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Detecting Outliers from Quiz Response Times and Scores by Classifying Weekly Learning Patterns in a Blended Learning Course

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Abstract

Learning management systems are now widely used in many classes, and learning logs are accumulated daily, making it increasingly important to mine knowledge and data for learning analytics. In this study, a new experimental class was conducted to collect and analyze Moodle learning logs in a blended learning course in which 57 university students had pre-enrolled. Weekly learning analytics were conducted focusing on quiz answer times and scores. Furthermore, the clustering heatmaps were generated to visualize the transition of learning status. Outliers were identified using the interquartile range, 3σ method, and Mahalanobis' generalized distance. The experimental results observed that there were weeks when outlier learners appeared, whereas in other weeks, they did not. Although the majority of learners did not fall under the outlier category, it became clear that some learners were identified as outlier multiple times. Learners who repeatedly fall into the outlier category are at risk of encountering challenges in their learning, so early academic intervention is desirable. Clustering heatmaps and outlier visualizations, which depict learning status, are influenced by attendees' learning motivation and prerequisite knowledge, resulting in varying outcomes across different classes. By performing outlier detection according to this paper every week, teachers can easily discover learners who are having trouble learning.

Keywords: classification, learning analytics, learning log, learning management system, outlier,

1 Introduction

Learning management systems (LMSs) have been utilized in many classes to date, and educational institutions that use LMS have accumulated a huge amount of learning logs [1]. Learning logs keep a record of the individual learning behavior of learners, making them valuable data for analyzing the effectiveness of classes. Through an LMS, teachers can obtain various data about the learners in their classes. This is also expected to increase learners' motivation because they can immediately check quiz results. Leveraging LMS and learning logs is essential for improving educational outcomes for both teachers and learners [2].

Even before LMS was developed, many researchers advocated the necessity of learning analytics. However, the current LMS lacks sufficient functionalities to analyze and display learning logs. Some research is using database to compensate for this deficiency [3]. Moreover, there are often

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intricate relationships between items in the learning log, such as those between teaching materials clicks and quiz scores or between quiz response times and scores. The authors use Moodle LMS for the weekly classes and learning analysis. Currently, the main statistical analysis is a simple aggregation of each learning log and lacks the capability for multivariate analysis to examine relationships between log items. Hence, there is ongoing research and development of dashboards aimed at improving the analysis and display functionalities of LMS learning logs and visualizing analysis results in a more user-friendly manner [4].

On the other hand, the motivation levels of learners who participate in classes vary, and there may be participants who do not fully engage, such as those who do not read the teaching materials, those with low test scores, and those who engage in rapid guessing [5]. However, merely aggregating items in the learning log is insufficient to detect the causes of insufficient efforts; it is necessary to appropriately correlate multiple pieces of data and perform analysis. Furthermore, outliers may appear in learning log data in various forms, indicating abnormal learning behavior. Nonetheless, the current LMS lacks sufficient functionality for robust statistical analysis or outlier detection. Therefore, the research question for this paper was formulated as follows:

RQ: What method should be used to classify learning patterns from learning logs collected by LMS and extract outliers?

This paper discusses the methods and results of classifying learning patterns and extracting outliers using Moodle learning logs from an experimental class recently conducted at a university. Moreover, learners who require early intervention can be identified from the analysis results of learning logs, revealing a robust relationship between inappropriate learning behavior and the occurrence of outliers. Furthermore, based on the results of the new experimental class, it can be stated that this method is effective for supporting classes.

2 Related Research

LMSs are equipped with various management functions for conducting online classes. These include publishing teaching materials, tracking learner attendance, submitting reports, responding to quizzes and surveys, and supporting communication through chat and bulletin boards, which are used in numerous classes [6]. Research on outliers in the field of education aims to understand the characteristics of outliers at an early stage and examine their effects on learning. The purpose is to prevent outlier learners from dropping out [7] and is being investigated in massive open online courses (MOOCs), which utilize the Internet, in addition to regular classroom lessons [8].

The LMS in MOOCs also accumulates a huge amount of learning logs. Research has utilized machine learning or hybrid methods to take apart the behavior of dropout students and identify those with insufficient engagement at an early stage [9]. Moreover, the purpose of outlier extraction in the education sector should be tailored to align with the organization's research and educational goals, as well as the type and content of the collected learning logs.

Furthermore, research on learning pattern analysis in the education field is closely aligned with outlier research. Learners who repeatedly engage in inefficient and inappropriate learning behaviors are detected as early as possible, and they are guided back to appropriate learning behaviors to maintain normal class functioning. [10]. Commonly employed methods to find various characteristics of learning patterns include utilizing questionnaires about the psychological state of learners and performing factor analysis [11].

On the other hand, research has been conducted to collect quiz response times using computer-based testing (CBT) and LMS and set thresholds to analyze abnormal test responding behavior among learners [12]. The behavior of test takers who read very few questions and answer them in a very short time is often called rapid guessing. Data on examinees who were not sufficiently motivated to take the test were identified and used to adjust the analysis of test scores [13]. Test takers in a state of rapid guessing often fail to read the questions thoroughly and answer the questions in a very short time. Consequently, their learning status and knowledge may not be accurately reflected in the test results. Scores become abnormally negatively skewed, reducing the overall reliability and credibility of the test. Some argue that quick guessing should not be included in the assessment because it would negatively impact the measurement of the test [14].

The research by Wise and Kong (2005) on the effort of response time assumed that discouraged examinees tend to finish test responses very quickly. They attempted to measure the time each learner took to answer questions and differentiate between test takers who engaged with the questions and responded within an appropriate timeframe and those who lacked motivation and answered in an extremely short time [15]. The cumulative proportion method (CUMP) involves collecting test response times and item response accuracy times [16]. It calculates different thresholds for each item based on the cumulative accuracy rate [17]. This makes it possible to classify rapid guessing more appropriately and can be used when conducting tests with many learners.

3 Method

3.1 Setup of the Experimental Class to Accumulate Learner Logs

In this research, the subject of analysis was a class called "Introduction to Social Data Analysis." This class is an introductory data science course at Aichi University, a four-year university in Japan and is offered once every six months in the spring and fall semesters. It is a regular course with two credits for undergraduate students. Initially, 57 students enrolled in the class, with 47 learners participating in the final test. The average weekly participation rate was 49.8 learners. The gender ratio of learners was 36.8% female and 63.2% male, with the majority aged between 18 and 22 years old. Learners were selected through a random lottery from a large pool of applicants. A new experimental class was held for use in the analysis of this paper, and learning logs were collected over 108 days from September 20, 2023 to January 19, 2024.

