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Fairness Analysis in the Assessment of Several Online Parallel Classes using Process Mining

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Abstract
The learning process in online lectures through the Learning Management System (LMS) will produce a learning flow according to the event log. Assessment in a group of parallel classes is expected to produce the same assessment point of view based on the semester lesson plan. However, it does not rule out the implementation of each class to produce unequal fairness. Some of the factors considered to influence the assessment in the classroom include the flow of learning, different lecturers, class composition, time and type of assessment, and student attendance. The implementation of process mining in fairness assessment is used to determine the extent to which the learning flow plays a role in the assessment of ten parallel classes, including international classes. Moreover, a decision tree algorithm will also be applied to determine the root cause of the student assessment analysis based on the causal factors. As a result, there are three variables that have effects on student graduation and assessment, i.e attendance, class and gender. Variable lecturer does not have much impact on the assessment, but has an influence on the learning flow.

Keywords
Fairness Analysis, Process Mining, Parallel Class, Website Development Course.

I. Introduction

Online learning has changed paradigms and perspectives in education. Online learning activities provide very useful data to improve the quality, process, and learning methods. This improvement has the aim of producing graduates who have the required competencies. By implementing machine learning and process mining, data from learning activities can be used to determine student learning styles, predict student performance, course recommendations, and predict student drop-outs. The implementation of machine learning, data mining or mining processes on online learning data has resulted in a lot of research, frameworks and applications that help education in developing learning methods, improving learning experiences, and predicting student performance and even predicting student drop-outs.

The use of machine learning has become an integral part of educational technology. With a growing number of applications using machine learning modeling such as student performance prediction, course recommendations, and dropout predictions, there are concerns about model bias and inequity. Unfair models lead to unfair outcomes for learning outcomes [1]. The application of these techniques is also not always acceptable. In certain situations, unfair diagnoses lead to unfair conclusions and discrimination [2]. Moreover, research on the implementation of process mining has carried out a lot of participatory analysis on active learning [3], prediction of assessment based on the use of LMS based on petri net [4] and the suitability between lecturer planning and use of LMS to improve learning ability [5] [6]. Overall, the research framework related to process mining in the field of education has also been mentioned in [7] where it is necessary to compare one process model with other process models. Furthermore, to make comparisons, an approach is used using the process cube [8]. Thus, each dimension can be compared to determine whether there is discrimination or not in the assessment of lectures.

II. Related works

Research on fairness learning analytics is increasingly attracting the attention of researchers who are concerned about education. Studies related to fairness to answer some unfair problems to process modeling that can lead to unfair and detrimental result. Related to educational research of fairness, there are some discoveries. Based on [9], the results indicate that the teachers' conceptions of fairness were influenced by three reasons: (a) individual mechanisms, (b) social mechanisms, and (c) dialectical relationships between individual and social mechanisms. Each of them was the factor from teacher's perspective that influenced the assessment. Moreover, the study [10] yielded three categories: distributive justice, procedural justice, and interactional justice. The study concludes by proposing a range of implications for different testing stakeholders.

Mahnaz Sadat Qafari and Wil van der Aalst in the Fairness-Aware Process Mining research, the results of the application of machine learning and data mining techniques are not always acceptable. In many situations, this approach tends to make an overt or unfair diagnosis and applying it can lead to erroneous or even discriminatory conclusions. This study presents a solution to this problem by creating a fair classifier for such situations. Unwanted effects are eliminated at the expense of reducing the accuracy of the resulting classifier [2].

Research by Qian Hu and Huzefa Rangwala highlights concerns about model bias and injustice causing unfair outcomes for some groups of students and negatively impacting their learning. This study demonstrates by concrete examples that biased educational data leads to biased student modeling. This research encourages the development of equitable formalization and algorithms for educational applications. The proposed formalization is individual fairness and group fairness. This study proposes a model based on the idea that predictions for students (identifying students at risk) should not be influenced by their sensitive attributes. The proposed model is proven to be effective in removing the bias from this prediction and hence, making it useful in helping all students [1].

Other research examines possible forms of discrimination, as well as ways to measure and define fairness in Virtual Learning Environments (VLE). Prediction of student course outcomes was carried out on the VLE dataset and analyzed with due regard to fairness. Two measures are recommended for investigation of previous learning data, to ensure their balance and suitability for further data analysis [11].

Subsequent research proposes a systematic process for framing, detecting, documenting, and reporting the risk of unfairness. The results of a systematic approach are combined into a framework called FairEd, which will help decision makers to understand the risks of unfairness along the environmental and analytical fairness dimensions. This tool makes it possible to identify data containing a risk of unfairness, identifying models to see that potentially unfair outcomes can be reduced without compromising performance [12].

