# IMPACT OF LEARNING ANALYTICS TOWARDS STUDENTS PERFORMANCE

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## Abstract

*The fast pace of big data analytics advancement makes it necessary for any organization to coincide it with their management and measurement process. It has become essential for education sectors to analyze this for the development of both learning and academic activities (Shikha. A, 2014). Learning analytics (LA) is the measurement and analysis of the collection of data with regards to learners and their context for making learning more effective. LA is much concern with improving learner's success. Four dimensions have been identified; data and environment, stakeholders, objectives, and methods. This paper investigates the impact of learning analytics on student's performance. The focus group was students in Technology Management program at UTM SPACE, Kuala Lumpur. Two research objective has been identified; (i) to find the level of LA understanding among academic staff and (ii) to investigate the relationship between learning analytics and student performance. The research focused on (i) data collection and population at Centre of Diploma Studies, UTM SPACE, KL; (ii) the selected sample will be students in Technology Management's program; (iii) the research*

*focused on learning analytics with main focus on course assessment reports of core course which are (a) technology management and (b) operation management.*

**Keywords**

Learning Analytics, Technology Management, UTMSPACE, Kuala Lumpur

## 1. Introduction

Living in era of fourth industrial revolution (4IR), data have been one of the main components in 4IR. Data is generated almost from every sector (Saptarshi, 2013). Be it in the sport sector, construction or education sector as well. The primary focus of this paper is to analyze the relationship between big data gathered by learning analytic in improving student's performance. Numbers of academic institutions face significant pressure from the administrators and stakeholder itself in term of detailing the students learning within departments, majors, or programs. Apart from that, sizable resources and effort have taken into action to develop and implement striking array of evidence-based practices within classrooms, curriculum, and campuses. Unfortunately, despite the development and implementation independently of above initiatives, researches have shows that there is little intentional communication among disciplines, academic and also administrative units. (Henderson, Beach & Finkelstein, 2011). It seems acceptable to hypothesize that a large effect on education might be achieved along more synergetic approach. This is merely based on a concerted and collaborative effort on the part of educators, researchers, staff as well as the administration itself. Henderson *et.al* (2011) stated that designing compatible long-term strategies with complex and dynamic nature of colleges and universities is the most effective approach. However, the challenge arise when it comes to find a practical and systematic way to connect these individual and separate practices into a unified process. This process could potentially promote student retention and success by permit the exploration of data immediately which relevant to designers of individual courses, groups and individuals responsible for higher-level of problematic curricular design and evaluation. The elucidation to these problems such as student retention and success usually cannot be reached by only adjusts the factors independently in separate units of an institution.

In order to facilitate the goals of increased student's performance on a campus or a program, we must nurture it in the classroom through course design that filled with diverse types of data, typically collected disparately across an institution. Collecting data is easy but to effectively using the data to inform curricular design will present massive challenge. Top down approaches to academic analytics or any curricular change initiatives are usually unsuccessful (Buerck & Mudigonda, 2014).

### 1.1 Research Objectives

This research approach designated from our current understanding of learning analytics, academic analytics, design theory, and the principles of institutional change. Researches objectives draw are as below; (i) to find the level of LA understanding among academic staffs and (ii) to investigate the relationship between learning analytics and student performance.

### 1.2 Research Hypothesis

The hypotheses are draw upon the objectives of this research which are:

- There is high level of understanding about LA among academic staffs.

- There are relationship between learning analytics and student performance.

### 1.3 Scope And Limitation

The research focused on (i) data collection and population at Centre of Diploma Studies, UTMSPACE, KL; (ii) the selected sample will be students in Technology Management's program; (iii) the research focused on learning analytics with main focus on course assessment reports of core course which are (a) technology management and (b) operation management.

## 2. Learning Analytics

Numbers of factors have been identified as trigger in motivating interest in learning analytics. Every educational institution is feeling the pressure to understand and enhance their knowledge on student's learning behavior. In addition with online learning, the pressures have become higher than before. LA has the ability to provide numerous methods in documented students learning behavior as well as their performance. Other goals of LA include (i) predicting learner performance, (ii) suggesting to learners relevant learning resources, (iii) increased reflection and awareness on the part of the learner, (iv) detection of undesirable learning behaviors, and (v) detecting affective states (e.g., boredom, frustration) of the learner (Verbert, Manouselis, Drachsler, & Duval, 2012). LA have the ability to ensure all the data in the faculty to be data-driven and easy to access and measures.

