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Identifying students' behavioral online learning patterns through learning analytics: A case of Universitas Terbuka

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Abstract

Universitas Terbuka (UT) is a university in Indonesia that implements open and distance education system. As a distance education institution, UT's students are learning independently using pre-produced learning materials. As one of its support services, UT provides online tutorials with which students can interact with tutors and other students in the same tutorial classes. The online tutorial is designed asynchronously using Moodle-based LMS, which automatically records all students' learning activities and thus provide rich data of learning analytics. This paper reports the results of study on learning analytics to see students' online learning behavioral patterns (in the online tutorials) and their correlations with students' performances. The study is explorative and correlational in nature. The population of the study is all students who registered for online tutorials in 2019 in all courses offered by four faculties at UT. The results of the analysis show that in general, the trend of student participations in online tutorial decrease as the semester progresses. The correlational analysis results show that there are positive significant relationships between students' performance in tutorial and examination, tutorial and final course score, as well as between students' performance in the examination and final course score. The analysis also found significant differences in students' final course performance in a different course category, which indicates that course size does have an impact on students' performance. The analysis also indicates that course size significantly correlates to students' performance. The results of this research imply that course size is one of the effects that need to be considered in the learning model. In this case, the course size as namely a random effect in statistical modeling. The involvement of random effects in modeling needs to be considered.

Keywords: *Learning analytics, Moodle, course size, random effect Universitas Terbuka*

1. Introduction

Online learning offers many benefits for both students and instructors, as well as for the institution. Following the more conventional distance learning modes using earlier technologies such as radio and television, online learning that is heavily depending on the internet can be used to provide education to the masses. But unlike radio and television that are one-way and strong in providing mass education in nature, the use of a learning management system (LMS) in online learning can provide ample opportunities for the institution to individualize and personalize quality learning process. In addition, LMS is also very beneficial in recording the data of the whole learning process thus providing ample data to be used by both the institution and the instructor to enhance the quality of learning process. The learning analytics data is also very useful

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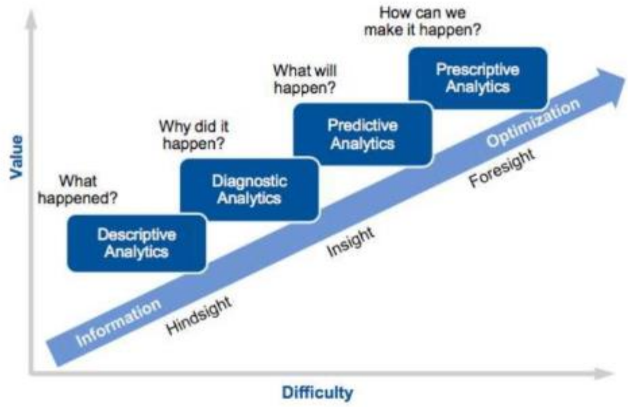
to forecast the likelihood of student success based on their learning activities for early intervention from either the institution or the instructor. [1] said that open, flexible, and distance learning (OFDL) has a long history of making opportunities available to audiences that have fallen out of scope of the traditional education sector. Likewise, as LMS offer both synchronous and asynchronous communication opportunities, students can revisit the course materials in a more flexible manner, assuring no one miss the lectures and or assignments.

Universitas Terbuka (UT) as an open university offering thousands of online courses to about 350 thousand students, also uses an LMS that built based on an open-source LMS Moodle. Moodle is one of the best best [2] and most used [3] open-sourced LMS that offers many features to facilitate quality online learning. The features in Moodle include, among others, affordances to upload and download materials in various format, discussion, to give and mark assignment in various types, calendar, and archive. The online learning at UT is positioned as an online tutorial complimentary to pre-produced main course materials that are sent in advance to students in both printed and digital e-modules format. Students are expected to study the modules independently and participate in online tutorials. The LMS is used as the main virtual class platform through which the main course materials and enrichment (mostly multimedia materials) are delivered, the interactions between students and tutors as well as among students themselves are conducted, and the assignments are given and marked. Thus, students' assessment is based on their performance in the tutorials (based on scores of their participation, discussion activation, and assignment score) combined with their performance in the final examination. Students' final grade for individual course is calculated based on weighted scores of those assessment aspects.

The statistics recorded by the LMS include their logging in/out data, their activities in the discussion forum, their assignment submission, as well as the scores given by the tutors for those activities and assignments. The data allows the institution to see the pattern of students' behavior in the online tutorials, as well as their performances. Those data are very meaningful and can be analyzed to find pivotal indicators to students' learning success. These are the data for learning analytics, which is defined by the 1st International Conference on Learning Analytics and Knowledge [4], [5] as "… the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.", as well as to enhance the quality of teaching and learning [6] and [7]. More specifically, [8] as shown in Figure 1, states that the benefits of learning analytics are to: (1) describe what is happening in the learning process, (2) predict what is going to happen di the future, (3) diagnose the why of what is happening happened, and (4) prescribe what to enhance in the learning process. In line with this, [9] earlier proposed that to utilize learning analytics holistically for learning enhancement, it must be done in five steps namely capture, report, predict, act, and refine.