Furthermore, the following research advocates the use of simulation as the main tool in studying algorithm fairness. The study explores three examples of previously studied dynamic systems in the context of equitable decision making for bank loans, college admissions, and attention allocation. By analyzing how learning agents interact with these systems in simulations, it is shown that static analysis does not provide a complete picture of the long-term consequences of ML-based decision systems. This study provides an open-source software framework that can be extended to implement fairness-focused simulation studies and further reproducible research [13].

III. Methods

In the process of assessing the website application development course, there are several factors that are considered to assess fairness in determining student graduation. These factors include student attendance, lecturers, gender, and student batch and assessment index. Online lectures result in students and lecturers not being able to meet in person, but attendance can still be calculated through activities carried out during lectures. The existence of differences in lecturers in each parallel class is also possible to have an impact on assessment bias due to different standards. Although using the same semester learning plan, the implementation and treatment of each lecturer may be different. Furthermore, gender differences are a factor that is often used as an identification of discrimination in an assessment [12]. The last factor to be considered in this study is the class, where students who repeat or are more senior are also possible to be one of the causes of differences in assessment standards. Assessment in the form of numbers is not included because it is hypothesized that the assessment index is carried out in a discriminatory way without looking at the scoring rubric. Based on Fig. 1, the causal factors of the lecture process discrimination in a fishbone diagram can be divided into machine, man, measurement, method and milieu. Material is not included because the lecture process has no material differences and moreover the data is not recorded in the lecture.

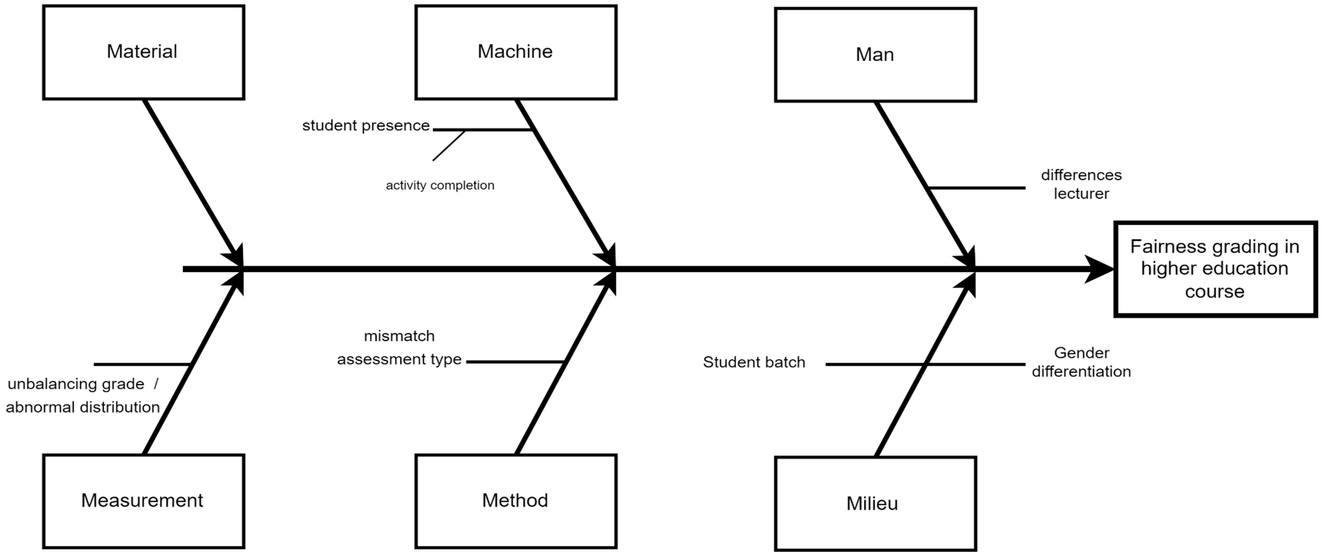


Fig. 1. Fishbone Diagram of Lecturer Grading

IV. Results and Discussion

A. Class Distribution

In conducting the analysis, statistical calculations are first carried out based on the gender distribution, the graduation of each gender and the distribution of grade. In general, there are more males in each class than females (Figure 2).