Learning analytics (LA) is defined as the 'measurement, collection, analysis and reporting of data about learners and their contexts (Siemens & Long, 2011). Apart from that, they also added the main purpose of LA is to get better understanding and enhance learning experience as well as the environment in which it occurs. EDUCAUSE's Next Generation learning initiative (2010) explained LA as the use of data and models to forecast student progress and performance, and the ability to react on that information through feedback and action. Johnson et al. (2011), in addition, defined LA as tools to interpret wide range of data produced by and gathered on behalf of issues.

## 2.1 Applications of Learning Analytics

LA has been used as tools used to improve learning and education. Elias, T. (2010). Other series field of study also used analytics such as business intelligence, web analytics, academic analytics and action analytics. This uprising field has been identified as the ladder in real time use of LA by students, instructors, and academic advisor to improve student success. Wayne. E (2006) support the use of LA as tool to predict behavior, act on predictions and feed those results back into the process for improvement of the prediction over the time. Dietz-Uhler & Hurn (2013) stated that LA not only provides one of many methods to not only documentation of student performance but also providing encouraging tools that helps for continuous improvement that accrediting bodies are seeking.

## 2.2 Model in Learning Analytics

The research used reference model proposed by Chatti (2004) as it is easily to be understand about this research flow in learning analytics. As shown in figure 1, there are four dimensions in the reference model for LA which is; (i) *What?-Knowing and analyze types of data that the system gather, manage, and use for analysis,* (ii) *Who?- Determine the subject of analysis,* (iii)*Why?- Objective for analyzing collected data by the system*, lastly (iv) *How?-Techniques and tools used in analyzing the collected data.*

### 2.2.1 Data and Environments

Data used in LA involve varied sources of educational data. There are two sources of data which are (i) centralized educational systems and (ii) distributed learning environments. Data from centralized educational systems are presented by learning management systems (LMS). Examples of the LMS data are Blackboard, e-learning portal, Moodle and many more. LMS is a systems that store large logs of data of students' activities and interaction data which include reading, writing, accessing and uploading learning material, quizzes and many more (Romero & Ventura, 2007). LMS is the extend of traditional face-to-face teaching methods in order to cope with the need of fourth industrial revolution which rapidly concern with enhancing technology in teaching experiences. Apart from that, LMS also used to support long-distance learning.

Main producer of data in educational mainly come from the learners that come from varied learning environment and system. Another source of data, distributed learning environment had gain increasingly popular and vital with the growth of user-generated content. Personal learning environment (PLE) concept represents the open and distributed learning environments. PLEs gather data from different source beyond LMS. The data can be in formal and informal learning channels,

different format, and distributed across space, time, and media. Nurhayati (2019) from her speech in 21st Century Learning Shift at UTM Kuala Lumpur stated that data from formal learning data, for example, course assessment report can be used to interpreted LA. For this research, distributed learning environment have been used. Course assessment report (CAR) is the formal summarization of each course that has been highlighted in this study which is Technology Management and Operation Management.
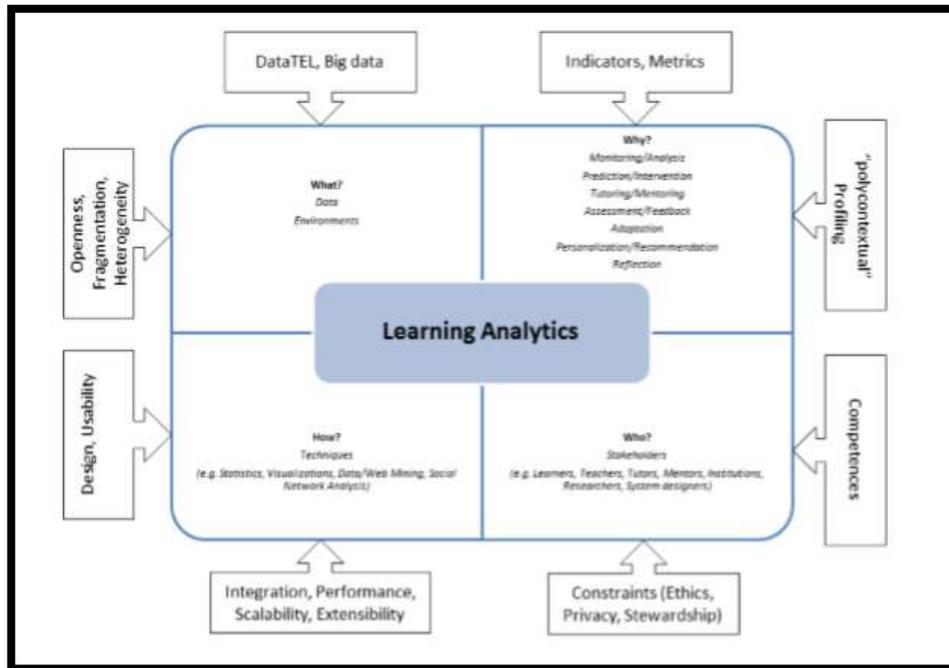