Many institutions already incorporate learning analytics features in their systems and use the data to investigate students' behavior and performances. LMS' rich data need to be collected, organized and analyzed using various statistical tools such as data mining [10], [11], [12], [13], [14], and [15]. Many studies show that using data mining in learning analytics can help develop a model for student's profiling. Furthermore, using algorithm, machine learning, and other analytical tools can help predict student's performance and formulate recommendation for intervention to support learning success in accordance with students' learning styles [16] and [17].

As an illustration, [18] used LMS data analytics to detect and classify students' learning styles using Felder-Silverman Learning Styles Model (FSLSM). Based on their learning styles, the learning strategy was then designed to be adaptive to students' learning behavior.



Source: Gartner (2012)

Figure 1.1. *Benefits of learning analytics*

The Regarding the types of influential information that can be mined and analyzed from an LMS, [14] found that the frequency and nature of what students post in a discussion forum significantly influence their performances. The findings revealed that the more active students in the discussion, the better their performances were. Further findings of [14] also show that discussion posts, inter-student interactions, and self-exercise were significant factors to students' online learning performance. Interestingly, [14] did not find the duration of time spent inside the LMS, number of downloads, and log-in frequency to be significant influences for online learning success. [13] identified students' activity and learning pattern, and revealed that class size, the number of tutors, and course characteristics have significant impacts on students' online learning process. Another study done by [19] also analyzed students' behavior and learning success using *Association Rule Curating (*ARC) and found that students' background had a significant influence on students' success (GPA). Poonsirivong also found that students with 'better and stronger' background and spent more time in understanding/completing assignments/quizzes tended to have better examination grades and thus higher GPAs. Similar to Park and Poonsirivong, [15], [20] used machine learning to reveal students' online learning behavior to predict students' grades. [21] found that their study revealed that different patterns of learning design were associated with statistically significant differences in behaviour, but not in pass rates or satisfaction. Furthermore, [21] highlighted that applying learning analytics to learning design might, in a virtuous circle, contribute to the validity and effectiveness of both, and to the enhancement of online distance learning.

This paper reports a learning analytics study of UT's online learning, better known as online tutorial, specifically on the pattern of students learning and their performances, as well as on the analysis of the relationships among those indicators. Based on Campbell's steps, the study tries to capture, report, and predict students' success based on the indicators from the online tutorials at UT. Specifically, the paper focuses on learning analytics to describe students' behavioural patterns in online tutorials through their participation rates, activities in discussion, and assignment submissions; and whether or not those behavioral patterns correlate to their performances. Such correlations would indicate the indicators for student success.

2. Method

The study is explorative and correlational in nature. The population of the study is all students who registered for online tutorials in 2019 (2 semesters) in all courses offered by four faculties at UT, namely the Faculty of Education (FEDUC), the Faculty of Science and Technology (FST), the Faculty of Law, Social, and Political Sciences (FLSPS), and the Faculty of Business and Economics (FBE). UT offers around 1.363 courses, and the total number of students registering in online tutorials in 2019 was around 310.974.

The sample of the study was all students in selected courses, and course selection was done through two steps: (1) course categorization and (2) course selection. The online tutorials at UT are conducted for individual courses through virtual classes consisting of maximum of 50 registered students [22]. Each course has different number of registered students resulting in different number of tutorial virtual classes; courses with larger number of registered students would have larger number of virtual tutorial classes. Accordingly, for sample selection purposes, courses were categorized as large, middle size, and small courses. Further, as courses can also be categorized as exact and social sciences in nature, sample was also selected based on this categorization. Therefore, the sample courses were grouped into six types namely (1) large exact courses, (2) middle size exact courses, (3) small exact courses, (4) large social courses, (5) middle size social courses, and (6) small social courses.

The criteria for determining large, middle size, and small courses are different for different faculties due to the difference in average number of students registering in the respective faculties. In general, FBE and FLSPS have large number of students while FEDUC and FST have relatively smaller number of students, and thus the criteria for each course categorization follow accordingly as presented in Table 1. As shown by the table, for FBE and FLSPL the cutting numbers for categorization are larger than those for FEDUC and FST. It is important to note that the courses in FEDUC excludes those in the Study Program of Elementary School Teacher due to its unique characteristics where tutorials are conducted through face-to-face meetings.

Table 1. *The number of virtual class by course category by faculty*

Faculty	Number of Class in Each Course Category		
	Large Course	Middle Course	Small Course
FBE & FLSPL	1.640	2.285	949
FEDUC & FST	704	289	637

Table 2. *The criteria of course size categorization by faculty*

Faculty	Number of Class in Each Course Category		
	Large Course	Middle Course	Small Course
FBE & FLSPL	> 100	20 - 100	< 20

FEDUC & FST	> 20	10 - 20	< 10

Sample course was selected through the following steps:

1. Based on the course category as presented in Table 1, courses were sorted based on their number of tutorial classes. Naturally, there are many courses that have the same number of classes and data show that majority of courses in each course category have number of classes close to the minimum criteria as shown in Table 2.
2. To maximize the course size differences, sample was purposely selected based on the courses with the largest number of tutorial classes. The result is shown in Table 3.

