Conformance Analysis of Student Activities to Evaluate Implementation of Outcome-Based Education in Early of Pandemic using Process Mining

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Abstract. The learning management system has a core component of a system event log that contains data on activities carried out by students and lecturers in the system. Educational process mining is a field in educational data mining that is concerned with finding, analyzing, and improving the overall educational process based on information hidden in educational data sets and event logs. The learning process in student lectures through the learning management system will produce a process flow according to the event data. In one semester in the information technology-based study program, the subjects taken are data from programming and non-programming courses in the 5th semester of the information systems department, namely Data Warehouse and Business Intelligence (DWBI) and Enterprise Architecture (EA). The Data Warehouse and Business Intelligence course is chosen because the main role in the graduate profile is as a data engineer. While the Enterprise Architecture course is chosen because being an IT Consultant requires knowledge of EA. Each course has different measured learning outcomes and each course has a different pattern in obtaining learning outcomes. To get a pattern for each learning achievement, an analysis of learning patterns, Bloom's taxonomy level, and CLO pass scores was carried out using process mining. Course Learning Outcomes (CLO) is a competency standard or minimum qualification criteria for graduates' abilities which include attitudes, knowledge, and skills assigned to courses. The existence of a bloom level indicates the level of expected learning achievement, where the higher the bloom level, the higher the expected ability. The mining process is carried out using Disco and PROM 5.2. The modeling process uses a heuristic miner algorithm because of its ability to express the main behavior recorded in the event log well. Heuristic miner algorithm can also take into account the frequency of the relationship between activities in the log to determine causal dependencies. The results of this study indicate that there is a difference between those that pass the course learning outcomes and those that do not pass. The passed CLO is indicated by the realization value of passing the course exceeding the threshold of 85.50%, while the failed CLO is indicated by the realization value of course graduation that is less than the threshold. In addition, control-flow, the frequency of activities that are often carried out indicate the appropriate learning path and are carried out by students to achieve a minimal assessment of course learning outcomes. In the Enterprise Architecture course, the activity that has the highest frequency in CLO1 is Attempt Quiz, while in CLO6 is View Course. In the Data Warehouse and Business Intelligence course, the activity that has the highest frequency in CLO3 is View Course, while in CLO4 is Attempt Quiz. The initial activity of the learning pattern produced in the two courses begins always with the view course activity. The highest bloom level in the Data Warehouse and Business Intelligence course is C6 Creation, while in the Enterprise Architecture course is C5 Evaluation. Thus, it can be said that Data Warehouse and Business Intelligence courses have a higher level of difficulty than Enterprise Architecture. Previously, in the DWBI course there was one CLO that failed in its implementation. With this research, it is hoped that this research can have a positive impact on adding new insights regarding the use of event logs in the field of education, so implementation of outcome-based education can be used as a benchmark for student learning to succeed in the course which include attitudes, knowledge, and skills.

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1 Introduction

Educational process mining is one of the fields in educational data mining that is concerned with finding, analyzing, and improving the overall educational process based on information hidden in educational data sets and event logs [1, 23].

Learning Management System (LMS) is a type of software adopted in e-learning. The LMS consists of several tools that allow users to organize content and perform assessment activities. LMS also provides synchronous and asynchronous communication that can be used between users [1, 20]. LMS has a core component in the form of a system event log containing data on activities carried out by students and lecturers in the system [2].

This study focuses on student activities or behavior in carrying out their activities at LMS by identifying various student behaviors in the pattern of learning activities recorded in the Telkom University LMS event log. In this study, the mining process is applied to event logs for programming and non-programming courses, namely Data Warehouse & Business Intelligence and Enterprise Architecture. The behavior performed by students in using the LMS can be used as data to predict student scores based on the correlation of attendance or lesson materials [24].

This study applies process mining to determine the differences in student learning patterns in programming and non-programming courses. Process mining is a science that combines machine learning and data mining as well as processing modeling and analysis [12]. Process mining is a method used to generate business process models to find, monitor, and improve real processes by extracting knowledge from event logs, which are available in information systems derived from event log processes [3, 11, 13, 21]. Process mining has three processes, including Discovery, Conformance Checking, and Enhancement [15]. The first process is discovery. This process will create a model based on the event log where the information used is an assumption. The second process is conformance checking, this process checks whether the actual events that occur follow the existing model and vice versa. The third process is enhancement, processing the event log to get a new model. This process aims to expand or improve the existing process model by using the information obtained from the event log [16].