**Figure 1:** *Chatti (2004) Reference Model*

## 2.2.2 Stakeholders

The use of LA can be channel toward variety of stakeholders that come with different goals, objectives and expectation from LA exercise. For instance, student might be interested in knowing the use of analytics in improving their grade. Teachers probably looking forward to know augment of analytics towards effectiveness of teaching practices. The researcher believed that educational institution especially higher education institution can utilize analytics to be data-driven decision making. Campbell et al., (2007) stated that the use of analytics tools in supporting decision making can be use in educational institutions as well. They added that it can be used to identify potential students at risk in their study and improving student success. EDUCAUSE (2010) stated that analytics tools in educational institutions can act as the driver in the development of student requirement policies, financial decisions, hiring purpose and also improving course planning.

### 2.2.3 Objectives

Different stakeholders will derive different types of objectives within their point of view. Possible objectives of LA includes; (i) *Monitoring and analysis* – The aim of monitoring is to track student activities and generate reports in order to support decision-making be it by the educational institution and teacher as well. Other purpose is to continuously improving the learning environment through the evaluation of learning. Apart from that, analysis will help to detect patterns and make decisions on the future design of learning activity; (ii) *Prediction and intervention* – The goal in prediction is to develop a model that helps to predict learner knowledge and future performance with reference from learner current activities and accomplishments. In addition, it can also be use in intervention for problematic student who need additional assistance and support by suggesting actions to help learners improve their performance; (iii)*Tutoring and mentoring* – Tutoring focusing more on helping students in limited context of course and limited to teaching process. In contrast, mentoring is supporting students in a whole process ranging from career planning, supervision on goal achievement in both academic and personal, and so forth; (iv)*Assessment and feedback* – Focus on improving effectiveness and efficiency of learning process. Receiving intelligent feedback from the students and teachers/mentors is also vital. It provides generated information which generated by user's interest and learning context; (v) *Adaptation* – The LA's aim in this objective is to portray a clear picture about steps the students need through adaptation of organizing learning resources and instructional activities; (vi) *Personalization and recommendation* – LA is considering highly learner-centric in personalization. The focus is to guide the learners in their learning and refinement their PLEs whenever they need to achieve their learning goals. Recommender systems help by fostering self-directed learning; (vii) *Reflection* – learning by reflection promotes the chance of learning by returning to and evaluation of past work and personal experiences with the aim of improving future experiences and encourage life-long learning (Boud et al, 1985).

Based on the above objectives, the researcher had chosen reflection as the main objective of using LA in this research. In previous chapter, the researcher had mentioned about finding relationship between LA with student performance. Therefore, by evaluating past course assessment report (CAR), the researcher can detect for patterns in student performance and improve future learning experiences for the student.

### 2.2.4 Methods

Application of different techniques helps to detect patterns hidden in educational data sets. Chatti (2004) describe four techniques that have gain popularity in LA literature in the past couple of year's research which are; (i) *Statistics*: LMS system provides reporting tools that enable people to

know basic statistics of student's interaction with the system. These provide simple statistical operations for example; mean, median, average and standard deviation. (ii) *Information visualization:* Another way to represent forms of reports that is user-friendly. It facilitates the interpretation and the analysis of educational data. Romero & Ventura (2007) stated that variety of information visualization techniques such as charts, scatterplot, 3D representations, or even map, can be used to represent information in clear and understandable format. (iii) *Data mining:* Another term of data mining is *Knowledge Discovery in Database (KDD)* is the process of exploring useful patterns or knowledge from data source (Liu, 2006). There are three categories of data mining which are; (a) supervised learning (*classification and prediction*), (b) unsupervised learning, and (c) association rule mining (Han & Kamber, 2006; Liu, 2006). (iv) *Social network analysis (SNA):* This tool analyzes on particular data which is student participation in online discussion forums. The design is to provide summaries of this participation for the benefit instructional and advisory personnel.