Table 3. *The number of sample courses by course category*

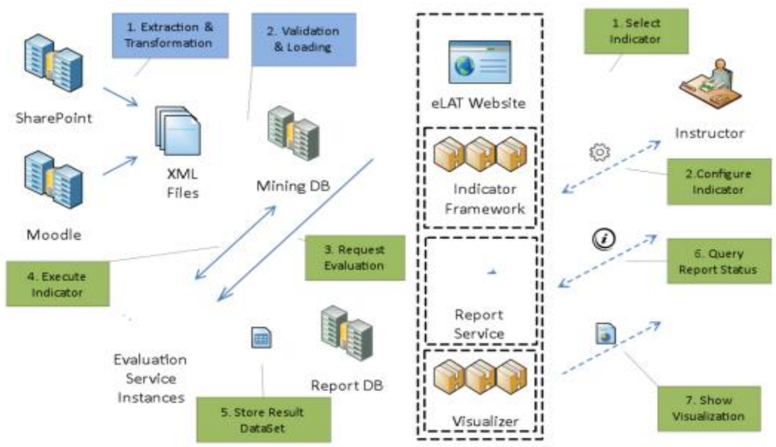
Faculty	Large Courses		Middle Courses		Small Courses		Total Courses
	Exact	Social	Exact	Social	Exact	Social	
FBE & FLSPL	8	8	4	4	2	2	28
FEDUC & FST	6	6	4	4	2	2	24
Sub-total	14	14	8	8	4	4	52

Table 4 presents the name of sample courses in each course category by faculty. Based on the selected courses, the total number of students involved is 5,044.

Table 4. *The name of sample courses for each category per faculty*

Faculty	Large Course		Middle Course		Small Course	
	Exact	Social	Exact	Social	Exact	Social
FBE	ESPA4123.01	EKMA4111.01	EKSI4202.07	EKMA4569.03	ESPA4428.02	ESPA4512.01
	ESPA4123.23	EKMA4111.57	EKSI4202.18	EKMA4569.23		
	ESPA4123.47	EKMA4111.85				
	ESPA4123.60	EKMA4111.115				
FLSPL	ISIP4215.01	MKDU4107.01	ADBI4211.01	ADPU4130.03	PAJA3331.05	PUST4101.04
	ISIP4215.25	MKDU4107.30	ADBI4211.37	ADPU4130.25		
	ISIP4215.52	MKDU4107.85				
	ISIP4215.70	MKDU4107.160				
FEDUC	PDGK4301.03	IDIK4012.01	PEMA4210.03	PAUD4403.01	PDGK4406.03	PBIN4102.02
	PDGK4301.07	IDIK4012.10	PEMA4210.11	PAUD4403.08		
	PDGK4301.09	IDIK4012.20				
FST	KIMD4110.02	MKDU4112.03	MATA4110.03	BIOL4110.05	SATS4323.01	PWKL4305.01
	KIMD4110.07	MKDU4112.08	MATA4110.09	BIOL4110.11		
	KIMD4110.13	MKDU4112.15				

Data collection was conducted through two first step of Campell steps, capture and report, which are basically data minning activities to generate all the indicator data from the Moodle database [23], which consists of 569 tables with the size of 6.5 GB. The data is very rich involving many variables that are interrelated to each other. The data for students' participations and activities in discussion was collected from their attendance (logging in) in all sessions of tutorials (the tutorial consists of 8-12 sessions depending on the course's credit unit), and students' activities in discussion including posting questions/comments, commenting on others, responding/answering tutor's questions, etc.), and submission of assignments. Students' peformances were measured through students' tutorial scores (combined participation and assignment score), examination scores at the end of the semester, and final course score (combine tutorial and examination score). The final course score is used for grading of course completion. Data mining to generate an indicator variable requires a careful and thorough process (see Figure 2).

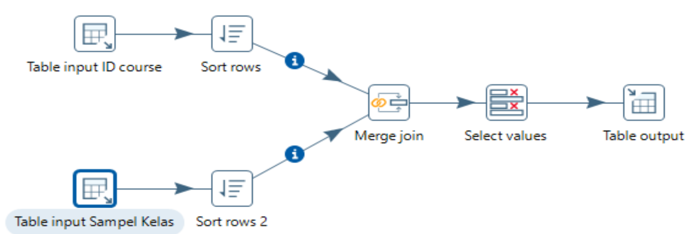


Source: Dyckhoff et al. (2012)