The data for the two categories of courses is preprocessed to meet the event log requirements. Another study [25] built an application that successfully preprocesses Moodle event log data and can display the results visually, as a control flow analysis tool and dotted chart analysis. Then the event log will be analyzed using Disco Tools, PROM 5.2 and the Heuristic Miner plugin. Heuristic Miner is a mining algorithm that can be applied because it can handle noise, and can be used to represent the main events registered in the event log [4]. For example, research on online learning [14] showed that in order to get maximum results by using a sequential pattern mining approach to understand general patterns, a heuristic approach to process mining to get good workflows and statistics. In another study [17-18] showed that process mining using a heuristic miner algorithm was able to extract the learning path into the process model from beginning to end, present process variants and could strengthen the effectiveness of the extracted process model. Data for the Data Warehouse & Business Intelligence and Enterprise Architecture courses will be analyzed in terms of each CLO based on learning patterns, Bloom's taxonomy level, and CLO pass scores. For example, in previous studies [19, 22] found students' independent learning processes and studied students' use of learning resources, with respect to planned assignments and the relationship between students' behavior and their final grades.

Previous related research [5] focused on student activity in online quizzes from various courses with different settings and showed that process mining methods can be used to detect standard quiz-taking behavior patterns and distinguish them from non-standard or deviant behavior. Furthermore, research to find patterns of behavior that occurs in event logs collected from the learning management system used by Juraj Dobrila University of Pula produces a process model that describes user behavior based on real facts and evidence obtained by applying process discovery, a subset technique of process mining. 6].

A research study uses the heuristic miner algorithm to get a process model. The heuristic miner algorithm is chosen because it can express the main behavior recorded in the event log well [7]. Other studies [8] can show the use of different IDE patterns for students with different skills and performances. As well as showing that fuzzy-based process mining techniques can be effectively exploited to understand students and developers. Other studies have also presented process mining as an approach to understanding student behavior in relation to student problem solving processes. [9]. Process mining is a promising method for mining trace data. In this study a mining process was used to examine usage data from CBLE to elucidate the latent mechanisms that mediate diagnostic performance, and the case-specific effects found in diagnostic reasoning.

2 Methodology

This study uses data from programming courses, namely Data Warehouse and Business Intelligence, and non-programming, namely Enterprise Architecture.

The two data are processed based on the Semester Learning Plans (RPS) for each course using the Jupyter Notebook tools to comply with the event log provisions.

The activities used in this study are only activities carried out by students. So that activities carried out by other than students such as lecturers and admins will be deleted. Making the case id will be determined based on the CLO with a period of time based on the RPS for each course. Other attributes such as user, timestamp, case, component, and user id will be adjusted based on the conditions of the event log. This stage is data cleaning, because the raw event log used is not structured to implement the mining process, so at this stage data containing noise and inconsistent or irrelevant data are removed [10].

The data that has been successfully cleaned and processed in accordance with the provisions of the event log, then the data will be processed using the Disco tool to perform discovery analysis on the two courses. After doing data discovery, the event log data of the courses will be analyzed using the ProM tool with the Heuristic Miner algorithm to perform further analysis.

Heuristic miner process model in each CLO will be calculated by a causal dependency matrix to determine the effect of the sequence of activities that affect the success of student learning patterns [1].

$$X \Rightarrow_W Y = \frac{(|X >_W Y| - |Y >_W X|)}{(|X >_W Y| + |Y >_W X| + 1)} \tag{1}$$

3 Result and Discussion

The first analysis carried out in this study was to analyze each CLO in each course by grouping CLO at the appropriate Bloom Level. Table 5 will explain the learning reference for each CLO and the Bloom Level mapping.

Table 5. CLO Level Bloom

Course	CLO	Level Bloom
Enterprise Architecture	**CLO-01** Able to identify problems and map the needs of the enterprise architecture domain (business, data, application and technology)	C4 Analysis
	CLO-02 Able to determine the right framework and identify the need for artifacts in enterprise architecture design	C3 Application C4 Analysis
	CLO-03 Able to compose, model, and analyze existing business architecture	C3 Application C4 Analysis
	CLO-04 Able to compile, model, and analyze existing information system (data, application) architecture	C3 Application C4 Analysis
	CLO-05 Able to compose, model, and analyze existing technology architecture	C3 Application C4 Analysis
	CLO-06 Able to evaluate and provide proposals for enterprise architecture improvements in the form of architectural design targets covering business, data, applications and technology	C5 Evaluation
Data Warehouse and Business Intelligence	**CLO-01** Students are able to apply the concept of business intelligence to support decision making based on data	C3 Application
	CLO-02 Students are able to apply data analytics to solve problems in companies or organizations	C3 Application
	CLO-03 Students are able to apply the concept of data visualization in designing dashboards	C3 Application C6 Creation
	CLO-04 Students are able to analyze and create data sources for the creation of a data warehouse	C4 Analysis
	CLO-05 Students are able to apply data mining concepts and methods to solve problems	C3 Application
	CLO-06 Students are able to apply the concept of big data in a case study	C3 Application