## 2.3 Process in Learning Analytics

Researcher has found several series of different process relating to learning analytics. Baker *et.al* (2008) had developed *Knowledge Continuum* framework for business. The starting points for this process start with obtaining raw data. Raw data consists of characters, symbols, and other input that meaningless in the first place. By attaching meaning to the data, it becomes information. The information have the capable to answering questions of who, what, where and when. After adding up synthesis and analysis on the information, it then becomes knowledge capable of answering the questions of why and how. Last step is use the knowledge to establish and achieve goals through its application and it becomes wisdom. Campbell, Deblouis and Oblinger (2008) proposed *The Five Steps of Analytics* as the continuity of Knowledge Continuum process. The steps consist of (i) capture, (ii) report, (iii) predict, (iv) act, and (v) refine. The first four steps have the same step as Knowledge Continuum. It begins by capturing meaningless data which then reported as information which enable predictions based on knowledge and wise action. The additional step 'refine' recognizes analytics as the step where it consist monitoring impact of continuous self-improvement and the need for statistical models to be updated on a regular basis. However, literatures pertaining this process is scarce (Elias, 2010).

Dron and Anderson (2009) presented a model that useful in defining the process of learning analytics which is *Collective Application Model.* Their model has divided three cyclical phases which consisted of five layers. This model emphasizes on cyclical nature of analytical processes and the continuous need in self-improvement. Apart from that, they also highlighted on the need of improving the system through successive phases of gathering, processing and presenting information. Gathering

includes data selection and capture. Processing involves the aggregation and reporting of information. Lastly, application includes the use, refinement and sharing of knowledge in attempts to improve the system.Another LA processes in terms of educational environment has been proposed by Chatti (2004). The processes include (i) data collection and pre-processing, (ii) analytics and action, and lastly (iii) post-processing. In the first process, the core data for this process will be the educational data. The data come from the educational environment as well as the system itself. This is vital steps in order to discover the useful patterns. Data collection will be too large or too irrelevant (Liu, 2006). Therefore, to minimize it, there is a need to do data processing or also known as data preparation (Liu, 2006). Data processing will allow data transformation into a suitable format to be used as input for a particular LA method. Examples of data pre-processing tasks (from data mining field) include data cleaning, data integration, data transformation, data reduction, data modeling, user and session identification as well as path completion (Han and Kamber, 2006; Romero & Ventura, 2007)

In the second processes, analytics and action, different LA techniques can be used to explore the data in order to discover hidden patterns. Thus, it can help to provide more effective learning experience. The main focus in this step is about actions which include monitoring, analysis, prediction, intervention, assessment, adaption, personalization, recommendation, and reflection.

Last step in this process is post-processing where continuous improvement is the core of this process. The refining process includes gathering new data from additional data sources, data refining, determine new attributes for new iteration, identify new indicators/metrics, modify variables of analysis or choose new analytics methods. The researcher had concluded by combining and comparing the processes from different past research prioritize processes which are (i) data capturing and processing, where the data will be capture in meaningful form and be process into easily use input of data, (ii) data analytics and information presentation, in this step, data will be analyze, report through visualization information and presentation (iii) continuous improvement which include add on any meaningful data from meaningful data sources, modify, alter, and determine any new indicators, variables and attributes. For this research, the researcher only focus on step one and two in order to achieve research objective 2 (RO2). Intervention, refinement and continuous improvement will not be done due to internal, time and cost constraint.