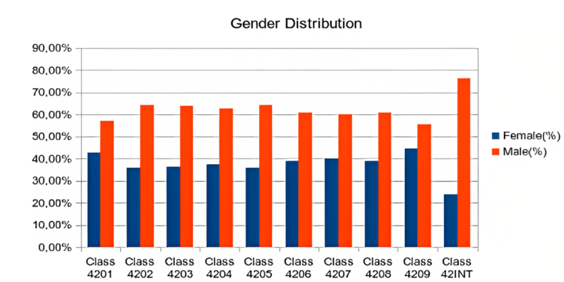


Fig. 2. Comparison of gender distribution for each class

Moreover, it is also found in Figure 3 and 4 that the average of each class, more than 90% who graduate with female students in general. Only in the 4201 and 4208 classes there are female students who did not pass, this is different from the male students who did not pass in the 4203, 4204, 4205, 4206 and 4207 classes. While the distribution of values

in general found that the score with the highest frequency was AB, followed by A, B, C, D and E (Figure 5).

B. Business Process Discovery

Based on this data, business process discovery was carried out using the Disco application, which is an application devel-

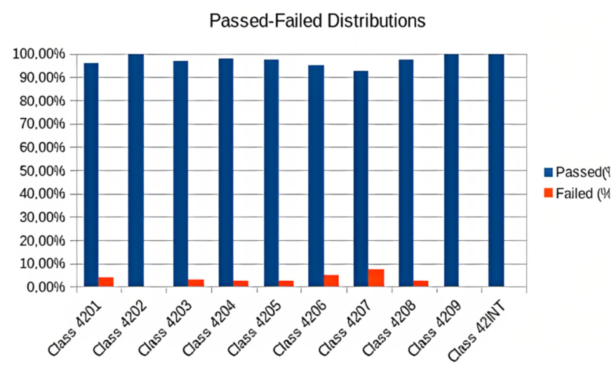


Fig. 3. Comparison of passed-failed for each class

oped by Fluxicon. Based on statistical data obtained from the event log, it was found that the event log used in this study consisted of 118039 events, 1670 cases, 9 activities, median duration of 27.3 days, mean duration of 26.4 days. This lecture process starts from September 7, 2020 to January 10, 2021. For the determination of one case ID, it is carried out based on the start of an assessment of learning achievements until completion, where this lecture consists of 5 learning outcomes in one semester. Using Disco applications, business process is generated based on several dimensions, for example each lecturer, based on class, passed per lecturer, failed per lecturer, passed for female and passed for male.

Figure 6 shows the result of the discovery from the lecture process on the web application development course, where the activities carried out include accessing the course page (loop) → quiz (loop) → assignment → label. On a different