In the Enterprise Architecture course, the bloom level is C4 Analysis, while in the Data Warehouse and Business Intelligence course, the bloom level is C3 Applications. Judging from the bloom level that dominates in each course, it can be interpreted that the Non Programming course learns more related to the ability to decompose a material into its parts. While the Programming course focuses more on studying the application of information in real situations or the ability to use concepts in practice or new situations.

At the end of each semester, the lecturer makes a lecture portfolio in each Outcome-Based Education-based course. Table 6 shows the achievement of CLO in each subject.

Table 6. CLO Achievement

Course	CLO	Average Student Score	Number of Students			Realization of students passed course	Gap Increase	CLO Achievement
			Score > 50.01	Score = 50.01	Score < 50.01			
Enterprise Architecture	CLO 1	70.43	373	6	23	92.76%	7.29%	PASSED
	CLO 2	72.06	377	5	20	93.78%	8.28%	PASSED
	CLO 3	78.42	382	0	20	95.02%	9.52%	PASSED
	CLO 4	77.17	387	0	15	96.27%	10.77%	PASSED
	CLO 5	81.32	385	0	17	95.77%	10.27%	PASSED
	CLO 6	76.09	388	0	14	96.52%	11.02%	PASSED
Data Warehouse	CLO 1	81	362	11	22	94.43%	8.93%	PASSED

and Business Intelligence	CLO 2	73	344	24	40	90.20%	4.70%	PASSED
	CLO 3	57	278	57	106	75.96%	-9.54%	FAILED
	CLO 4	83	373	0	11	97.14%	11.64%	PASSED
	CLO 5	82	372	3	12	96.90%	11.40%	PASSED
	CLO 6	83	372	5	12	96.92%	11.42%	PASSED

Judging from the CLO achievement in both courses, the student scores in each CLO of the Enterprise Architecture course passed, while in the CLO of the Data Warehouse and Business Intelligence course there was one failed CLO, namely CLO3. When viewed from the bloom level, CLO3 includes the C3 application and C6 Creation bloom levels, where the bloom level, especially C6, is the most difficult level compared to other bloom levels. The average score obtained by students in CLO3 is also very low, namely 57 and the number of students who get scores below the threshold (50.01) is also very large at 106 students so that CLO3 fails in the Data Warehouse and Business Intelligence course.

3.1. Enterprise Architecture

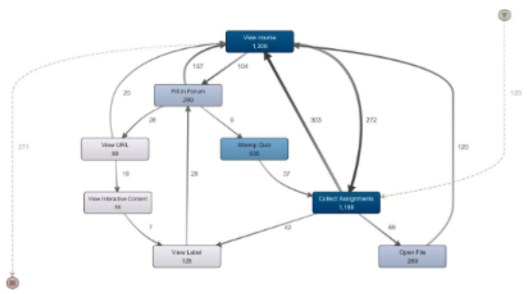

Fig. 1. Process Model of CLO6 Enterprise Architecture

The realization of the highest CLO6 graduation compared to other CLOs was 96.52%. The activity that is often done is the View Course activity. While the activity that is rarely carried out is View Interactive Content. At CLO 6 students always start the learning pattern with Collect Assignment activities and end activities with View Courses. There are 3 activities that always return to View Course activities, namely Collect Assignment, Fill in Forum, and Open File activities.

