULTS

Item	Cluster	
	1	2
Difficulty	2.98	2.13
Importance	2.84	1.68
Prerequisite subject	3.70	2.06
Grade	4	4

From the professor's point of view, cluster analysis based on cross-analysis of the subject shows that the subject's difficulty, importance, and player–subject association all play an important role, and actual academic grades were not affected. Therefore, when designing, organizing, and operating a curriculum, it is very important to organize the order of taking courses, and it can be seen that a roadmap for the curriculum should be designed based on the difficulty and importance of the course. Table 4 shows the results of analyzing the correlation between grade, interest, assignment mount, assignment difficulty, textbook, and understanding factors.

TABLE IV
FACTOR CORRELATION ANALYSIS RESULTS

	Grade	Interest	Assignment amount	Assignment difficulty	Textbook	Understanding
Grade	1					
Interest	.407**	1				
Assignment amount	-.151*	.034	1			
Assignment difficulty	-.068	-.005	.629**	1		
Textbook	.016	.081	.125	-.002	1	
Understanding	.169*	.640**	.069	-.066	.194**	1

**. The correlation coefficient is significant at the 0.01 level (both sides). *. The correlation coefficient is significant at the 0.01 level (both sides).

Grades were found to be correlated with interest in the subject, number of assignments, and level of understanding. Interest degree was correlated with the degree of understanding, and the number of assignments had a strong correlation with the difficulty of assignments and were also correlated with grades. Textbooks were found to be related to lecture comprehension, and lecture comprehension had a strong correlation with interest, and there was a correlation between textbooks and grades. Based on the results that were similar to those of common sense, it can be considered that the students' responses appeared correct. Table 5 shows the results of the distributed analysis of professors teaching the subject through a group performance analysis.

TABLE V
RESULTS OF ANOVA BY GROUP CLUSTER

Item	Cluster		Error		F	p
	Mean Square	df	Mean Square	df		
Grade	18.46	1	.77	180	23.91	.000
Interest	140.15	1	.52	180	268.07	.000
Assignment amount	.11	1	.75	180	.16	.693
Assignment difficulty	.03	1	.78	180	.04	.843
Textbook	5.61	1	.80	180	7.06	.009
Understanding	116.50	1	.66	180	175.93	.000

Table 6 shows the cluster analysis results of group (1), which successfully completed the professor's course, and group (2), which did not, according to the analysis of grade variance by group.

TABLE VI
CLUSTER-CENTERED ANALYSIS RESULTS

Item	Cluster	
	1	2
Grade	3.02	2.32
Interest	4.09	2.16
Assignment amount	2.66	2.60
Assignment difficulty	2.62	2.65
Textbook	3.04	2.65
Understanding	4.09	2.33

Based on the results of checking the distribution of grades by semester and identifying changes in the number of students or grades by semester, interest in the subject and understanding of the content of the class were very important factors, whereas task volume and difficulty did not have a significant impact. From the perspective of instructors and learners, students' grades can be identified in more detail based on group performance analysis. Individual responses can be made based on this, the curriculum can be improved, and students' learning performance can be improved.

The relevance analysis of prerequisite subjects analyzes the performance of students who took them as prerequisite subjects before taking a specific subject to understand and learn about the importance of the prerequisite subjects. Through this, it was possible to confirm the level at which students should complete the prerequisite course and how they can strengthen these courses in the curriculum.

By classifying students' grades based on the list of prerequisites based on whether they completed the course, students who completed the course and those who did not complete the course had better grades in the course. Through this analysis of the relevance of prerequisite subjects, one can understand how to improve prerequisite subjects in the curriculum or provide supplementary education for students who have not completed them; this can help students learn more effectively and improve their learning performance.

IV. CONCLUSION

This study obtained the following results by analyzing data such as students' course records, subject grades, player subject relevance, and credits to derive measures for improving the curriculum. The basis for determining whether the subject is popular with students and whether it is essential in the current curriculum has been established by grasping the trends concerning each subject.

For popular subjects or professors, finding ways to further strengthen or supplement the subject is necessary. Although this is an essential subject, it was found that if the enrollment rate or the number of students who have completed it is low, it is necessary to analyze the motivation of students to take the course and find ways to improve it.

As a result of conducting cluster analysis based on cross-analysis and average group analysis, it was possible to identify the subjects with which students had difficulties. Students who have difficulty taking a course can improve their understanding by providing opportunities to retake or review the course. In addition, students with excellent grades can be further developed by providing feedback on class content or activities that they can actively participate in.