LA processes include (i) data collection and pre-processing, (ii) analytics and action, and lastly (iii) post-processing (Chatti *et al*, 2014). In the first process, the core of this process will be the educational data. The data come from the educational environment as well as the system itself. This is vital steps in order to discover the useful patterns. Data collection will be too large or too irrelevant (Liu, 2006). Therefore, to minimize it, there is a need to do data processing. In analytics and action

process, different types of LA techniques can be used to know hidden patterns for that processed data at step one. The utmost focus in this process is for taking action. Lastly, to ensure continuous improvement of analytic and action, the execution post-processing is vital. Learning analytics (LA) measure and analyze data collection with regards of learners and their contexts for making learning more effective (Sikha, 2014). Norris D. (2011); Shum, B (2012) & Siemens & Long (2011), indicated that LA mostly concerned on improving learners success. Greller, W. *et.al* (2012) on the other hand have used general morphological analysis (GMA) to separate the LA domain into six critical dimensions which are; stakeholders, objectives, data, instruments, internal limitations and external constraints. There are also reference model by Chatti *et.al* (2012) that based on four dimensions; data and environment (what?), stakeholders (who?), objectives (why?), and methods (how?).

In this model by Chatti *et al.,* (2014), data and environment used to answering the question of *what kind of data the systems gather does, manage, use for analysis?* There are two big categories; (i) centralized educational system, presented by learning management system and (ii) distributed learning environment, presented by formal and informal learning. Stakeholders come from different peoples which are the students, lecturers, educational institution and so forth that have different aims from LA. All of them are answering the question of *who is targeted by the analysis?* For instance, the students may want to know how analytics can improve their grades or help to build personal learning environment. Next is the objective which pose a question of *why does the system analyzed the collected data?* There are many objectives that can derive but vary according to stakeholders which include monitoring, analysis, prediction, intervention, tutoring/mentoring, assessment, feedback, adaptation, personalization, recommendation and reflection. Lastly, methods on *how does the system perform the analysis of the collected data?* Different techniques that could be used to detect interesting patterns hidden in educational data sets are statistics, information visualization (IV), data mining (DM) and social network analysis (SNA).For this study, LA process will be as below.
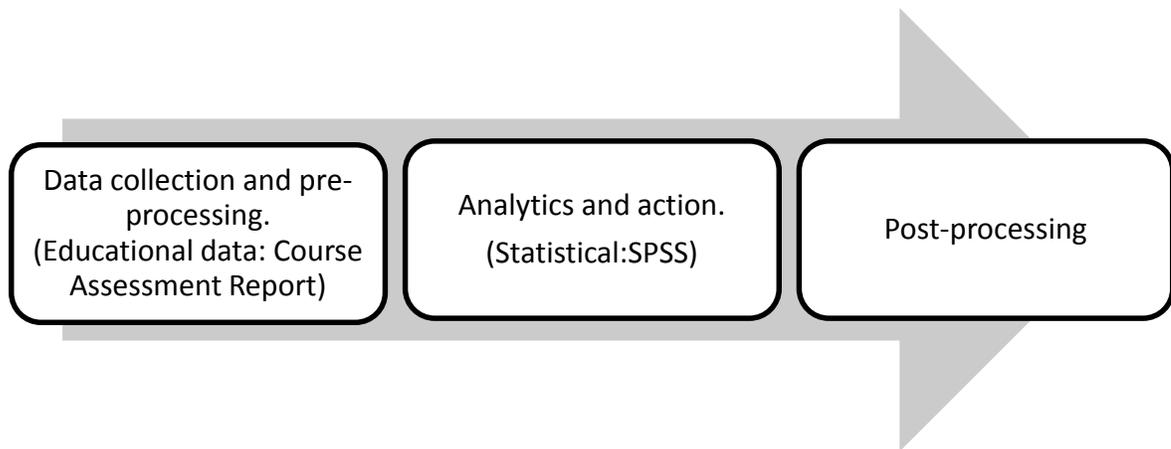
**Figure 2:** *Research LA Process*