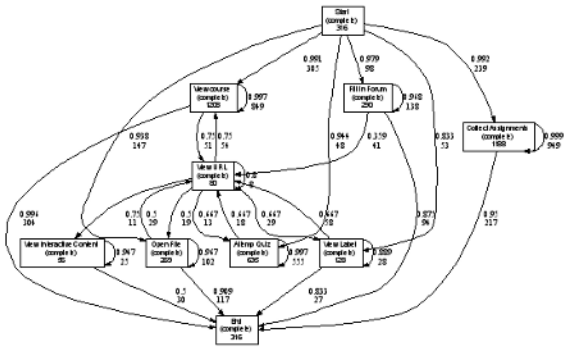

Fig. 2. Heuristic Miner Process Model of CLO6 Enterprise Architecture

CLO 6 : Start - View Course - View URL - View Label - Open File - Attempt Quiz - View Interactive Content - Collect Assignment - Fill in Forum - End

Table 1. Causal Dependency Matrix of CLO6 Enterprise Architecture.

	View Course	Fill in Forum	Open Other	Attempt Quiz	Collect Feedback	View Label	View URL	View Interactive Content	Open File	Collect Assignment
View Course	-	-	-	-	-	-	-0.028	-	-	-
Fill in Forum	-	-	-	-	-	-	-	-	-	-
Open Other	-	-	-	-	-	-	-	-	-	-
Attempt Quiz	-	-	-	-	-	-	0.156	-	-	-
Collect Feedback	-	-	-	-	-	-	-	-	-	-
View Label	-	-	-	-	-	-	0.330	-	-	-
View URL	0.028	-	-	-0.156	-	-0.330	-	-	-0.204	-
View Interactive Content	-	-	-	-	-	-	-	-	-	-
Open File	-	-	-	-	-	-	0.204	-	-	-
Collect Assignment	-	-	-	-	-	-	-	-	-	-

Based on the causal dependency matrix Table 1 with a value close to 1 is View Label → View URL (0.330) obtained from 58 occurrences (View Label → View URL) and 29 occurrences (View URL → View Label) which means that the order of these activities affect the success of student learning patterns in CLO6 Enterprise Architecture.

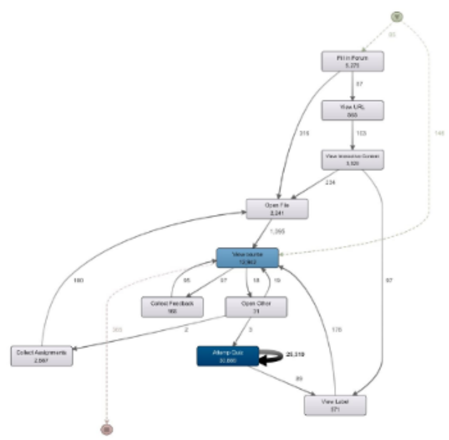

Fig. 3. Process Model of CLO1 Enterprise Architecture

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The realization of passing CLO1 is the lowest compared to other CLOs. The activity that is mostly done is the Attempt Quiz activity and there is a loop in the activity which means that many students return to access the Quiz to reattempt the Quiz. Meanwhile, Open Other activities are activities that are rarely carried out by students. There are 2 activities that start CLO 1, namely the Fill in Forum and View Course activities. However, View Course activities are activities that are mostly carried out as initial activities when compared to Fill in Forum activities. There are 4 activities that always return to the View Course, namely Collect Feedback, Open File, Open Other, View Label. In CLO 1 students always end the learning pattern with View Course activities.

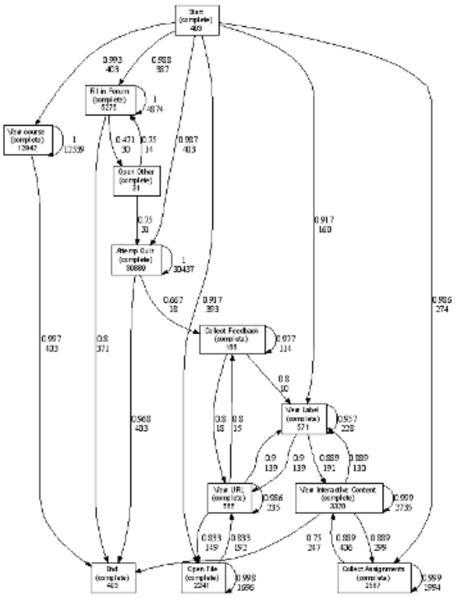

Fig. 4. Heuristic Miner Process Model of CLO1 Enterprise Architecture

CLO 1 : Start - View Course - Attempt Quiz - Fill in Forum - Open Other - Open File - Collect Assignment - View Interactive Content - View Label - View URL - Collect Feedback - End

Table 2. Causal Dependency Matrix of CLO1 Enterprise Architecture.