The experimental classes in this paper utilized online teaching materials on Moodle created as PDF files, and blended learning courses are held in the computer classroom every year. Various statistical data published on the Internet by Japanese national institutions were used during classes, and students learned the basics of statistics using Excel. The main contents of this course are (1) Excel operations, (2) graph creation, (3) functions, (4) basics of probability, (5) dice simulation, (6) frequency distribution, (7) histograms, (8) deviation/variance/standard deviation, (9) normal distribution, (10) cross-tabulation, (11) attribute correlation, (12) covariance, (13) correlation, and (14) regression analysis. These lessons were spread over 15 weeks.

The teaching materials in the PDF files had 14 chapters, 94 sections, and a total of 190 pages.

The average number of pages per chapter was 13.57, with an average of 6.71 sections per chapter and an average of 2.02 pages per section. Additionally, a multiple-choice fill-in-the-blank quiz was conducted based on explanatory passages from the teaching materials. There was an average of 10.7 questions per chapter, resulting in a total of 139 quizzes. To check the learners' prerequisite knowledge, a pretest consisting of 30 questions was conducted during the first class, with a time limit of 30 minutes. Following the study of each chapter every week, a five-minute, five-question quiz was conducted at the beginning of the subsequent week's class, repeated 13 times. Additionally, during the last class, a final test was conducted, comprising 30 questions to be completed within 30 minutes. Moodle creates logs such as quiz clicks, response time, score, and analysis results based on item response theory, which was used for the analysis in this paper.

3.2 Investigating Dataset Normality and Correlation

In this paper, Moodle learning logs were reorganized into 18 datasets to analyze weekly lessons. These were datasets for the pretest, weekly chapter quiz (14 times), final test, chapter subtotals, and totals. These datasets included data on quiz response times and scores, resulting in a total of 54 datasets for analysis.

Generally, in the case of one variable, the classification of collected numerical data is affected by the distribution state of the data. However, in the case of multivariate variables, the classification is affected by both the distribution state of the data and the correlation between items. Moreover, the extraction of outliers and classification of learning patterns are similarly affected. Therefore, various approaches have been proposed to reflect the form of the accumulated data, and each method has its own characteristics.

In this study, as a preprocessing step to classify learning patterns and detect outliers, we assessed the normality of quiz response times, scores using the Shapiro–Wilk test [18]. Table 1 shows that 18 (33.3%) of the 54 datasets obtained during the class period were normally distributed. This breakdown comprised 4 for quiz response times, and 2 for quiz scores. Other than these, no normal distribution was found (Table 1).

Table 1: Shapiro–Wilk normality test results.

		Pretest	Chap1	Chap2	Chap3	Chap4	Chap5	Chap6	Chap7	Chap8	Chap9	Chap10	Chap11	Chap12	Chap13	Chap14	Subtotal	Final	Total
Time	statistic	0.956	0.920	0.972	0.957	0.878	0.854	0.907	0.886	0.941	0.897	0.884	0.852	0.843	0.897	0.815	0.988	0.766	0.873
	p-value	0.063	0.002	0.348	0.061	0.000	0.000	0.002	0.000	0.022	0.001	0.000	0.000	0.000	0.001	0.000	0.855	0.000	0.000
	N	49	51	45	52	45	44	42	45	46	46	44	46	43	42	46	56	46	56
Score	statistic	0.965	0.865	0.806	0.874	0.856	0.911	0.818	0.863	0.901	0.891	0.882	0.921	0.897	0.909	0.831	0.913	0.970	0.914
	p-value	0.151	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.001	0.000	0.000	0.004	0.001	0.003	0.000	0.001	0.286	0.001
	N	50	51	45	52	45	44	42	45	46	46	44	46	43	42	46	56	46	56

In Table 2, in the case of analysis that combined two datasets, a correlation test was also performed. Because a greater part of the quiz response times and scores discussed in this paper were not normally distributed, Spearman's rank method was applied to examine the correlation between these two datasets. Consequently, positive correlations were found in 4 (16%) out of the 18 datasets, with no correlations found in the others. Additionally, a correlation between material clicks and quiz scores was investigated. Out of 18 datasets, correlations were observed in 6 (33.3%) of them, whereas no correlation was observed in the remainder.

Table 2: Testing the correlation coefficient between weekly quiz response times and scores.

	Pretest	Chap1	Chap2	Chap3	Chap4	Chap5	Chap6	Chap7	Chap8	Chap9	Chap10	Chap11	Chap12	Chap13	Chap14	Subtotal	Final	Total
Rs	-0.215	-0.032	0.061	-0.003	0.116	-0.008	0.233	-0.031	0.366	0.359	-0.086	0.085	-0.091	0.125	-0.182	0.778	0.142	0.722
Sample	50	52	45	53	46	44	42	46	47	47	45	46	44	43	47	57	47	57
T-value	1.523	0.229	0.404	0.019	0.775	1.915	1.513	0.209	2.639	2.583	0.565	0.568	0.591	0.807	1.240	9.171	0.960	7.733
DOF	48	50	43	51	44	42	40	44	45	45	43	44	42	41	45	55	45	55
P-Value	0.134	0.820	0.688	0.985	0.443	0.960	0.138	0.836	0.011	0.013	0.575	0.573	0.557	0.212	0.111	0.000	0.185	0.000
	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p<0.05$	$p<0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p>0.05$	$p<0.05$	$p>0.05$	$p<0.05$

Regarding the correlation between weekly quiz response times and scores, often there was no correlation, and in cases where a correlation existed, it tended to be weak (Chaps. 8 and 9). However, a strong positive correlation was observed between Subtotal and Total. Subtotal is the sum of Chaps. 1 to 14, and Total is the sum of Subtotal, Pretest, and Final. Subsequently, based on the aforementioned analysis results, the classification of learning patterns and outlier detection methods utilized in this paper were examined for the case of one and two variables.