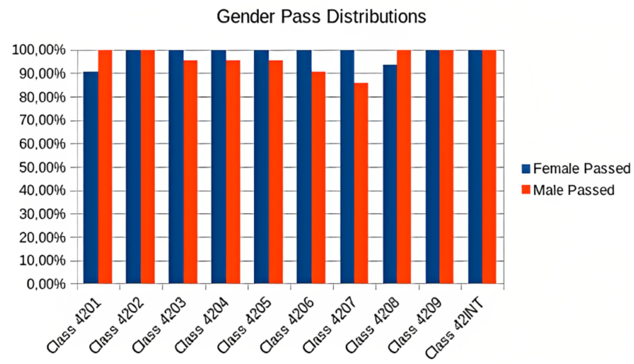


Fig. 4. Comparison of passed-failed for each gender

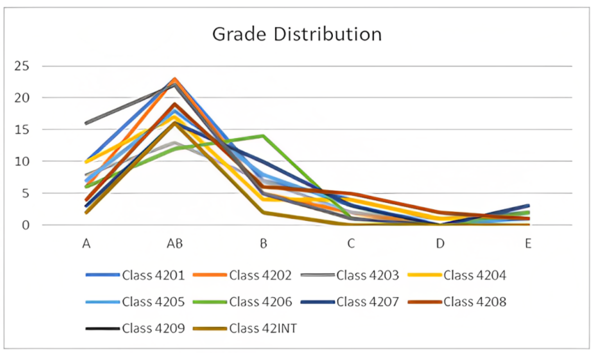


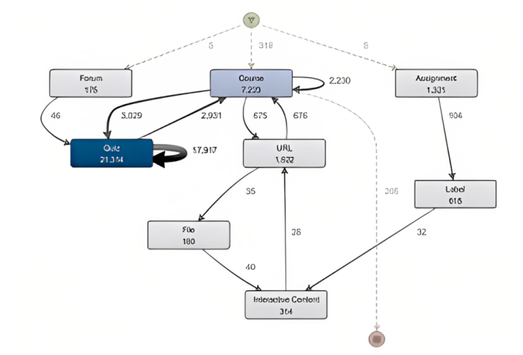
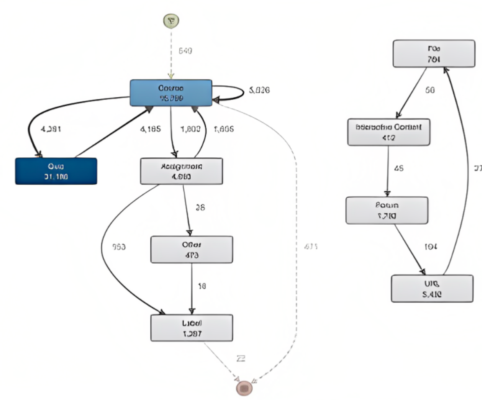
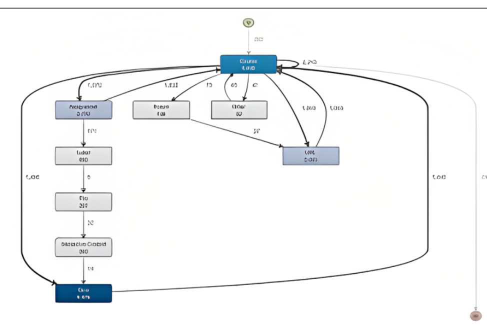
Fig. 5. Grade distribution

time, accessing interactive content → forum → URL → file (loop). Based on this process, it shows that forum activities are generally carried out at different times compared to quizzes and assignments, or that these activities are not continuously carried out.

Furthermore, the analysis of each lecturer found that each lecturer has a different path in the implementation of learning (Table I). The most visible thing is that lecturers with VPW code have a flow that is almost the same as the whole business process, where "interactive content" activities are separated from the main activities of quizzes, assignments, etc. This is because VPW handles 5 out of 10 classes, while RFZ and ETO have 3 and 2 classes, respectively. Generally, the three lecturers have loop activities on course activities, and specifically the RFZ class has loops on quiz activities. However, the activities carried out in the RFZ class affect the general flow of activities quiz (loop). Moreover, there is one more difference where in the VPW and ETO classes there are 9 activities, while in RFZ there are 8 activities. In the RFZ class there is no "other" activity, while in the VPW class there is a significant "other" activity.

For the analysis in each class (Appendix I), website application development lectures are almost the same as the

TABLE I.
BUSINESS PROCESS OF ALL CLASS FOR EACH LECTURER

Lecturer	All Class
RFZ	
VPW	
ETO	

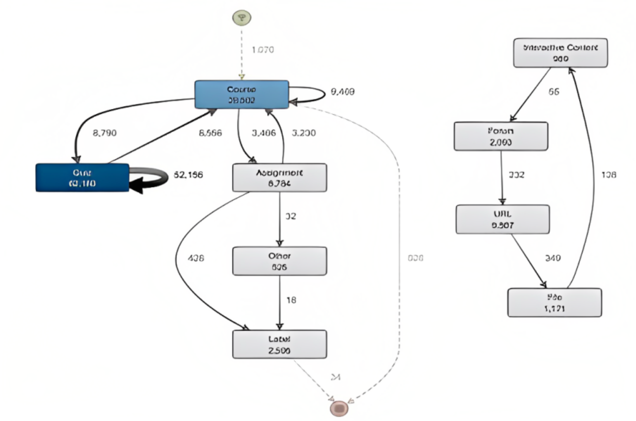


Fig. 6. Business Process of Web Application Course

conditions for each class taught by the relevant lecturer. for example, for classes taught by VPW (Class 4201-05), by RFZ (Class 4206-08) and by ETO (Class 4209-INT). Generally, loops exist in course activities (except classes 4204 and 4208). Then, loops also occur in the "quiz" activity, namely in class 4206, 4207, and 4208. While the loop in the "assignment" activity is only found in class 4204. The existence of this loop indicates that the activity is carried out repeatedly or it is possible for the lecturer to provide remedial to the class. related activities, such as quizzes and assignments.

To analyze the business processes that are carried out for both female and male students who pass the course, it can be identified as follows. For female, the activities carried out include course (loop) → quiz → course (loop) → URL → file → interactive content → forum → assignment → course → label. As for the male, the activities carried out include, course (loop→ quiz → course (loop) → assignment → course (loop) → forum → URL → file → interactive content → forum (Table II) On Table III, a comparison is obtained for students who passed and failed according to their lecturers. In general, activities that have a high frequency are courses and quizzes, but in the whole class for graduating students there is a loop in the "quiz" activity. This is similar to the class taught by RFZ where there is repetition of the "quiz" activity. The existence of "quiz" repetition in the overall learning process shows that the 3 classes taught by RFZ and remedial have a significant impact on the graduation of all students.