	View Course	Fill in Forum	Open Other	Attempt Quiz	Collect Feedback	View Label	View URL	View Interactive Content	Open File	Collect Assignment
View Course	-	-	-	-	-	-	-	-	-	-
Fill in Forum	-	-	0.356	-	-	-	-	-	-	-
Open Other	-	-0.356	-	-	-	-	-	-	-	-
Attempt Quiz	-	-	-	-	-	-	-	-	-	-
Collect Feedback	-	-	-	-	-	-	0.088	-	-	-
View Label	-	-	-	-	-	-	0.000	0.189	-	-
View URL	-	-	-	-	-0.088	0.000	-	-	-0.126	-
View Interactive Content	-	-	-	-	-	-0.189	-	-		0.152
Open File	-	-	-	-	-	-	0.126	-	-	-
Collect Assignment	-	-	-	-	-	-	-	-0.152	-	-

Based on the causal dependency matrix Table 2 with a value close to 1 is Fill in Forum → Open Other (0.356) obtained from 30 occurrences (Fill in Forum → Open Other) and 14 occurrences (Open Other → Fill in Forum) which means that the sequence of these activities affects the success of student learning patterns in CLO1 Enterprise Architecture.

3.2. Data Warehouse and Business Intelligence

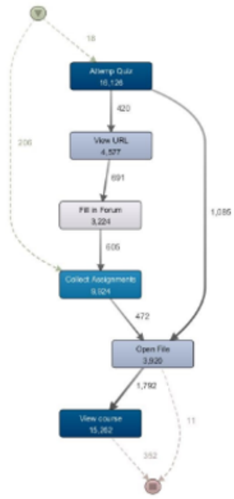

Fig. 5. Process Model of CLO4 Data Warehouse and Business Intelligence

The realization of graduation in CLO4 is the highest realization compared to other CLOs. In CLO 4, the activity that is mostly done is the Attempt Quiz activity. There are 2 activities that start the CLO 2 learning pattern, namely the Attempt Quiz and Collect Assignment activities. However, the Collect Assignment activity is the activity that is mostly done as an initial activity when compared to the Attempt Quiz. As for the final activity, there are 2 activities that are usually carried out by students, namely View Course and Open File, but the pattern ends with View Course activities. It can be concluded that at CLO 4 students always start the learning pattern with Collect Assignment activities and end with activities with View Courses.

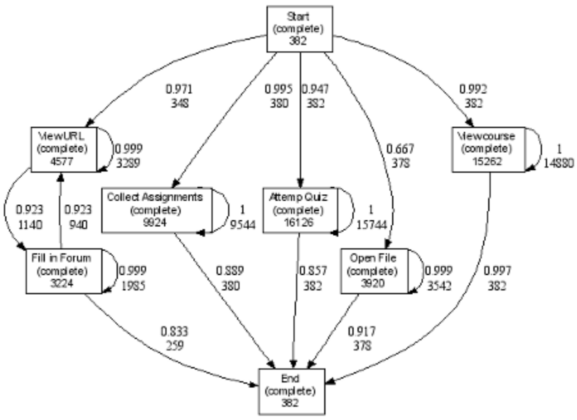

Fig. 6. Heuristic Miner Process Model of CLO4 Data Warehouse and Business Intelligence

CLO4 : Start - View Course - Attempt Quiz - Collect Assignment - Open File - View URL - Fill in Forum - End

Table 3. Causal Dependency Matrix of CLO4 Data Warehouse and Business Intelligence

	Open File	View Course	Attempt Quiz	Open Other	Collect Assignment	View URL	Open Book	Fill in Forum
Open File	-	-	-	-	-	-	-	-
View Course	-	-	-	-	-	-	-	-
Attempt Quiz	-	-	-	-	-	-	-	-
Open Other	-	-	-	-	-	-	-	-
Collect Assignment	-	-	-	-	-	-	-	-
View URL	-	-	-	-	-	-	-	0.096
Open Book	-	-	-	-	-	-	-	-
Fill in Forum	-	-	-	-	-	-0.096	-	-

Based on the causal dependency matrix Table 3 with a value close to 1 is View URL → Fill in Forum (0.096) obtained from 1140 occurrences (View URL → Fill in Forum) and 940 occurrences (Fill in Forum → View URL) which means that the sequence of these activities affects the success of student learning patterns in CLO4 Data Warehouse and Business Intelligence.