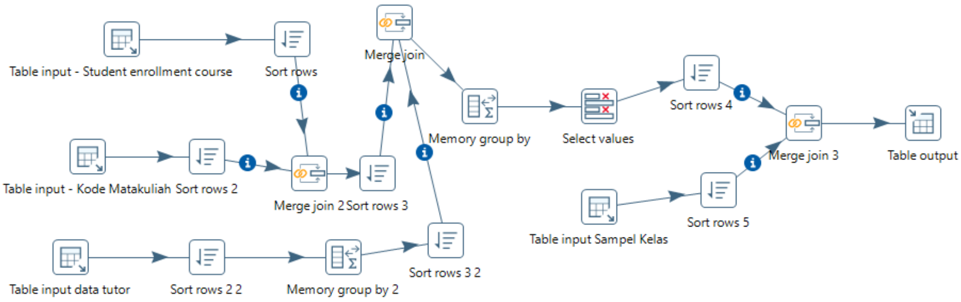
Figure 2.1. *Indicator identification process in learning analytics*

As seen in Figure 2, data for an indicator needs to be identified and captured through (1) extraction and transformation, validation and loading, evaluation, execution, and storing the dataset results. The following diagrams illustrate the process of data minning for ID course identification, course size, student participation, and student activities in discussion.

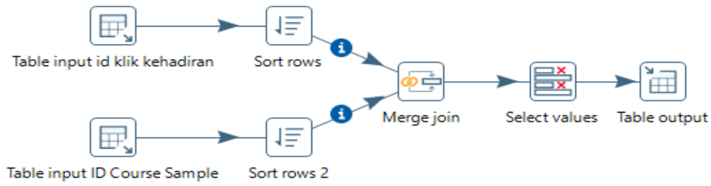
1. ID Course identification



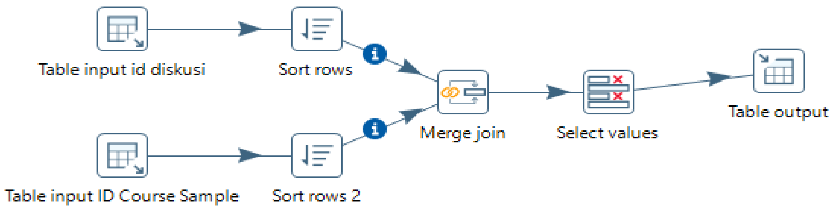
2. Course size



3. Student participation in online tutorials



4. Students activities in discussions



Data mined were then analyzed using both descriptive and inferential statistics. Descriptive analysis is used to describe the patterns of students' behavioral patterns within the online tutorial classes, while the inferential analysis was employed to see the correlations among the indicator variables. The inferential statistics used was the General Linear Model (GLM) of ANCOVA considering the number of data in each course category are not equal and the performance data is not normally distributed [25], [26], [27], [28], and [29].

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3. Results and Discussion

Student behavioral patterns in online tutorials can be observed through three main activities, which are their participation, activities in the discussion, and assignment submission.

3.1. Participation Patterns

Students' participation data is measured based on their attendance in the tutorial sessions and their activities in the discussion forum. As mentioned earlier, even though the UT online tutorials are conducted throughout the semester using an LMS, the management of 'learning' activities is divided into nine sessions/weeks. Students are expected to log in, attend, and participate in all the sessions asynchronously, and for each session their attendance will be recorded. Figure 3.1.1, Figure 3.1.2, and Figure 3.1.3 presents the participation pattern of students in each course category.

Figure 3.1.1, Figure 3.1.2, and Figure 3.1.3 shows that participation patterns in all course categories are similar. In general, students' participation decreases as the semester progresses. The median percentages of students attending Session 1 are all higher than that in the following sessions in all course categories. A closer look to the pattens however, shows that in general the median of attendance rates in social courses (yellow box plots) seem to be higher than those in exact courses (blue box plots) regardless of the course size. This indicates that the percentages of students' attendance in social courses are higher than those in exact courses.