3.3 Learning Log Classification and Outlier Detection Method

The main purpose of detecting outliers in quiz response times and scores is to identify data points that deviate significantly from the average. Traditional statistical techniques such as the standard normal distribution and the quartile method are commonly used for outlier extraction or data classification. Moreover, methods such as hierarchical clustering [19] and k-means [20] in the field of machine learning have been applied in recent years.

Conventional methods for extracting outliers include the 3σ method and the interquartile range (IQR), but various methods have been devised depending on the data distribution and number of variables. For clustering and outlier extraction with a single variable, both the quadrant method and 3σ method are used. The quartile point uses the median, whereas the 3σ method uses the mean. This allows quiz scores to be scattered around the median or mean value. Consequently, it becomes easier to create a scatter diagram to identify outliers and visually comprehend the relationships between learner data.

Table 3: Interquartile range and clustering heatmap cell definitions.

Range	Definition	Label for heatmap sell
$Q2 < x \leqq Q3$	high-normal	+ normal
$Q3 < x \leqq Q3 + 1.5IQR$	high-value	+ high
$x > Q3 + 1.5IQR$	high-outlier	+ outlier
$Q2 \geqq x > Q1$	low-normal	− normal
$Q1 > x \geqq Q1 - 1.5IQR$	low-value	− low
$x < Q1 - 1.5IQR$	low-outlier	− outlier

When detecting outliers using the 3σ method, x is determined such that x > 3σ, and 0.3% of the data corresponds to the characteristics of a normal distribution. On the other hand, in the quartile point, the first quartile is Q1, the third quartile is Q3, and IQR = Q3 - Q1. Additionally, Q1 -

Table 4: Interquartile range and clustering heatmap cell definitions.

A	B	C	D	E	F	G	H	I	J	K	L
	Chapter 1		Z-score		Taxonomy by IQR		Euclidean	Group	IQR	Mahalanobis	3σ
Student	Time	Score	Time	Score	Time	Score			Outlier	x>0.95	x>σ*3
Student01	186	6	-0.492	-0.706	-normal	-low	0.860	G3			
Student02	115	8	-1.641	0.314	-low	-normal	1.671	G2			
Student03	276	6	0.965	-0.706	+high	-low	1.195	G4			
Student04	292	8	1.224	0.314	+high	-normal	1.263	G1			
Student05	-	-	-	-	-	-	-	-	-	–	-
Student06	254	6	0.609	-0.706	+normal	-low	0.932	G4			
Student07	168	10	-0.784	1.333	-normal	+high	1.546	G2			
Student08	-	-	-	-	-	-	-	-	-	–	-
Student09	272	8	0.900	0.314	+high	-normal	0.953	G1			
Student10	233	8	0.269	0.314	-normal	-normal	0.413	G1			
Student11	140	10	-1.237	1.333	-low	+high	1.818	G2			outlier
Student12	-	-	-	-	-	-	-	-	-	–	-
Student13	-	-	-	-	-	-	-	-	-	–	-
Student14	251	8	0.560	0.314	+normal	-normal	0.642	G1			
Student15	246	10	0.479	1.333	+normal	+high	1.417	G1			
Student16	168	8	-0.784	0.314	-normal	-normal	0.844	G2			
Student17	147	6	-1.123	-0.706	-low	-low	1.327	G3			
Student18	272	2	0.900	-2.745	+high	-outlier	2.888	G4out	+outlier		outlier
Student19	157	8	-0.962	0.314	-low	-normal	1.011	G2			
Student20	133	8	-1.350	0.314	-low	-normal	1.386	G2			
Student21	205	10	-0.185	1.333	-normal	+high	1.346	G2			
Student22	76	8	-2.273	0.314	-low	-normal	2.294	G2			outlier
Student23	144	10	-1.172	1.333	-low	+high	1.775	G2			outlier
Student24	223	6	0.107	-0.706	-normal	-low	0.714	G4			
Student25	292	6	1.224	-0.706	+high	-low	1.413	G4			
Student26	285	6	1.110	-0.706	+high	-low	1.316	G4			
Student27	-	-	-	-	-	-	-	-	-	–	-
Student28	117	2	-1.609	-2.745	-low	-outlier	3.181	G3out	+outlier	outlier	outlier
Student29	288	4	1.159	-1.725	+high	-low	2.078	G4			outlier
Student30	258	8	0.673	0.314	+normal	-normal	0.743	G1			
Student31	171	8	-0.735	0.314	-normal	-normal	0.799	G2			
Student32	262	8	0.738	0.314	+normal	-normal	0.802	G1			
Student33	251	10	0.560	1.333	+normal	+high	1.446	G1			
Student34	254	6	0.609	-0.706	+normal	-low	0.932	G4			
Student35	258	8	0.673	0.314	+normal	-normal	0.743	G1			
Student36	249	10	0.528	1.333	+normal	+high	1.434	G1			
Student37	156	8	-0.978	0.314	-low	-normal	1.027	G2			
Student38	203	6	-0.217	-0.706	-normal	-low	0.738	G3			
Student39	295	6	1.272	-0.706	+high	-low	1.455	G4			
Student40	284	8	1.094	0.314	+high	-normal	1.138	G1			
Student41	254	8	0.609	0.314	+normal	-normal	0.685	G1			
Student42	274	6	0.932	-0.706	+high	-low	1.169	G4			
Student43	226	4	0.155	-1.725	-normal	-low	1.732	G4			outlier
Student44	262	10	0.738	1.333	+normal	+high	1.524	G1			
Student45	177	10	-0.638	1.333	-normal	+high	1.478	G2			
Student46	150	8	-1.075	0.314	-low	-normal	1.120	G2			
Student47	174	4	-0.686	-1.725	-normal	-low	1.857	G3			outlier
Student48	134	6	-1.334	-0.706	-low	-low	1.509	G3			
Student49	166	8	-0.816	0.314	-low	-normal	0.874	G2			
Student50	260	8	0.706	0.314	+normal	-normal	0.772	G1			
Student51	300	10	1.353	1.333	+high	+high	1.900	G1			outlier
Student52	191	8	-0.411	0.314	-normal	-normal	0.517	G2			
Student53	189	6	-0.444	-0.706	-normal	-low	0.834	G3			
Student54	244	8	0.447	0.314	+normal	-normal	0.546	G1			
Student55	290	8	1.191	0.314	+high	-normal	1.232	G1			
Student56	291	6	1.207	-0.706	+high	-low	1.399	G4			
Student57	90	8	-2.046	0.314	-low	-normal	2.070	G2			outlier
Average	216.4	7.4	0.0	0.0					2	1	10
Stdev	61.8	2.0	1.0	1.0							

1.5IQR indicates the lower limit value, and Q3 + 1.5IQR denotes the upper limit value. Hence, outliers identified using the quadrant method satisfy x > Q1 + 1.5IQR and x < Q1 - 1.5IQR.