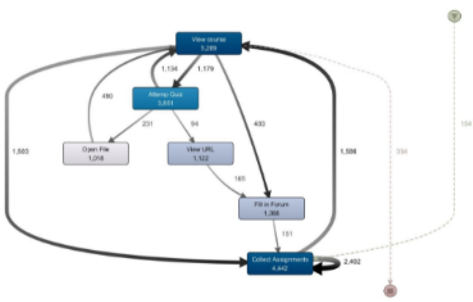

Fig. 7. Process Model of CLO3 Data Warehouse and Business Intelligence

The lowest realization of CLO3 pass compared to other CLOs. CLO3 also has a passing realization below the threshold, so CLO3 failed. In CLO 3, the activities that are mostly carried out are View Course activities. In the Collect Assignment activity there is a loop, which means that at CLO 3 students do the activity repeatedly. This happens because students have a lot of assignments to collect and students can make changes to assignments before the deadline ends, making students re-access these activities repeatedly. There are 2 activities that always return to the View Course, namely Collect Assignment activities and Attempt Quiz activities. In CLO 3 students always start the learning pattern with Collect Assignment activities and end with View Course activities.

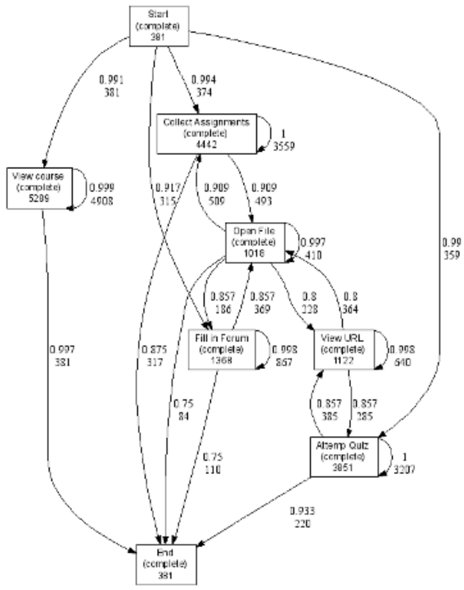

Fig. 8. Heuristic Miner Process Model of CLO3 Data Warehouse and Business Intelligence

CLO3: Start - View Course - Collect Assignment - Open File - View URL - Attempt Quiz - Fill in Forum - End

Table 4. Causal Dependency Matrix of CLO3 Data Warehouse and Business Intelligence

	Open File	View Course	Attempt Quiz	Open Other	Collect Assignment	View URL	Open Book	Fill in Forum
Open File	-	-	-	-	0.016	-0.229	-	-0.329
View Course	-	-	-	-	-	-	-	-
Attempt Quiz	-	-	-	-	-	0.149	-	-
Open Other	-	-	-	-	-	-	-	-
Collect Assignment	-0.016	-	-	-	-	-	-	-
View URL	0.229	-	-0.149	-	-	-	-	-
Open Book	-	-	-	-	-	-	-	-
Fill in Forum	0.329	-	-	-	-	-	-	-

Based on the causal dependency matrix Table 4 with a value close to 1 is Fill in Forum → Open File (0.329) obtained from 369 occurrences (Fill in Forum → Open File) and 186 occurrences (Open File → Fill in Forum) which means that the sequence of these activities affect the success of student learning patterns in CLO3 Data Warehouse and Business Intelligence.

4 Conclusion

Based on the research results obtained by analyzing the heuristic miner process model, bloom taxonomy, and CLO graduation for each course, it can be concluded that CLO3 in the Data Warehouse & Business Intelligence course is the only CLO that has a Failed passing score. CLO3 in this course has a bloom level of C3 Application and C6 Creation where the bloom level, especially C6 Creation, is the bloom level which has the highest/most difficult bloom level compared to other bloom levels. Meanwhile, other CLOs included in the C3 application bloom level and C4 Analysis resulted in a CLO Passed passing score because the difficulty level was below the C6 Creation bloom level. Meanwhile, all CLOs in the Enterprise Architecture course have a Passed pass value, judging by the bloom taxonomy analysis of the CLO courses, these courses are dominated by the bloom level C4. Analysis is included in the bloom medium level. Therefore, the level is not too difficult, making it easier for students to apply the material in problem solving so that students get scores above the threshold.

Judging from the learning patterns carried out by students, each CLO of the two subjects studied always begins with a view course activity and then goes to other activities. So that there is no difference in the initial activity of learning patterns between programming and non-programming courses.

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