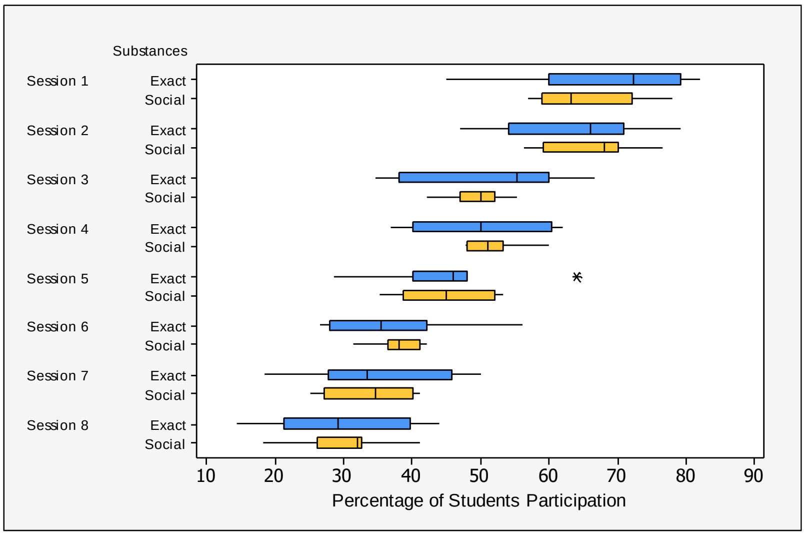

***Figure 3.1.1** Attendance pattern of small courses*

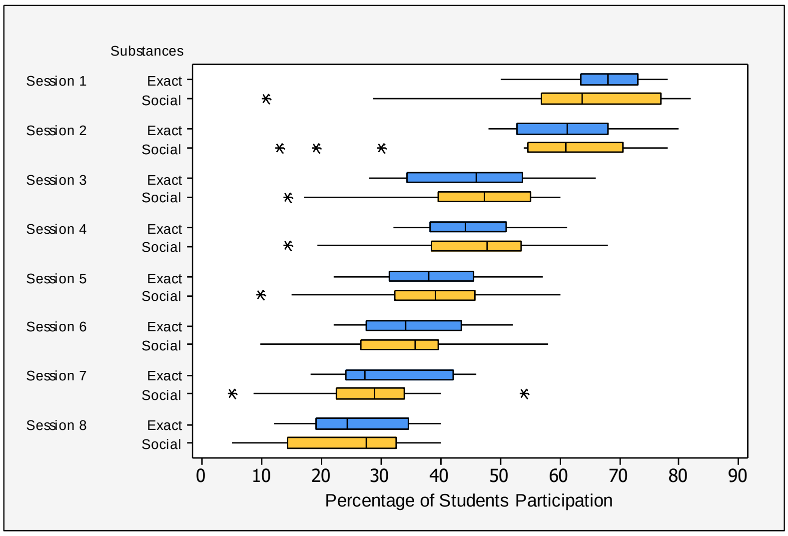

***Figure 3.1.2.** Attendance pattern of middle course*

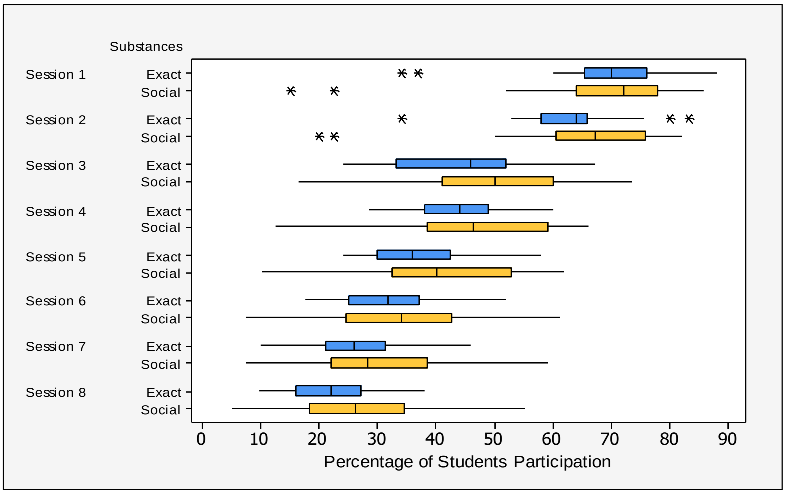

Figure 3.1.3. *Attendance pattern of large course*

Further look at the participation data, similar to attendance patterns, students' activities in the discussion seem to also show that students' participation in discussion decreases as the semester progresses. Even though the online tutorial is designed as asynchronous tutorial, it is expected that students would actively involve in the class discussion during the learning process. The discussion is conducted in each session in where tutor would trigger it with either a case study or simply intriguing questions. Upon tutor's initiation, students can respond as comments, probing questions, opinions, etc. In each session, tutor will evaluate student's activity and engagement in the discussion and translated into tutorial participation score. Figures 3.1.4, Figure 3.1.5 and Figure 3.1.6 show students' discussion pattern by course category.