Furthermore, a relationship exists between the interquartile range and ±3σ, as -3σ < Q1 -1.5IQR < -2σ and 3σ > Q3 + 1.5IQR > 2σ. The difference between these values is approximately ±0.3σ. Given this difference in values, 0.8% of the data corresponds to outliers within the interquartile range. Based on the discussion so far, the criteria for extracting and classifying outliers from the learning log using interquartile ranges are shown in Table 3. Additionally, Table 4 shows an example of classifying quiz response time data based on the criteria in Table 3.

4 Results

4.1 Dataset

In this paper, the learning log required for extracting outliers and classifying learning patterns was downloaded as an Excel file from Moodle. Table 4 shows the quiz response times and scores from the first class (Chap. 1), aggregated for each learner, along with the z-scores used to identify outliers. Given the non-normal distribution often observed in quiz response times and scores, the IQR method was used to detect outliers. The results of Mahalanobis' generalized distance (MGD) and the 3σ method are shown for discussion. Hyphens in blank cells within Columns B to I of Table 4 denote learner absence, and Columns J to L indicate the outlier determination results. The main processing method and its significance for the data shown in Table 1 are indicated in Table 5.

Table 5: Main processing method and meaning for the data shown in Table 4.

Column name	Processing method and meaning
Column A	Anonymized learner IDs.
Column B	The time data of Chap. 1 and the quiz response time in seconds.
Column C	The quiz scores for Chap. 1 with a mean of 7.4 and a standard deviation of 2.0.
Column D & E	Z-scores were calculated from times and scores.
Column F & G	Taxonomy by IQR: "Time" and "Score" show the pattern classification of quiz response times and scores, respectively.
Column H	The distance from the origin using Euclidian's z-score. The maximum value was 3.181, and the minimum value was 0.413.
Column I	The corresponding patterns from G1 to G4 regarding the classification of learning patterns for each z-score of times and scores.
Column J	IQR shows the detection results of outliers. In Column J of Table 4, there were two outliers: Students 18 and 28 (outlier > 2.520).
Column K	"Mahala" shows the detection results of outliers, obtained by MGD from the origin. The CHISQ.DIST function in Excel was used, and column values where H2 > 95% were considered outliers. In Table 4, only Student 28 was applicable.
Column L	The outlier detection results using the 3σ method. Column values where H2 > 3σ were defined as outliers. In Table 4, Students 11, 18, 22, 23, 28, 29, 43, 47, 51, and 57 were outliers (outlier > 1.696).

4.2 Outlier Detection and Cluster Analysis for Quiz Response Time

Figure 1 uses the quiz response time data in Column F of Table 4 to generate a cluster heatmap of 18 datasets from the pretest of the first class to the final test of the last class. In Figure 1, the data were initially sorted so that the data "+ high" for learners with a large value of quiz response time are placed at the upper part of the map. Subsequently, a second sorting was done so that the data "-outlier" with a small value of quiz response time is displayed at the lower part of the figure. A total of 13 pink cells (11 registrants, 19.2%) corresponded to the outlier "-outlier," which means that the quiz response time was extremely short. Of these, two learners were identified as outliers twice (Students 05, 53), and 9 learners were outliers only once (Students 02, 11, 12, 13, 15, 27, 38, 43, 54).