Identification of the root of the causality is done by using a decision tree based on the variables that are considered to play a role in the assessment in class. The results of the implementation of the decision tree show that the first root that affects graduation is attendance, for attendance above 96 % followed by student years, if in 2018 the class is checked, for classes 4206 and 4207 then gender checks are carried out, if male then get an A, if women get AB. In addition, in other

TABLE II.
GENDER COMPARISON BASED ON PASSED COURSE

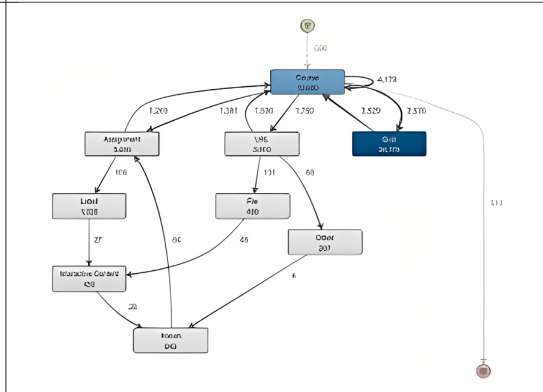
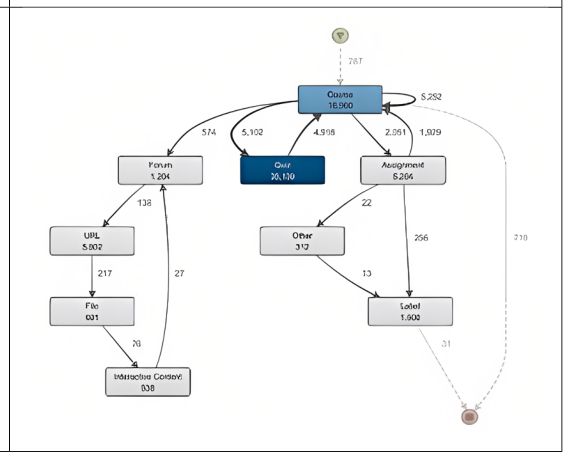
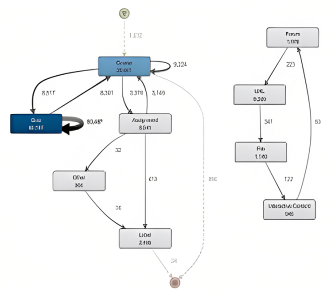
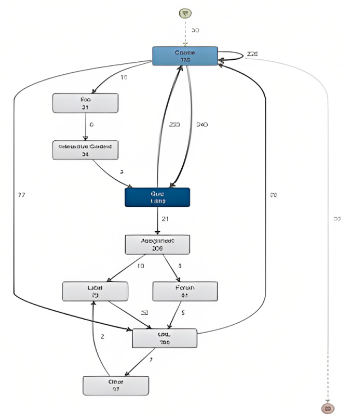
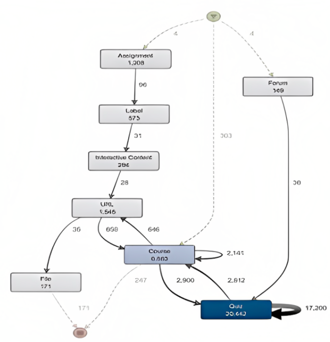
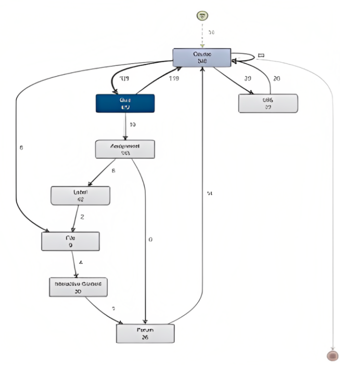
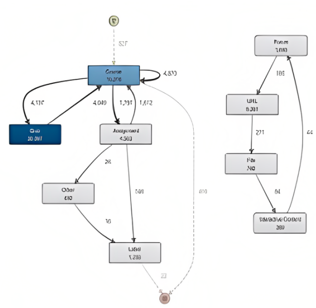
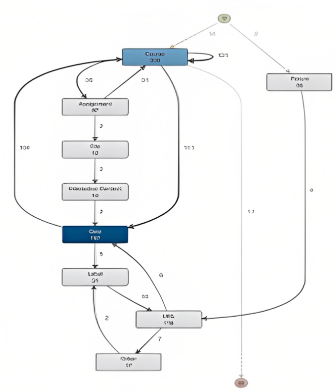
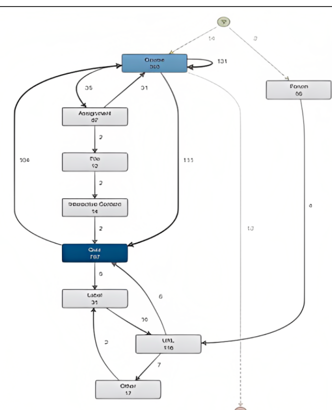
Gender	Passed
Female	
Male	