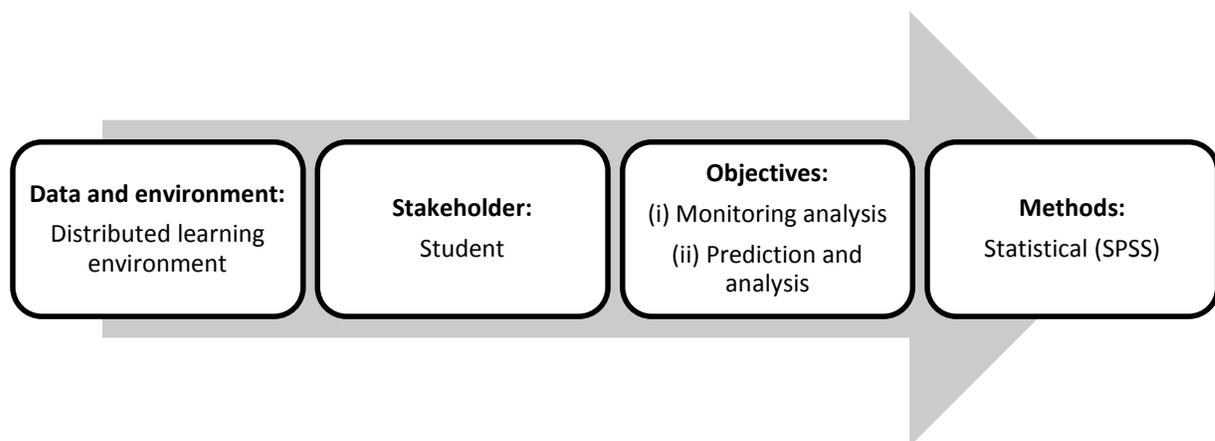For the research four dimensions, researchers have fill out the Chattis *et al.,* (2014) reference model as below;



**Figure 3:** *Research Domains*

## 3. Research Methodology

By referring to the research question of this study, the researcher attempts to investigate the relationship of learning analytics and student performance for technology management program at UTMSPACE. In answering the questions, researchers used and adapted related method from previous study and also qualitative research design. This method is seconded by Henn, Weinstein, and Foard (2005) whom stated that qualitative surveys are apposite for studying the relationship between two or more variables. The use of quantitative descriptive research design will be exercises. For RO1, it has been done through distribution of online questionnaires. Google Form is the tools of this questionnaire. This tools is publicly use, user-friendly as well as cost effective. One of the drawbacks of using online questionnaires is that the validity of the respondent cannot be detected.

In order to achieve RO2, secondary data have been used. Data used come from the course assessment report (CAR). Throughout the CAR, researcher found out that there are numbers of subject in the technology management's program (DDWG). To investigate use of LA in prediction of students performance, researcher decided to use subject on Year 2 semester 3; Technology Management (DDWG 2243) and Year 3 semester 4; Introduction to Operation Management (DDWG 2223).

## 3.1 Flow of Research Activities

In this research, researchers first define the research objectives to acknowledge the research path and what researchers want to achieve in this research. After that, the researchers will review concepts, theories as well as previous finding to build up and enhance knowledge and understanding on this research. After that, the research formulated research hypothesis that the researchers want to test in this study. Research design drawn upon which include the methodology, questionnaire structures, set the population and sample, validity of instruments, conducting pilot study, set the reliability of instruments, location study, and lastly statistical analysis. After obtaining all the analyze data, the research interpreted data and made a report upon the analyze data. Conclusion, discussion, implication as well as recommendation have been report as well.

## 4. Data Analysis

### 4.1 Data Analysis for RO1

Total population of this study is 53 which consist of the staff academics in UTMSPACE, excluding staffs from UTM. According to Krejcie and Morgan's sample size (1970), for that particular amount of known population, the amount of sample size is 44 with population proportion of 0.5 and confidence 95%. The feedback received is only 24. Half of the respondents in this questionnaire aged between 25 to 30 years old. Then 33% aged range from 31 to 35, 17% ranged aged from 36-40% and none for age group of 41 until 45. All the targeted sample belief is 100% Islam. For marital status, the amount of married respondents is 92% and 8% of the respondents is single. Only 60% of the respondents are master's holder and the rest of it own a degree in their respective field.

### 4.1.1 Understanding Learning Analytics

Questionnaire is adapted from Learning Analytics framework by Greller and Drachsler (2011). For the question 1, the respondents have been asked about their acknowledgement with the term of learning analytics. Only 13% of respondent have known about the term 'learning analytics'. 87% of them never heard about the term themselves. Correlation between their knowledge on learning analytics terms with the respondent's educational level shown a negative relationship, (-0.31944).

Hence, H1 is rejected. For question 2, respondents were asked about the beneficiary of learning analytic. 38% of the respondents choose that the main beneficiary of learning analytics is lecturers. 37% is organization itself, UTMSPACE; 17% students and the rest of 8% is faculty/department. In question 3, respondents were been asked about the influence of learning analytics in the following area.