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	S	T	U
Student	Pretest	Chapter1	Chapter2	Chapter3	Chapter4	Chapter5	Chapter6	Chapter7	Chapter8	Chapter9	Chapter10	Chapter11	Chapter12	Chapter13	Chapter14	Subtotal	Final test	Total	Outlier
Student18	+normal	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	0
Student03	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	-	+high	+high	+high	+high	0
Student04	+normal	+high	+high	+high	+normal	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	+high	-normal	+high	0
Student21	+high	-normal	+high	+high	+high	+high	+normal	+normal	+normal	+high	+high	+high	+high	+high	+high	+high	+high	+high	0
Student09	+high	+high	-normal	+normal	+high	+high	+normal	+high	+high	+normal	+normal	+normal	+high	+high	+high	+high	+high	+high	0
Student39	+high	+high	+high	+high	+high	+high	+normal	+high	+high	-normal	+normal	+high	+normal	+normal	+normal	+high	-normal	+high	0
Student42	+normal	+high	+high	+high	+high	+normal	+high	+normal	+normal	+normal	+normal	+high	+high	-normal	+high	+high	+normal	+high	0
Student44	-low	+normal	+normal	+normal	+high	+high	+high	+normal	+normal	+high	+high	+high	+high	+high	+high	+high	-normal	+normal	0
Student55	+high	+high	+normal	+high	+high	+normal	+high	+normal	+normal	+high	+normal	+normal	-low	+normal	+high	+high	+normal	+high	0
Student35	+high	+normal	+high	+normal	+high	+high	+high	+normal	+normal	-	+normal	+normal	-normal	+high	+normal	+high	+high	+high	0
Student30	+high	+normal	+normal	+high	+normal	+high	+high	+high	+high	-normal	+high	-normal	-	+normal	-normal	+normal	+normal	+high	0
Student40	+high	+high	+high	+normal	-low	+normal	-low	-	-	+high	-normal	+high	+normal	+normal	+high	+normal	+high	+high	0
Student36	-normal	+normal	+normal	+high	+normal	-normal	-normal	+normal	+normal	+high	-normal	+high	+high	+normal	+normal	+high	+high	+high	0
Student51	-normal	+high	-normal	+high	+normal	+normal	+normal	-normal	-normal	+high	+normal	-normal	+normal	+normal	+high	+high	+normal	+high	0
Student06	-low	+normal	-normal	-normal	+normal	+high	-	+normal	+normal	-normal	+high	+normal	+normal	+high	-low	+normal	+high	+normal	0
Student10	+normal	-normal	+normal	+normal	+high	+normal	+normal	-	-	+high	+high	-normal	+normal	+high	-normal	+normal	-normal	+normal	0
Student50	+normal	+normal	+high	-normal	-normal	+normal	+high	-low	-low	+normal	-normal	+normal	+normal	-normal	-low	+high	-normal	+high	0
Student14	+normal	+normal	-	+normal	-normal	+high	+high	+normal	+normal	+normal	-	+high	-	-normal	-normal	-normal	+normal	+normal	0
Student26	-	+high	+normal	+normal	-normal	-normal	+normal	+normal	+normal	+high	+normal	-normal	+normal	+normal	-normal	+high	-normal	-normal	0
Student29	-normal	+high	+high	+high	+normal	+normal	-low	+normal	+normal	-normal	-low	-low	-normal	-low	-normal	+normal	+normal	+normal	0
Student33	+normal	+normal	-	+high	-	+normal	+normal	-	-	-	+high	+normal	+normal	-	+high	-normal	+normal	-normal	0
Student56	+high	+high	+normal	+normal	+high	-normal	-	-low	-low	-low	-low	-normal	-normal	-normal	+normal	+normal	+normal	+normal	0
Student25	+high	+high	+normal	-normal	-low	-	-normal	+normal	+normal	-low	-low	-low	-normal	-low	+high	+normal	-low	+normal	0
Student20	-	-low	+normal	-normal	+high	-	-	-	-	-	-	+high	+high	+normal	+normal	-low	+normal	-low	0
Student17	-normal	-low	-low	-normal	-normal	-low	-low	+high	+high	-normal	+high	-normal	-	-normal	+normal	+normal	-normal	+normal	0
Student37	-normal	-low	-low	+high	-normal	-low	-low	+high	+high	-normal	-normal	+normal	-normal	-low	-low	+normal	-normal	-normal	0
Student32	-normal	+normal	-low	-low	+normal	+normal	+normal	+high	+high	+normal	-normal	-normal	+normal	-normal	+normal	+normal	-normal	+normal	0
Student07	-normal	-normal	-normal	-normal	+normal	-normal	-low	-normal	-normal	+normal	+normal	-low	-low	-normal	-normal	+normal	+high	+normal	0
Student34	+high	+normal	-normal	-normal	+normal	-low	-normal	-normal	-normal	-normal	+normal	-normal	-low	-normal	-low	+normal	-low	+normal	0
Student41	-	+normal	-low	+normal	-low	-	+normal	-low	-low	-low	-normal	+normal	-low	+high	-low	-normal	-low	-low	0
Student28	-	-low	+high	-	-normal	-low	-	-low	-low	-low	-normal	+normal	+normal	-	-	-low	-	-low	0
Student48	+high	-low	-low	-normal	+normal	-low	-low	-low	-low	-low	-low	-low	-normal	-normal	-normal	-normal	-low	+normal	0
Student22	-low	-low	-low	+normal	-low	-low	-	-low	-low	-low	-normal	-normal	-low	-low	-low	-normal	+high	-normal	0
Student45	-low	-normal	-normal	-low	-	-normal	-normal	-normal	-normal	+normal	-normal	-low	-normal	-normal	-normal	-normal	+high	-normal	0
Student52	+high	-normal	-low	-low	-normal	-	-	-	-	-	-	-	-	-	-	-low	-	-low	0
Student57	-low	-low	-	-low	-low	-low	+high	-low	-low	-	-low	-low	-low	-low	-low	-low	-normal	-normal	0
Student31	+normal	-normal	-	-normal	+normal	-normal	-normal	-low	-low	+normal	-low	+normal	-normal	-normal	+normal	+normal	-low	+normal	0
Student16	+normal	-normal	-normal	+normal	-normal	-low	-low	+normal	+normal	-low	-low	-normal	-	-low	-normal	-normal	-normal	-normal	0
Student49	+normal	-low	-normal	+normal	-	-normal	-normal	-	-	-normal	-low	-	-normal	-	+normal	-low	+normal	-normal	0
Student19	-	-low	-normal	-low	-normal	-	-normal	+normal	+normal	+normal	-normal	-	-low	-low	-	-normal	-	-low	0
Student46	-low	-low	-low	+normal	-	-normal	-normal	-normal	-normal	-normal	-	-normal	-low	-low	-normal	-normal	+normal	-normal	0
Student01	-low	-normal	-	-low	-low	-	-low	-low	-low	-normal	-normal	-low	-low	-low	-low	-normal	-low	-normal	0
Student08	-low	-	-low	-normal	-	-	-	-	-	-	-	-	-	-	-	-low	-	-low	0
Student23	-normal	-low	-	-low	-	-	-normal	-low	-low	-low	-low	-	-	-low	-low	-low	-low	-low	0
Student24	-low	-normal	-low	-low	-low	-low	-normal	-normal	-normal	-low	-	-low	-low	-low	-low	-normal	-normal	-normal	0
Student47	-low	-normal	-low	-low	-	-	-	-	-	-	-	-	-	-	-	-low	-	-low	0
Student54	-normal	+normal	+normal	-low	-low	+normal	+normal	+normal	+normal	+high	+high	+high	+high	+high	+normal	+normal	-outlier	+normal	1
Student15	-low	+normal	-	-normal	-low	-normal	-low	-normal	-normal	-low	-low	-normal	-normal	+high	+normal	-normal	-outlier	-normal	1
Student12	-	-	-normal	-low	-	-low	-	-normal	-normal	-normal	-low	-low	-normal	-	-outlier	-low	+high	-low	1
Student11	-normal	-low	-low	-low	-normal	-normal	-normal	-normal	-normal	+normal	+normal	+normal	-	-	-normal	-normal	-outlier	-normal	1
Student43	-normal	-normal	-normal	-normal	-	-low	-outlier	-normal	-normal	-low	+normal	-low	+normal	+normal	-normal	-normal	-low	-normal	1
Student13	+normal	-	-	-low	-normal	-	-outlier	-low	-low	+normal	-	-	-	-	-	-low	-	-low	1
Student27	-low	-	-	-low	-low	+normal	-	-low	-low	-normal	-	-outlier	-low	-	-	-low	-	-low	1
Student38	+normal	-normal	-	-	-	-	-	-	-	-	-	-	-	-	-	-outlier	-	-low	1
Student02	-normal	-low	-	-	-low	-	-	-	-	-	-	-	-	-	-	-outlier	-	-low	1
Student53	-low	-normal	+normal	-low	-low	-normal	-	-normal	-normal	-low	-low	-outlier	-	+normal	-low	-low	-outlier	-low	2
Student05	-	-	-	-	-	-	-	-	-	-	-	-	+normal	-	-	-outlier	-	-outlier	2
Outlier	0	0	0	0	0	0	2	0	0	0	0	2	0	0	1	3	4	1	13

Figure 1: Quiz response time cluster heatmap (blanks indicate learner absence).