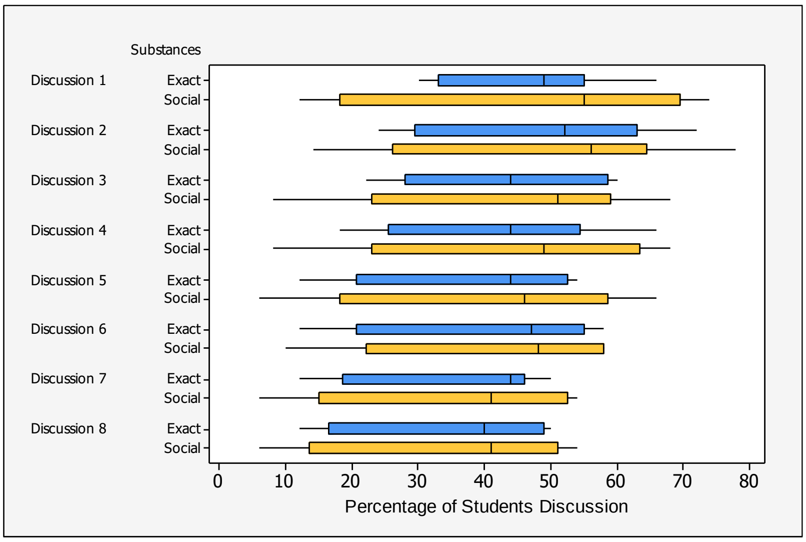

Figure 3.1.4. *Discussion tattern of small course*

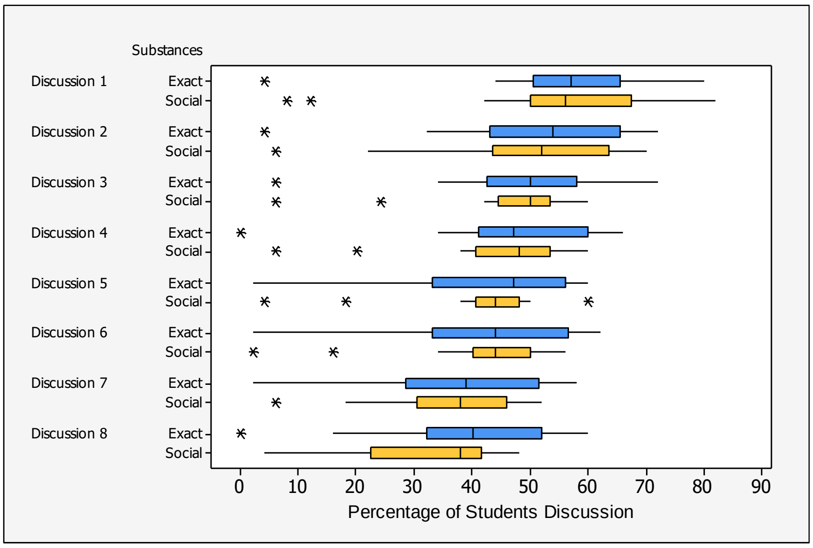

Figure 3.1.5. *Discussion pattern of middle course*

As seen in the figures, not all students who were attending the tutorial sessions actively participate in the discussions. It is interesting to note that for the large courses, students in the social classes seem to be more active than those in the exact classes. This is indicated by the higher percentage of students participating in the discussion shown by both the boxplots and the median values). In the small courses, although they are not as significant as in the large courses, the median values of the social classes also higher than those of the exact classes. Nevertheless, that trend is not seen in the middle-size courses. In fact, Figure 3.1.5 shows that the median values of the exact classes are slightly higher than those of the social classes.

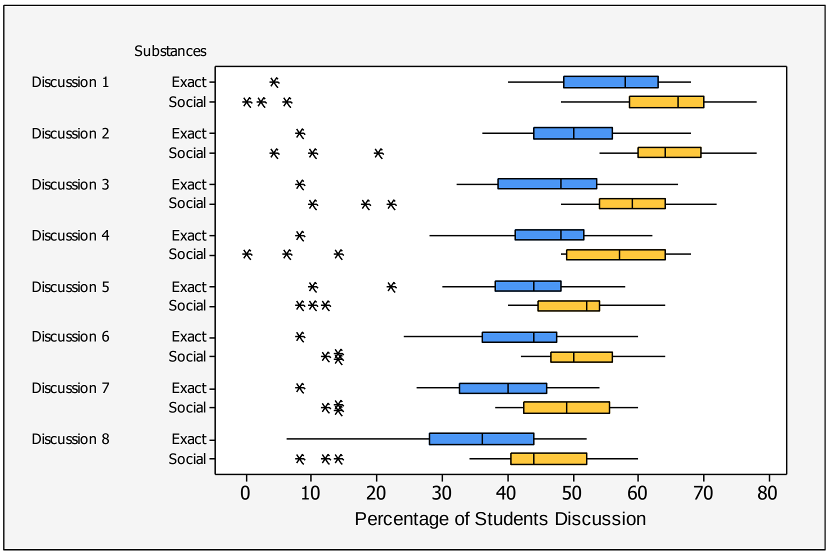

Figure 3.1.6. *Discussion pattern of large courses*

3.2. Assignment Submission Patterns

Each course has three assignments for students to submit. The assignments are given in tutorial session 3, 5, and 7. The assignments are marked/scored by tutors and the average score of the three assignments contribute 50% to students' total tutorial scores. Figure 3.2.1, Figure 3.2.2 and Figure 3.2.3 present the patterns of assignment submission in the large and middle size courses.

As seen in Figure 3.2.1, it is interesting to see that the right end side of boxplots picturing the assignment submission for large courses reach 100%. This means that there are classes in both exact and non-exact/social large courses with 100% submission in all assignment. However, as shown by Figure 3.2.2 and Figure 3.2.3, not every student in the middle-size and large courses submitted their assignments. In the large course, one specific trend that can be seen is that the median of the submission rate for social courses slightly higher than that for exact courses.