TABLE III.
COMPARISON PASSED AND FAILED OF EACH LECTURER

Lecturer	Passed	Failed
All		
RFZ		
VPW		
ETO		

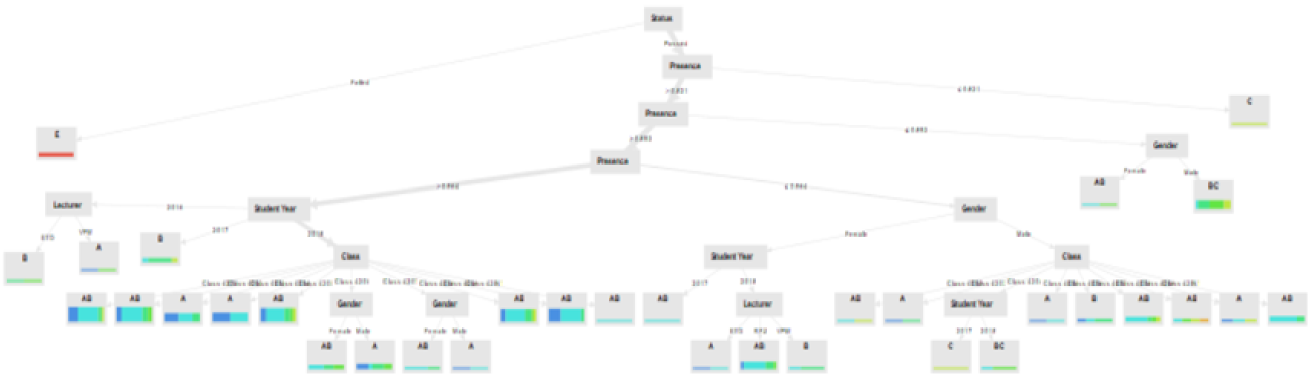


Fig. 7. Decision Tree of Web Application Course Grade Evaluation

accuracy: 38.46%

	true A	true AB	true B	true BC	true C	true D	true E	class precision
pred. A	4	15	6	1	1	1	0	14.29%
pred. AB	17	32	12	4	5	1	0	45.07%
pred. B	0	4	3	0	1	0	0	37.50%
pred. BC	0	0	1	1	1	2	0	20.00%
pred. C	0	0	0	0	0	0	0	0.00%
pred. D	0	0	0	0	0	0	0	0.00%
pred. E	0	0	0	0	0	0	5	100.00%
class recall	19.05%	62.75%	13.64%	16.67%	0.00%	0.00%	100.00%	

Fig. 8. Performance of Decision Tree Model

classes the range of values is between A and AB. Meanwhile, Class of 2017 gets a B and Class 2016 if the lecturer is VPW then the grade is A and if the lecturer is ETO, then the grade is B. For attendance below 96 % root decision making can be seen completely in Figure 6 and Appendix II.

Based on Figure 7, it can be grouped into students who pass and do not pass. Where grades A, AB, B, BC, C and D are students who pass lectures, while students with E grades are students who failed. Thus, if the assessment is grouped into pass and fail, the result obtained is an accuracy of 100 %, because failed student is predicted as failed, and vice versa.

V. Conclusion

Based on the result and discussion above, it can be concluded that each lecturer influences the flow of the learning process in the classroom. There are also differences between students who pass and do not pass in the learning path. In general, there are differences between the paths carried out by female and male students. For female, the activities carried out include course (loop) → quiz → course (loop) → URL → file → interactive content → forum → assignment → course → label.

As for the male, the activities carried out include, course (loop→ quiz → course (loop) → assignment → course (loop) → forum → URL → file → interactive content → forum. This is also in accordance with the results of the decision tree, that gender is a variable that affects student graduation and assessment. Differences in lecturers do not have much influence, but have an impact on the delivery of the learning process in the classroom, so that a different path is obtained for each lecturer.

Conflict of Interest

The author have no conflict of relevant interest to this article.