**Table 4:** *Influence of Learning Analytics*

| Items | Results |
|---|---|
| Pedagogic improvements and innovation | 20.83% |
| Better insight by institutions on what's happening in each course | 41.67% |
| Stimulate reflection of students on their progress | 12.50% |
| Predict potential drop out of students | 25.00% |

The highest items that been scored is "better insight by institutions on what's happening in each course" which is 41.67%. Next item is "predict potential drop out of students", 25%. Item "pedagogic improvements and innovation" scores 20.83% and lastly "stimulate reflection of students on their progress" scored 12.5%.

In question 4, the respondents have been asked to choose main objectives of learning analytics. The highest item scored is 62.5% for item" predict learner performance and lead to appropriate intervention. The lowest scored item is 12.5% for item "stimulating organization to reflect on their performance and learning behavior".

**Table 4.1:** *Main Objectives of Learning Analytics*

| Items | Percentage |
|---|---|
| Stimulating organization to reflect on their performance and learning behavior | 12.5% |
| Predict learner performance and lead to appropriate intervention | 62.5% |
| Make invisible information about learners visible | 25.0% |

For question 5, the respondents have been asked about the present of operate ethical guidelines that regulate the use of student data (for example in research). Most of the respondents did not have idea about it.

**Table 4.2:** *Operate Ethical Guidelines*

| Items | Percentage |
|---|---|
| Yes | - |
| No | 8.3% |
| Don't know | 91.7% |

**4.2 Data Analysis for RO2**

Number of students is 26 for that current semester. In term of gender, the allocation is 32% male and 68% female. In terms of religions, the researcher found that the numbers of students with Islam belief is 90% and equal percentage of 5% each for Buddhist and Hindu. Researchers also showed the percentage results for SPM in Bahasa Melayu in this targeted sample. It shown that 50% of the students got grade range of "B+ until B-" in their Bahasa Melayu. Another 42% got "A+ until A-"and the rest of "C+ until C" showed 8% for their result in Malay language.

**4.2.1 Course: Technology Management (DDWG 2243)**

Technology management is one of the core subjects in this program. For this course, there are several program learning outcomes that have been designated in mapping the program learning outcomes (PLO) with the respective domains. In PLO 1, it indicated the level of knowledge that students achieved throughout the course. While PLO3 shows the social skills and responsibilities. The key performance index (KPI) that has been set for this course is 65%.

**Table 4.3:** *Course Assessment Report for Technology Management (DDWG 2243)*

| Program Outcomes | PLO1 | PLO3 |
|---|---|---|
| **KPI Achieved** | 65% | 77% |
| **Expected KPI** | 65% | 65% |

**4.2.2 Course: Introduction to Operation Management (DDWG 2223)**

In program learning outcomes for this course, it used PLO are PLO1 and PLO3 (same explanation as technology management's course).

**Table 4.4:** *CAR for Introduction to Operation Management (DDWG 2223)*

| Program Outcomes | PLO 1 | PLO3 |
|---|---|---|
| **KPI Achieved** | 69% | 58% |
| **Expected KPI** | 65% | 65% |