At the bottom of the right side of Figure 1, Students 05 and 53 are displayed as outliers in quiz response time, and each was an outlier twice. Student 05 was absent from most of the classes, attending only three times, and his/her quiz response time was "+ normal" once and an outlier twice. Student 53 was absent twice, but she/he met the positive normal value "+ normal" twice,

"-normal" four times, and "-low" eight times. Given that the average number of times "-low" was applicable was 3.68, and the maximum number of "-low" was 13, Student 53 was found to apply to "-low" more often.

In addition, in Column P (Final test) in Figure 1, there are white cells with hyphens, indicating the learners who abandoned the final test at the end of the semester, totaling 10 learners (17.5%). Moreover, no outliers with extremely large quiz response times, "+ outlier," appeared in these results. This is because the upper limit of quiz response time was set at 300 seconds for Chap. 1 to 13, and 1800 seconds for the pretest and final test, respectively.

4.3 Outlier and Cluster Heatmap

To classify learning patterns using quiz response times and scores, we conducted a two-variable cluster analysis, treating quiz response time as an independent variable and quiz scores as a dependent variable. Initially, z-scores were computed for each variable, and a scatter plot was created [21]. In the scatter diagram, data were placed in one of four quadrants, from the first to the fourth quadrant based on the positive or negative sign of the numerical data. Subsequently, they were classified into four groups from G1 to G4, as shown in Table 6.

Table 6: Classification learning patterns and quadrant (quiz response times and scores).

Group	Condition	Quadrant	Cell color
G1	response time > 0 and score > 0	one	green
G2	response time < 0 and score > 0	two	blue
G3	response time < 0 and score < 0	three	pink
G4	response time > 0 and score < 0	four	yellow

Additionally, the Euclidean distances of the two variables from the origin were deter-mined at points on the scatter diagram, and outliers were identified using the IQR. When an outlier was found, characters such as "G1out" were added to the cell and displayed. The procedure for classifying learning patterns is outlined as follows:

Step 1: Download quiz response time and score data from Moodle. Step 2: Aggregate the data from Step 1 by student and week, and normalize the da-ta by z-score. Step 3: Classify the z-scores into six learning patterns using the IQR, and indicate labels such as "+normal" on the cells. Step 4: Classify cells using six colors, and create a weekly cluster heatmap. Step 5: Determine the groups G1 to G4 from the positive and negative signs of the z-scores. Step 6: Calculate the Euclidean distance from the z-scores, and detect outliers using the IQR method. Step 7: Display outliers in cells, and classify the cell colors into four colors. Step 8: Concatenate Pretest, Chap. 1 to 13, Subtotal, Final, and Total chronologically.

Figure 2 displays an example of a cluster heatmap representing learning patterns using two variables: quiz response times and scores. It has been redrawn by initially sorting the G1 group in descending order, followed by sorting the G3 group in ascending order. The upper part of Figure 2 lists the learners (Students 04, 21, 30, etc.) whose quiz response times and scores were both