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APPENDIX I

TABLE IV.
BUSINESS PROCESS OF EACH CLASS

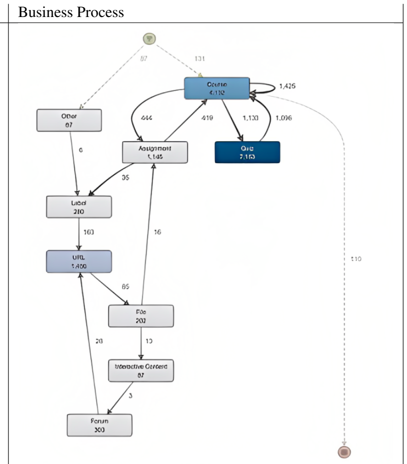
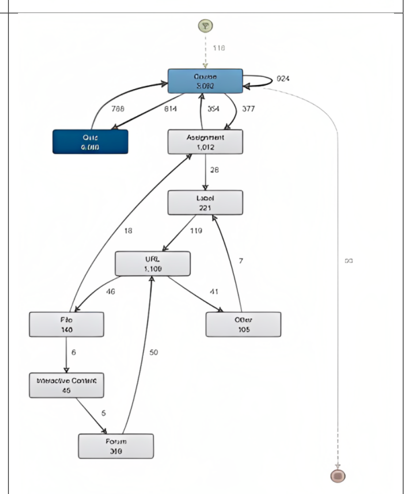
Class	Business Process
Class 4201	
Class 4202	

TABLE V.
BUSINESS PROCESS OF EACH CLASS

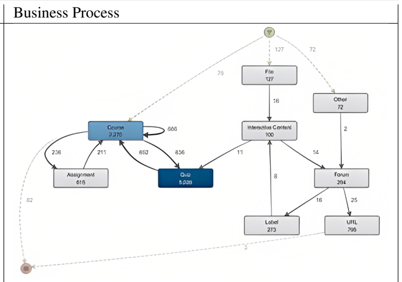
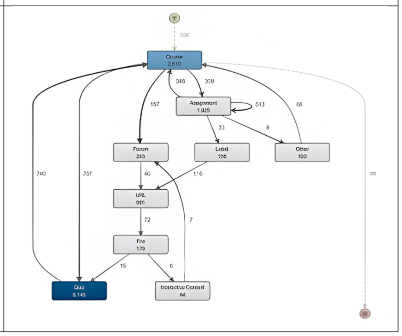
Class	Business Process
Class 4203	
Class 4204	

TABLE VI.
BUSINESS PROCESS OF EACH CLASS

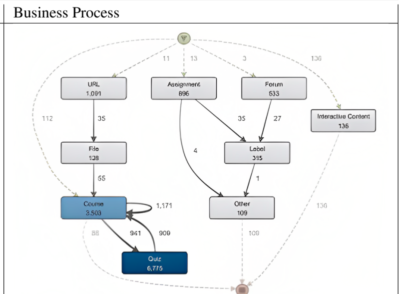
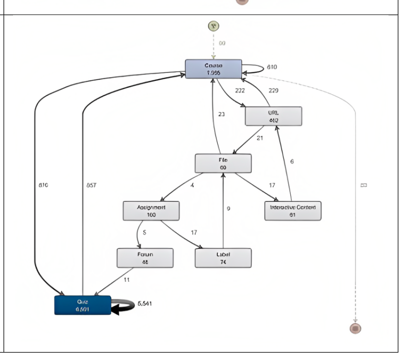
Class	Business Process
Class 4205	
Class 4206	

TABLE VII.
BUSINESS PROCESS OF EACH CLASS

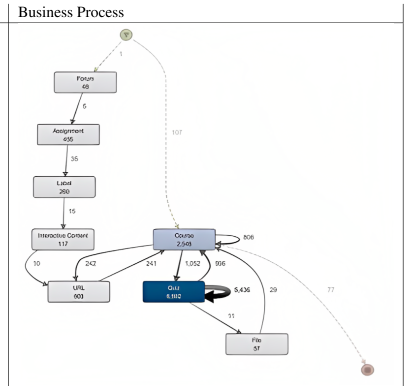
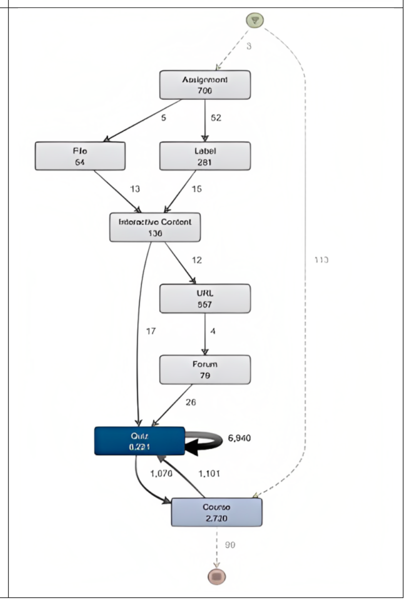
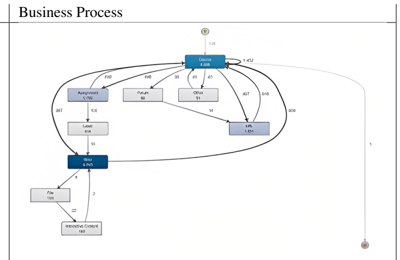
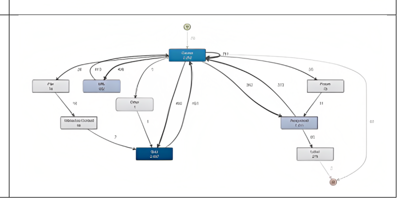
Class	Business Process
Class 4207	
Class 4208	