## 5. Summary and Interpretation

### 5.1 Summary of Research Objective 1 (RO1): Understanding Learning Analytics

Data from human resources department indicated that numbers of lecturers and executive academics hired by UTMSPACE is 53. Age of respondent is 25 until 30 years old which indicates that most of the current lecturers hired by UTMSPACE are fresh graduate with ample industry experience. Other respondents age 41 until 45 most probably come from UTM itself. Though respondent age 25 until 30 years old have the highest numbers of staff working in UTMSPACE, they still did not have better understanding in learning analytics as they were fresh graduate that come from different industry background. Respondents are mostly Islam by religion. For marital status, the result shows higher percentage of married respondents. Other than that, most respondents are master's holder and the least are the degree's holder. Even though master's holder has the highest number, but they are not from educational industry background hence affect the level of understanding in learning analytics. Thus contribute to negative relationship in between knowledge on terms *learning analytics* and educational background. In question 2, respondents were asked about the beneficiary of learning analytic. Respondents promptly choose lecturer to have more benefits in learning analytics. This result second to Dietz-Uhler & Hurn (2013) argument that LA not only provides one of many methods to not only documentation of student performance but also providing encouraging tools that helps for continuous improvement that accrediting bodies are seeking. For question 3, all the respondents were been asked about the influence of learning analytics in the following area. The highest percentage is item "better insight by institutions on what's happening in each course". The uses of CAR help the institution to have knowledge on problematic course that should be address well. This supported by Campbell et al., (2007) stated that the use of analytics tools can be used to identify potential students at risk in their study and improving student success. EDUCAUSE (2010) stated that analytics tools in educational institutions can act as the driver in the development of student requirement policies, financial decisions, hiring purpose and also improving course planning. In question 4, the respondents have been asked to choose main objectives of learning analytics. The highest item scored is 62.5% for item" predict learner performance and lead to appropriate intervention. This is employs by Eckerson (2006) stated the use of LA as tool to predict behavior, act on predictions and feed those results back into the process for improvement of the prediction over the time. In question 5, the respondents have been asked about the present of operate ethical guidelines that regulate the use of student data (for example in research). Most of the respondents did not have idea about it. This could be resulted from no proper briefing, documentation or training to address the issues of student's data.

### 5.2 Summary Results for RO2

Number of students is 26 for that current semester. In term of gender, the allocation is 35% male and 65% female. In terms of religions, the researcher found that the numbers of students with Islam belief is 90% and equal percentage of 5% each for Buddhist and Hindu. Researchers also showed the percentage results for SPM in Bahasa Melayu in this targeted sample. It shown that 50% of the students got grade range of "B+ until B-" in their Bahasa Melayu. Another 35% got "A+ until A-"and the rest of "C+ until C" showed 15% for their result in Malay language. For information, in Malaysia, the main entry requirement to enter public education or private education institutions is to at least obtain a credit for Malay language (vary according to programs. Example at UTM, to enter Degree in Technology Management, the least grade for BM is B+). There is importance of grade of SPM in Bahasa Melayu as all the lecturing will be in Malay language. Therefore, students need to have a good command in understanding the language as well. Inability to understand the language will lead to miscommunication in teaching and learning.

### 5.2.1 Course: Technology Management (DDWG 2243) and Operation Management (DDWG 2223)

For course technology management, in PLO 1, it indicated that the level of knowledge that students achieved throughout the course. The result shows that students achieve the same level par with KPI, 65%. For PLO3 shows the social skills and responsibilities and the class scores 77% for the respective program outcomes. At this stage, where the students are still in year 2, researchers observe that the students have the ability to understand the basic concepts, theories and application in technology management course. Apart from that, students have social skills and responsibilities which indicate the group project that they had been assign. As explain by the course coordinator, the students have been assign to do project innovation with reusable items and made a presentation as well as demonstration to the class. This contributes higher percentage in PLO 3 where the students need to be in group to build up their project, mingles with outsider to get the reusable items and lead their team with example.

Therefore, lecturers or even the department can predict that the selected sample students have high ability in understanding basic concepts, theories and application for course operation management. In PLO1 for operation management course, it showed an increase in percentage, 69%. With the basic concepts, theories and application in technology management, they perform better in this course as both subjects are inter-related. In PLO3, it showed a decrease pattern in terms of social skills, leadership and teamwork. In such, lecturers from both courses can make use the data in the PLO from technology management course to exploit it in teaching and learning for operation management

course. In return, this could help to increase the success pattern of the students and identify any "defect" in their study beforehand. Based on the PLO results, H2 is accepted. This result supported by Verbert, Manouselis, Drachsler, & Duval (2012) which stated that goal of LA include (i) predicting learner performance, (ii) suggesting to learners relevant learning resources, (iii) increased reflection and awareness on the part of the learner, (iv) detection of undesirable learning behaviors, and (v) detecting affective states (e.g., boredom, frustration) of the learner. Molina and Bansil (2018) stated that more confidence the students were, the higher their performance in their learning process.

## 5.3 Future Research

For future research, intervention process after analyzing the learning analytics data could help to make the research better. It is also advisable to include other stakeholders such as the faculty and educational organizational to gain better perspective in learning analytics.

## 5.4 Research Limitation

Time constraints have been one of the utmost limitations in this research. Time frame that has been allocated by UTMSPACE was only 6 months. Therefore, any further intervention cannot be apply and investigate.

## 5.5 Appreciation

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