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
Student	Pretest	Chap1	Chap2	Chap3	Chap4	Chap5	Chap6	Chap7	Chap8	Chap9	Chap10	Chap11	Chap12	Chap13	Chap14	Subtotal	Final	Total	Outlier
Student04	G1	G1	G1	G4	G1	G1	G1	G1	G1	G1	G4	G1	G1	G1	G1	G1	G1	G1	0
Student21	G1	G2	G1	G1	G1	G4	G1	G1	G4	G1	G1	G1	G1	G1	G1	G1	G4	G1	0
Student30	G1	G1	G4	G1	G1	G1	G1	G1	G1	G1	G1	G4	-	G1	G2	G1	G1	G1	0
Student35	G1	G1	G1	G4	G1	G1	G4	G4	G1	-	G1	G1	G1	G1	G1	G1	G1	G1	0
Student39	G1	G4	G1	G4	G1	G1	G1	G4	G1	G1	G1	G1	G1	G1	G1	G1	G2out	G1	1
Student09	G1	G1	G2	G1	G4	G1	G1	G1	G1	G1	G1	G1	G4	G4	G4	G1	G1	G1	0
Student32	G2	G1	G2	G2	G1	G4	G1	G1	G1	G1	G2	G1	G1	G1	G1	G1	G1	G1	0
Student51	G2	G1	G2	G4	G1	G1	G1	G4	G1	G1	G1	G2	G1	G1	G1	G1	G1	G1	0
Student18	G4	G4out	G4	G1	G1	G1	G1	G4	G1	G1	G1	G4	G1	G1	G4	G1	G4	G1	1
Student03	G4	G4	G1	G1	G1	G1	G4	G4	G1	G1	G1	G4	G4	-	G1	G1	G4	G1	0
Student36	G3	G1	G4	G4	G4	G1	G3	G4	G1	G1	G1	G1	G4	G4	G1	G1	G1	G1	0
Student44	G2	G1	G4	G4	G1	G4	G4	G1	G4	G1	G1	G4	G1	G1	G4	G1	G4	G1	0
Student50	G4	G1	G4	G4	G4	G1	G4	G2out	G1	G1	G1	G4	G1	G2	G2	G1	G1	G1	1
Student26	-	G4	G1	G1	G1out	G1	G4	G4	G1	G4	G4	G4	G4	G4	G2	G1	G1	G1	1
Student40	G4	G1	G4	G1	G2	G1	G3	-	G4	G1	G1	G4	G4	G4	G4out	G1	G1	G1	1
Student07	G2	G2	G3	G2	G4	G1	G3	G1	G1	G1	G4	G2	G2	G2	G2	G1	G1	G1	0
Student42	G4	G4	G1	G1	G4	G4	G4	G4	G1	G4	G4	G4	G1	G1	G4out	G1	G4	G1	1
Student10	G4	G1	G4	G1	G4	G1	G4	-	G4	G1	G4	G2	G4	G4	G2	G1	G4	G1	0
Student16	G1	G2	G3	G1	G2	G2out	G3	G1	G3	G3	G2	G2	-	G2out	G1out	G2	G1	G1	3
Student29	G2	G4	G4	G1	G1	G4	G2	G1	G4	G2	G2	G3	G4	G3	G3	G1	G1	G1	0
Student31	G4	G2	-	G3	G1	G2	G2	G3	G1	G4	G3	G1	G2	G4	G4	G1	G3	G1	0
Student41	-	G1	G3	G4	G2	-	G1	G3	G4	G3	G3	G1	G2	G1	G2out	G1	G2	G2	1
Student46	G2	G2	G2	G1	-	G1	G3	G2	G2	G1	-	G4	G2out	G3	G2	G2	G1	G1	1
Student55	G1	G1	G4	G4	G1	G4	G4	G4	-	G4	G4	G4	G3	G4	G1	G4	G4	G1	0
Student37	G2	G2	G2	G1	G1	G2	G3out	G4	-	G2	G4	G1	G3	G3	G2	G1	G2	G1	1
Student54	G3	G1	G4	G2	G2	G4	G4	G4	G2	G4	G1	G4	G4	G4	G1out	G1	G3out	G1	2
Student33	G4	G1	-	G4	-	G4	G4	-	G4	-	G4	G1	G1	-	G1	G3	G4	G4	0
Student45	G3	G2	G3	G3	-	G3	G3	G3	G3	G1	G2	G3	G3	G2	G2out	G1	G1	G1	1
Student48	G1	G3	G2	G3	G1	G3	G3	G2	G3	G3	G2	G3	G3	G3	G2	G1	G3	G1	0
Student56	G4	G4	G4	G1	G4	G3	-	G3	G1	G3	G3	G4	G4	G3	G4	G1	G4	G1	0
Student14	G4	G1	-	G4	G4	G1	G1	G4	G3	G1	-	G4	-	G3	G3out	G4	G4	G4	1
Student17	G3	G3	G3	G2	G3	G2	G2	G4	G3	G3	G4	G4	-	G3	G1	G1	G2	G1	0
Student20	-	G2	G4	G2	G1	-	-	-	-	-	-	G4	G4	G1	G1	G3	G4	G3	0
Student49	G4	G2	G3	G4	-	G4	G3	-	G2	G1	G2	-	G2	-	G1	G3	G4	G1	0
Student15	G2	G1	-	G2	G2	G3	G3	G3	G3	G3	G2	G4	G1	G4	G4	G1	G3out	G2	1
Student11	G2	G2	G3	G2	G4	G1	G3	G3	G4	G4	G1	G4	-	-	G4	G2	G2out	G2	1
Student19	-	G2	G3	G2	G1	-	G3	G4	G4	G1	G2	-	G2	G3	-	G2	-	G3	0
Student25	G4	G4	G4	G3	G3out	-	G4	G1	G3	G2	G3	G3	G4	G3	G1	G4	G2	G4	1
Student34	G4	G4	G3	G1	G4	G3	G4	G3	G3	G3	G1	G4	G2out	G3	G3out	G4	G3	G4	2
Student22	G2	G2	G2	G4	G2out	G2	-	G2	G2	G2	G3	G2	G3	G2	G2	G2	G1	G2	1
Student43	G3	G4	G3	G3	-	G2	G3	G3	G3	G3	G4	G3	G4	G1	G3	G4	G3	G4	0
Student53	G2	G3	G4	G2	G2	G1	-	G2	G2	G3	G3	G3	-	G4	G2	G2	G2	G2	0
Student57	G2	G2	-	G2	G2	G3	-	G3	G3	-	G2	G2	G2	G3	G2	G3	G1	G2	0
Student12	-	-	G3	G2	-	G2	-	G4	G2	G3	G2	G2	G4	-	G3out	G3	G1	G3	1
Student13	G1	-	-	G3out	G2	-	G2out	G2out	G2	G4	-	-	-	-	-	G3	-	G3	3
Student06	G3	G4	G3	G3	G4	G4	-	G4	G3	G4	G4	G4	G4	G4	G2	G4	G4	G4	0
Student23	G2	G2	-	G2	-	-	G3	G3	-	G2	G2	-	-	G3	G2	G3	G2	G3	0
Student24	G2	G4	G3	G2	G3	G2	G3	G4	G3	G2	-	G2	G3	G3	G2	G2	G2	G2	0
Student52	G4	G2	G2	G2	G3	-	-	-	-	-	-	-	-	-	-	G3	-	G3	0
Student27	G2	-	-	G3	G2	G4	-	G3	G4	G3	-	G3out	G2	-	-	G3	-	G3	1
Student28	-	G3out	G4	-	G2	G2	-	G3	G3	G2	G3	G4	G4	-	-	G3	-	G3	1
Student01	G3	G3	-	G3	G3	-	G3out	G3	G3	G3	G3	G3	G3out	G3	G3	G3	G3	G3	2
Student02	G4	G2	-	-	G2out	-	-	-	-	-	-	-	-	-	-	G3out	-	G3out	3
Student05	-	-	-	-	-	-	-	-	-	-	-	-	G4	-	-	G3out	-	G3out	2
Student08	G2	-	G3	G2	-	-	-	-	-	-	-	-	-	-	-	G3out	-	G3out	2
Student38	G4	G3	-	-	-	-	-	-	-	-	-	-	-	-	-	G3out	-	G3out	2
Student47	G2	G3	G3	G3	-	-	-	-	-	-	-	-	-	-	-	G3out	-	G3out	2
Outlier	0	2	0	1	4	1	3	2	0	0	0	1	3	1	9	5	4	5	41

Figure 2: Example of cluster heatmap by quiz response time and score.

above the median. Conversely, the lower part of Figure 2 lists learners below the median (Students 01, 43, 48, etc.). Additionally, the central part of Figure 2 shows learners whose learning patterns span multiple groups (Students 29, 37, 14, etc.), while also listing learners who were frequently absent (Students 02, 05, 08, 38, etc.).

In Figure 2, there are 41 cells labeled G*out, corresponding to outliers, but the actual number of learners who corresponded to them was 28. There were 3 learners (Student 16, 26, 54) who met the G1out pattern, while 11 learners (Students 2, 11, 13, 16, 22, 23, 24, 34, 39, 41, 45, 46, 50) met the G2out pattern.