The credits students receive on the subject are closely related to its difficulty, importance, and course trends. By analyzing this, the criteria for granting credit can be supplemented. The results of this study play a very important role in improving university curricula. The results of these studies can be used to improve the curriculum by identifying the achievement of students in each subject, the academic achievement of students, and the causes of success and failure in the curriculum; this can contribute to the further development of the university's educational program and the improvement of students' academic achievement.

REFERENCES

[1] Z. A. Pardos and W. Jiang, "Designing for serendipity in a university course recommendation system" in *Proc. Tenth International Conference on Learning Analytics & Knowledge*, pp. 350-359, 2020 doi: 10.1145/3375462.3375524.

[2] B. Mondal *et al.*, "A course recommendation system based on grades" in *international conference on* computer science*, engineering and* applications *(ICCSEA)*, IEEE, pp. 1-5 2020 doi: 10.1109/ICCSEA49143.2020.9132845.

[3] D. B. Guruge *et al.*, "The state of the art in methodologies of course recommender systems—A review of recent research," *Data*, vol. 6, no. 2, p. 18, 2021, doi: 10.3390/data6020018.

[4] N. W. Rahayu *et al.*, "'A systematic review of ontology use in E-Learning recommender system,' *Computers and Education*," *Artif. Intell.*, p. 100047, 2022.

[5] B. T. M. Wong, "Learning analytics in higher education: An analysis of case studies," *Asian Assoc. Open Universities J.*, vol. 12, no. 1, 21–40, 2017, doi: 10.1108/AAOUJ-01-2017-0009.

[6] S. Dhelim, et al., "A survey on personality-aware recommendation systems," *Artif. Intell. Rev.*, vol. 55, no. 3, pp. 2409–2454, 2022, doi: 10.1007/s10462-021-10063-7.

[7] W. Xiao *et al.*, "A survey on educational data mining methods used for predicting students' performance," *Eng. Rep.*, vol. 4, no. 5, p. e12482, 2022, doi: 10.1002/eng2.12482.

[8] M. Hooda, et al., "Integrating LA and EDM for improving students Success in higher Education using FCN algorithm," *Math. Probl. Eng.*, vol. 1–12, 2022, doi: 10.1155/2022/7690103.

[9] E. Alyahyan and D. Düştegör, "Predicting academic success in higher education: Literature review and best practices," *Int. J. Educ. Technol. Higher Educ.,* vol. 17, pp. 1-21, 2020.

[10] R. Jayashanka *et al.*, "Technology enhanced learning analytics dashboard in higher education," *Electron. J. e-Learning*, vol. 20, no. 2, pp. pp151–pp170, 2022, doi: 10.34190/ejel.20.2.2189.

[11] D. Ifenthaler and J. Y.-K. Yau, "Analytics for supporting teaching success in higher education: A systematic review," *IEEE Global Engineering Education Conference (EDUCON)*. IEEE, 2022, doi: 10.1109/EDUCON52537.2022.9766734.

[12] M. Yağcı, "Educational data mining: Prediction of students' academic performance using machine learning algorithms," *Smart Learn. Environ.*, vol. 9, no. 1, p. 11, 2022, doi: 10.1186/s40561-022-00192-z.

[13] B. Dietz-Uhler and J. E. Hurn, "Using learning analytics to predict (and improve) student success: A faculty perspective," *J. Interact. Online Learn.*, vol. 12, no. 1, pp. 17-26, 2013.

[14] H. Karbasian and A. Johri, "Insights for curriculum development: Identifying emerging data science topics through analysis of Q&A communities" in *Proc. 51st ACM Technical Symposium on Computer Science Education*, pp. 192–198, 2020, doi: 10.1145/3328778.3366817.

[15] Y.-E. Park, "A data-driven approach for discovery of the latest research trends in higher education for business by leveraging advanced technology and big data," *J. Educ. Bus.*, vol. 96, no. 5, pp. 291-298, 2021, doi: 10.1080/08832323.2020.1821344.

[16] R. F. Kizilcec and D. Davis, "Learning Analytics Education: A case study, review of current programs, and recommendations for instructors" in *Practicable Learning Analytics*. Cham: Springer International Publishing, pp. 133-154, 2023, doi: 10.1007/978-3-031-27646-0_8.