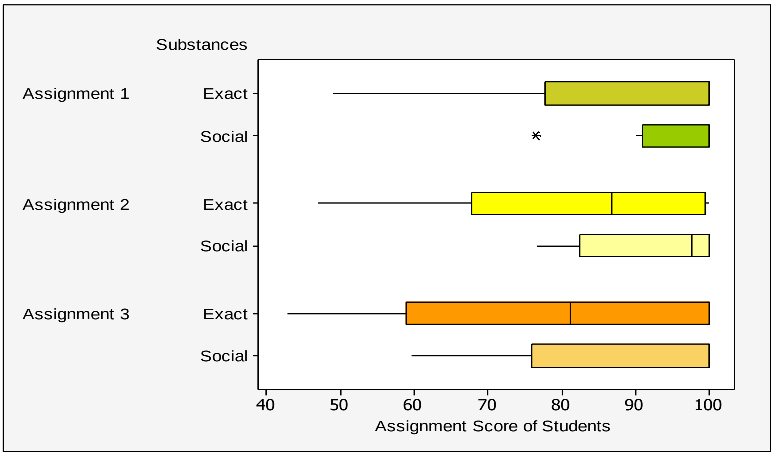

Figure 3.2.1. *Assignment score of students in small course*

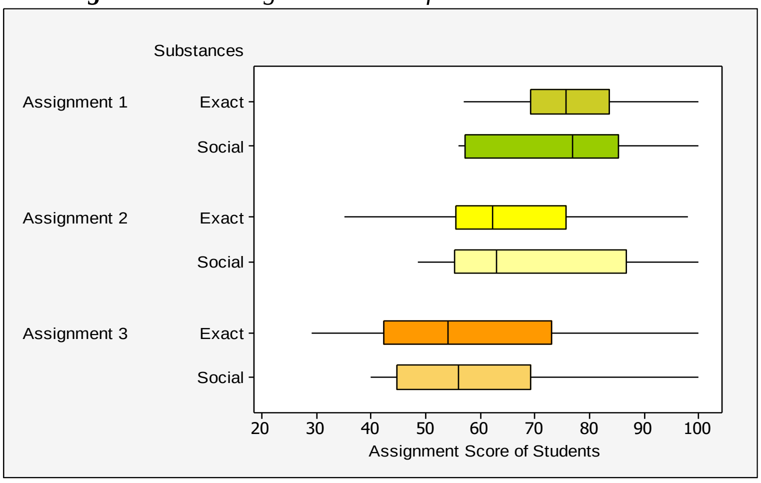

Figure 3.2.2. *Assignment score of students in middle course*

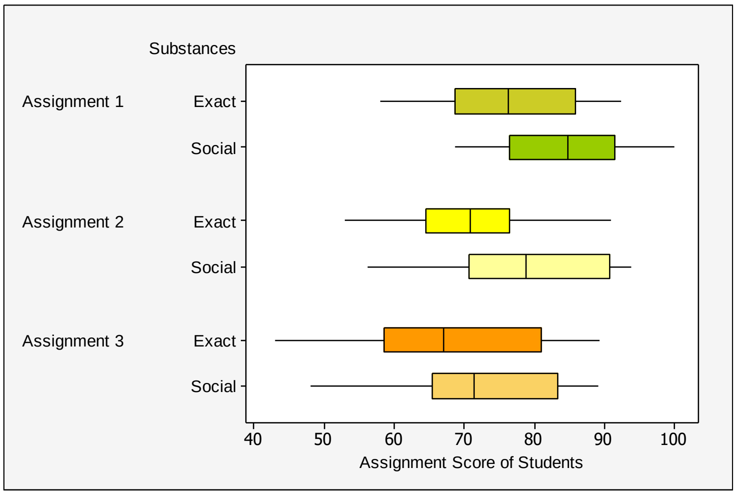

Figure 3.2.3. *Assignment score of students in large course*

Further look at assignment data also shows the punctuality of assignment submission. Students are given a deadline for submitting each assignment, mostly one week after the assignment was given. As shown by Figure 3.2.4, in general, there is no particular patterns in terms of students' punctuality in submitting the assignments. For large and small courses, it seems that students in social courses are more punctual than students in the exact courses. Whilst in the middle-size courses, the data show the reverse trend where the students in exact courses seem to be a little more punctual than those in social courses.