TABLE VIII.
BUSINESS PROCESS OF EACH CLASS

Class	Business Process
Class 4209	
Class 42INT	

APPENDIX II

Status = Failed: E A=0, AB=0, B=0, BC=0, C=0, D=0, E=6

Status = Passed

— Presence > 0.821

— — Presence > 0.893

— — — Presence > 0.964

— — — — Student Year = 2016

— — — — — Lecturer = ETO: B A=0, AB=0, B=1, BC=1, C=0, D=0, E=0

— — — — — Lecturer = VPW: A A=1, AB=0, B=0, BC=1, C=0, D=0, E=0

— — — — Student Year = 2017: B A=0, AB=1, B=4, BC=0, C=1, D=0, E=0

— — — — Student Year = 2018

— — — — — Class = Class 4201: AB A=7, AB=16, B=2, BC=1, C=1, D=0, E=0

— — — — — Class = Class 4202: AB A=4, AB=16, B=4, BC=3, C=0, D=0, E=0

— — — — — Class = Class 4203: A A=6, AB=6, B=3, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4204: A A=8, AB=8, B=0, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4205: AB A=4, AB=13, B=4, BC=2, C=2, D=0, E=0

— — — — — Class = Class 4206

— — — — — — Gender = Female: AB A=0, AB=3, B=2, BC=2, C=0, D=0, E=0

— — — — — — Gender = Male: A A=3, AB=1, B=3, BC=2, C=0, D=0, E=0

— — — — — Class = Class 4207

— — — — — — Gender = Female: AB A=0, AB=2, B=1, BC=0, C=0, D=0, E=0

— — — — — — Gender = Male: A A=1, AB=1, B=0, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4208: AB A=3, AB=13, B=4, BC=1, C=2, D=0, E=0

— — — — — Class = Class 4209: AB A=8, AB=14, B=2, BC=0, C=0, D=0, E=0

— — — — — Class = Class 42INT: AB A=0, AB=2, B=0, BC=0, C=0, D=0, E=0

— — — Presence ≤ 0.964

— — — — Gender = Female

— — — — — Student Year = 2017: AB A=0, AB=2, B=0, BC=0, C=0, D=0, E=0

— — — — — Student Year = 2018

— — — — — — Lecturer = ETO: A A=1, AB=1, B=0, BC=0, C=0, D=0, E=0

— — — — — — Lecturer = RFZ: AB A=1, AB=8, B=3, BC=1, C=0, D=0, E=0

— — — — — — Lecturer = VPW: B A=0, AB=1, B=2, BC=0, C=0, D=0, E=0

— — — — Gender = Male

— — — — — Class = Class 4202: AB A=0, AB=1, B=0, BC=0, C=1, D=0, E=0

— — — — — Class = Class 4203: A A=1, AB=0, B=1, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4204

— — — — — — Student Year = 2017: C A=0, AB=0, B=0, BC=0, C=2, D=0, E=0

— — — — — — Student Year = 2018: BC A=0, AB=1, B=0, BC=2, C=0, D=0, E=0

— — — — — Class = Class 4205: A A=1, AB=1, B=0, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4206: B A=1, AB=1, B=2, BC=0, C=0, D=0, E=0

— — — — — Class = Class 4207: AB A=0, AB=5, B=1, BC=1, C=1, D=0, E=0

— — — — — Class = Class 4208: AB A=0, AB=1, B=0, BC=1, C=1, D=1, E=0

— — — — — Class = Class 4209: A A=1, AB=1, B=0, BC=0, C=1, D=0, E=0

— — — — — Class = Class 42INT: AB A=0, AB=7, B=2, BC=0, C=0, D=0, E=0

— — Presence ≤ 0.893

— — — Gender = Female: AB A=0, AB=1, B=0, BC=1, C=0, D=0, E=0

— — — Gender = Male: BC A=0, AB=1, B=5, BC=6, C=3, D=0, E=0

— Presence ≤ 0.821: C A=0, AB=0, B=0, BC=0, C=2, D=0, E=0