[17] R. D. De Veaux, et al., "Curriculum guidelines for undergraduate programs in data science," *Annu. Rev. Stat. Its Appl.*, vol. 4, no. 1, pp. 15-30, 2017, doi: 10.1146/annurev-statistics-060116-053930.

[18] C. Fischer, et al., "Mining big data in education: Affordances and challenges," *Rev. Res. Educ.*, vol. 44, no. 1, pp. 130-160, 2020, doi: 10.3102/0091732X20903304.

[19] M. Buker and G. Niklason, "Curriculum evaluation & improvement model," *J. Health Admin. Educ.*, vol. 36, no. 1, p. 37, 2019.

[20] Y. Yamamoto, et al., "Increasing the sensitivity of a personalized educational data mining method for curriculum composition" in *Emerging Issues in Smart Learning*. Berlin Heidelberg: Springer, 201–208, 2015, doi: 10.1007/978-3-662-44188-6_28.

[21] Y. Huang and J. Zhu, "A personalized English learning material recommendation system based on knowledge graph," *Int. J. Emerg. Technol. Learn.*, vol. 16, no. 11, p. 160, 2021, doi: 10.3991/ijet.v16i11.23317.

[22] M. A. Pilotti, O. J. El-Moussa, & H. M. Abdelsalam, "Measuring the impact of the pandemic on female and male students' learning in a society in transition: A must for sustainable education," *Sustainability*, vol. 14, no. p. 3148, 2022, doi: 10.3390/su14063148.

[23] A. P. Trassi, S. J. Leonard, L. D. Rodrigues, J. A. Rodas, & F. H. Santos, "Mediating factors of statistics anxiety in university students: a systematic review and meta-analysis," *Annals of the New York Academy of Sciences*, vol. 1512, no. 1, pp. 76-97, 2022, doi: 10.1111/nyas.14746.

[24] J. Zhang, B. Hao, B. Chen, C. Li, H. Chen, & J. Sun, "Hierarchical reinforcement learning for course recommendation in MOOCs," In Proceedings of the AAAI conference on artificial intelligence, vol. 33, no. 01, pp. 435-442, 2019, doi: 10.1609/aaai.v33i01.3301435.

[25] P. Fidalgo, J. Thormann, O. Kulyk, & J. A. Lencastre, "Students' perceptions on distance education: A multinational study," *International journal of educational Technology in Higher Education*, vol. 17, no. 1, pp. 1-18, 2020, doi: 10.1186/s41239-020-00194-2.

[26] H. Zeineddine, U. Braendle, & A. Farah, "Enhancing prediction of student success: Automated machine learning approach," *Computers & Electrical Engineering*, vol. 89, p. 106903, 2021, doi: 10.1016/j.compeleceng.2020.106903.

[27] F. Han, & R. A. Ellis, "Identifying consistent patterns of quality learning discussions in blended learning," *The Internet and Higher Education*, vol. 40, pp. 12-19, 2019, doi: 10.1016/j.iheduc.2018.09.002.

[28] R. Murphy, & G. Wyness, "Minority Report: the impact of predicted grades on university admissions of disadvantaged groups," *Education Economics*, vol. 28, no. 4, pp. 333-350, 2020, doi: 10.1080/09645292.2020.1761945.

[29] J. Neroni, C. Meijs, H. J. Gijselaers, P. A. Kirschner, & R. H. de Groot, "Learning strategies and academic performance in distance education," *Learning and Individual Differences*, vol. 73, pp. 1-7, 2019, doi: 10.1016/j.lindif.2019.04.007.

[30] J. L. Rastrollo-Guerrero, J. A. Gómez-Pulido, & A. Durán-Domínguez, "Analyzing and predicting students' performance by means of machine learning: A review," *Applied sciences*, vol. 10, no. 3, p. 1042, 2020, doi: 10.3390/app10031042.

[31] K. M. Jones, "Learning analytics and higher education: a proposed model for establishing informed consent mechanisms to promote student privacy and autonomy," *International Journal of Educational Technology in Higher Education*, vol. 16, no. 1, pp. 1-22, 2019, doi: 10.1186/s41239-019-0155-0.

[32] Y. Lee, & J. Cho, "Crosstabs Analysis of ICT lecture for Welfare-Technology Course Recommendation," *International Information Institute (Tokyo). Information*, vol 20, no. 2B), p. 1115, 2017.