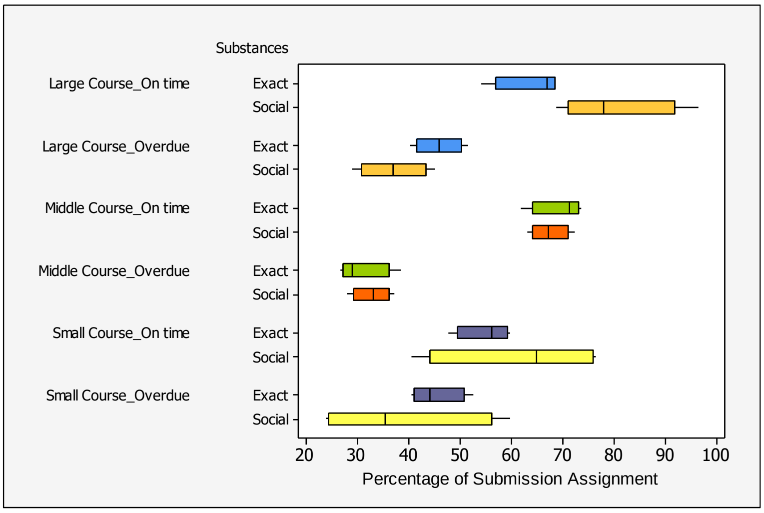

Figure 3.2.4. *Punctuality of sssignment submission*

3.3. Correlation Between Behavioral Patterns and Performance

Students' behavior during the learning process was indicated by their tutorial attendance, participation in discussion, and assignment submission as previously presented. One of the benefits of having those learning analytics data is to see whether or not those behavioral patterns correlated to their performance. Performance in this study is measured through tutorial score, final examination score, and final course score. Tutorial score is calculated based on the score of attendance in tutorial (20%), participation in discussion (30%), and assignment score (50%). Table 5 shows that individually, performances in tutorial, examination, and final course are significantly correlated with each other. The positive and significant correlation between tutorial and examination, although small (0.189), is reassuring because it indicates that attending and participating in tutorials do help students in their examination. The positive and significant relationships between both tutorial and examination scores to final course score is of course expected as the final course score is calculated based on tutorial (50%) and examination (50%) scores.

Table 5. *Correlation of performance indicators*

		Tutorial	Examination	Final Course Score
Tutorial	Pearson Correlation	1	.189**	.355**
	Sig. (2-tailed)		.000	.000
	N	4784	4784	4784
Examination	Pearson Correlation	.189**	1	.881**
	Sig. (2-tailed)	.000		.000
	N	4784	4784	4784
Final Course Score	Pearson Correlation	.355**	.881**	1
	Sig. (2-tailed)	.000	.000	
	N	4784	4784	4784

**. Correlation is significant at the 0.01 level (2-tailed).

To further analyze whether there are differences in students' performance in different course category, an analysis of covariance was conducted using General Linear Model (GLM) to consider differences in the numbers of data in each category. The GLM model was chosen based on the results of different modelling analysis, which shows the highest accuracy of 85%. As explained previously, students were grouped in six categories: (1) large exact courses, (2) middle size exact courses, (3) small exact courses, (4) large social courses, (5) middle size social courses, and (6) small social courses. The analysis results are shown in Table 6.

As shown by the R-square value, the variances of tutorial score, examination score, and course category could explain 85% of the variance in final course scores. This means that 85% of final course performance can significantly be explained by performances in tutorial, examination and course category. This table also indicates that students' final course performances are significantly different in different course category.

Table 6. *Results of analysis of covariance for final course score*

Source	db	Sum Square	Mean Square	F	Sig

Examination Score	164	1.199.077	7.311,45	119,23	0,000
Tutorial Score	99	356.916	3.605,21	15	0,000
Course Category	5	834	166,80	2.73	0.018
Error	4515	275.46	61,01		
Total	4783	1.832287			

R-square = 0.85

Further analysis to see which course category has the same 'influence' on students' final course performances, a Tukey test at alpha 95% was conducted. The results are presented in Table 7. The analysis resulted in three group of course category with different level of 'influence'. The groups in Table 6 are shown as A, AB, and B, each group indicating the same 'influence' level on the final course performance. The course categories once again are: (1) large exact courses, (2) middle size exact courses, (3) small exact courses, (4) large social courses, (5) middle size social courses, and (6) small social courses. As seen in the table, the large exact courses (1), small exact courses (5), and middle-size social courses (4) tend to have the same level of 'influence' on students' final course performance. Likewise, the large social courses (2) and small social courses (6) also tend to have the same level of influence on students' final course performance.

Table 7. *Similarity of 'influence' of course size on final course performance*

Category	N	Mean	Grouping	
3	723	48.74	A	
1	1317	48.22	A	B
5	342	48.05	A	B
4	741	47.75	A	B
2	1327	47.50		B
6	334	46.84		B

In summary, all the above analysis results indicate that course category influence students' final course performance, which can also mean that it influences the quality of students' learning process. This perhaps due to the variations in the quality of the tutorial classes as they are tutored by different people. The larger the course size the larger the number of tutorial class in that course, and thus the more variation it will have in terms of the quality of tutorials. Therefore, the significant differences among students' performances in different course size need to be understood within the online tutorial context. A separate analysis result shows that the variable of course size itself seems to not have any significant correlation with students' final course performance.

4. Conclusion

This study has explored students' behavioral online learning patterns as measured by their attendance and participation in online tutorials and their submission of assignments. The descriptive statistical analysis reveals that students' attendance in tutorials sessions and their participation in discussion decrease as the semester progresses. Regarding the submission of assignments, this study found that except for some classes in large courses of both exact and social courses, not every student in the middle-size and large courses submitted their assignments. However, the study did not find any particular patterns in terms of students' punctuality in submitting the assignments.

The correlational analysis results show that there are positive significant relationships between students' performance in tutorial and examination, tutorial and final course score, as well as between students' performance in examination and final course score. The analysis also found significant differences in students' final course performance in different course category, which indicates that course size does have an impact on students' performance.

5. References

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