Additionally, 18 learners (Students 01, 02, 05, 08, 12, 13, 14, 15, 25, 27, 28, 34, 37, 38, 47, 54) correspond to the G3out pattern, while four learners (Students 18, 40, 42) fell into the G4out pattern. Upon sorting, at the bottom of Figure 2, numerous G3 pattern learners were ranked. Among these, four learners (Students 02, 13, 34) fell into two patterns. Moreover, the number of times that outliers were applicable was three times for three persons, twice for seven people, and once for 18 people. These data are listed on the far right of the heatmap in Figure 2.

5 Discussion

There are various approaches for grouping or clustering multiple variables to detect outliers, and determining which method to apply is relatively important [22]. Figure 3 summarizes the results of comparing the outlier extraction results regarding the quiz response times and scores. In this paper, because there are two variables, each z-score was calculated, the Euclidean distance from the origin was determined, and the IQR was applied to the values to identify outliers. MGD and 3σ assume a normal distribution, but using these techniques on datasets that are not normally distributed can introduce errors. As shown in Figure 3, the cluster heatmap in this paper did not use the 3σ to detect univariate outliers due to its strong dependence on standard deviation, leading to the frequent occurrence of outliers when the standard deviation was small.

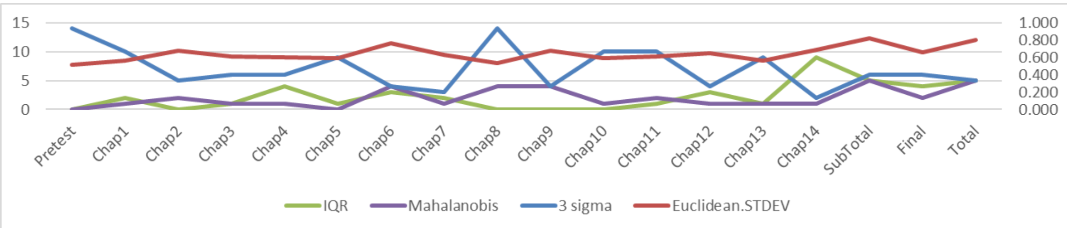

Figure 3: Comparison of outlier detection results: outliers in terms of quiz response times and scores.

Furthermore, because the MGD is defined using a correlation coefficient, its behavior is affected by this coefficient. As the value of the correlation coefficient in-creases, the MGD tends to deviate from the Euclidean distance. Conversely, as the value of the correlation coefficient decreases, the MGD approaches the Euclidean distance, becoming identical when the correlation coefficient is zero. In addition, in Figure 3, in each dataset, the same values were detected and the same learners were detected in the parts where outliers overlapped, which are the same as in Figure 1.

Classification by hierarchical clustering and k-means is also considered unsupervised learning in artificial intelligence. The common k-means method uses the distance from the centroid point during calculation. Therefore, in this paper's dataset, data points with the same distance from the origin were sometimes classified into the same group, even if the data points had large differences in response times. In hierarchical clustering, similar classification issues as with k-means arise because classification uses the distance between data points. Hence, it is important to analyze using multiple methods when applying multivariate clustering to outlier detection. Additionally, because uncertainties remain in the detection of boundary areas, even for outliers, it is ultimately necessary for the person in charge of data analysis to confirm the classification results visually. Furthermore, because this research is based on statistical methods, it can also be applied to the analysis of large datasets.

When calculating the time required to answer one quiz question, outliers occurred in data with short response times. One learner was an outlier in the answer time per quiz question calculated from the total answer time during the semester (Student 05 in Figure 1). The average response time per question for all learners was 37.9 seconds, whereas Student 05's answer time was 2.01 seconds. Because Student 05 only took the 5-minute quiz once, his/her total quiz response time was extremely small at 280 seconds, and the quiz consisted of 139 questions, making him/her an outlier.

Rapid guessing indicates the situation of answering a question within just a couple of seconds. When learners fail to read the questions carefully and tend to answer questions in a very short time. Thus, it becomes challenging for the test administrator to assess the learner's ability accurately. Particularly in national tests, there have been proposals to exclude data points corresponding to rapid guessing from test evaluations because they can adversely affect test score evaluations [14]. Previous research has involved methods for identifying rapid guessing by setting empirically defined thresholds [17]. Machine learning techniques in the field of artificial intelligence have also been applied to classification, and recently, Bulut et al. (2023) developed a method to determine thresholds using random search and genetic algorithms [22].

When informing learners that an abnormal value has been found, it is necessary to present results based on an algorithm that both teachers and learners can understand. Machine learning algorithms are difficult to understand in this regard, so their use in interventions should be carefully considered.

In this study, classes were held in15 times throughout the semester, but there were 7 learners, including Student 05, who were absent for 8 or more classes (Students 02, 05, 08, 13, 38, 47, 52). These learners should be excluded from the analysis data, along with instances of rapid guessing. It should be noted that in classes not covered in this paper, numerous outliers were observed in terms of the average time required per question.

Moreover, among the 11 learners listed at the bottom of Figure 1 (Students 02, 05, 11, 12, 13, 15, 27, 38, 43, 53, 54 are outliers in quiz response time), it was assumed that there was a hidden tendency for rapid guessing Additionally, attention should be paid to learners (Students 01, 22, 23, 24, 48, 57) who did not fall under the category of outliers but answered "low" more than 10 times, similar to the pattern observed for rapid guessing.

6 Conclusion

This paper presents an example of extracting outliers from the learning log of a recent Moodle course and discusses an example of analyzing learning patterns using cluster heatmaps. The upper and lower bound values obtained using IQR were used as thresholds for detecting rapid guessing.

The method outlined in this paper allows classes to be analyzed from multiple aspects, and when implemented by teachers in different settings, varied analysis results will be obtained. Additionally, cluster heatmaps featuring outliers were regenerated from the classification of learning patterns using quiz response times and scores, showing that the level and transition of engagement for students could be visualized. Moreover, the paper presents an example of identifying learners who exhibit abnormal or inappropriate learning behavior through outliers detected using Euclidean distance. In the classification of learning patterns, it was observed that students with relatively short quiz response times and low scores were outliers, indicating a tendency for rapid guessing.

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