Learning Analytics and Dashboards, Examining Course Design and Students' Behavior: A Case Study in Saudi Arabian Higher Education

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This thesis is submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy.

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This thesis results entirely from my own work and has not been submitted in substantially the same form for the award of a higher degree elsewhere.

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Abstract

The use of Technology in Saudi Arabian Higher education is constantly evolving. With the thousands of students' transactions recorded in various learning management systems (LMS) in Saudi educational institutions, the need to explore and research learning analytics (LA) in the Middle East and Gulf Cooperation Council region have increased in the recent years. This research is an exploratory case study at the University of Business and Technology (UBT), a private university in Jeddah, Saudi Arabia. The research aims to examine UBT's rich learning analytics and discover the knowledge behind it. 900,000 records of Moodle analytical data were collected from two time periods: Fall 2018, and a consecutive 4-year historic data. Romero et al., (2008) educational data mining process was applied on three analytical reports: Students statistics, Activity and Log reports. Statistical and trend analysis were applied to examine and interpret the collected data. A significant positive correlation was found (0.265) between students' final grades and their LMS movements in the course. The study also highlighted a trace of certain LMS engagement patterns associated with high GPA students such as viewing discussions, viewing profiles, and reviewing quizzes attempts. Additional data mining has also revealed high percentage of Turnitin and Moodle assignments' usage. These trigger an insight recommendation for what lecturers should incorporate in their course design and what motivates students to engage and perform better. Self-regulated learning (SRL) questionnaires have been used to examine students' and lecturers' behavior towards Moodle Learning analytics and the completion progress dashboard. A positive association of self-control and monitoring, SRL behavior elements, to high GPA students was a main questionnaire finding. Recommendations include highlighting the need to build automated data mining tools that facilitate the capture of complex Learning Analytics data and refining it to enable interpreting and predicting the actions needed in higher education learning environments.

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Acknowledgment

{رَبِّ أَوْزِعْنِي أَنْ أَشْكُرَ نِعْمَتَكَ الَّتِي أَنْعَمْتَ عَلَيَّ وَعَلَى وَالِدَيَّ وَأَنْ أَعْمَلَ صَالِحًا تَرْضَاهُ} [الأحقاف: 15]

(Thank you, God, for granting me and my family your blessings and I hope to always seek goodness with my work: -AlAhqaf – Quraan-15)

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هاله عثمان نصيف

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List of abbreviation

LA	Learning Analytics
EDM	Educational Data Mining
SRL	Self-Regulated Learning
LMS	Learning Management System
UBT	University of Business and Technology
OPERA	Oracle Program for Education, Registration and Admission
GCC	The Gulf Cooperation Council
MENA	Middle East and North Africa
SPSS	Statistical Package for the Social Sciences.

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Chapter 1: Introduction

1.1 Introduction

The use of Technology in Saudi Arabian Higher Education (HE) is constantly evolving in this digital age. Learning Management systems (LMS) used by most universities help in enhancing the educational environment for both lecturers and students (Alqarni, 2015). LMS generates thousands of transactions per learner (Klašnja-Milićević, et al., 2017).The generated students' input is collected by tracking students' activities in LMS. Activities include logging in, submitting assignments, participating in discussions, and taking quizzes and more. Collecting and analysing such activities is usually referred learning analytics. At the 1st International Conference on Learning Analytics and Knowledge, Siemens (2013) defined Learning Analytics (LA) as the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs .The process of discovering interesting patterns and knowledge from such data is called Data mining (Han, et al., 2011).

Why learning analytics are important? Learning analytics aim to analyse students' online data to improve the learning process and enhance the learning environment (Saqr, et al., 2017). Analysing online activities can highlight active and inactive students, which can also be used as an alert to lecturers. For individual students, LA dashboards (interactive visualization of the underlying data and subsequent analysis (Shacklock, 2016)) can help students track their own progress and personalize their own learning pathway.

Interest in exploring and using learning analytics in educational settings is increasing in most higher education institutions. According to (Davies, S. et al., 2017), the US and Australia have been the world leaders in the use of learning analytics. UK is intending to have a competitive advantage in learning analytics by forming a national learning analytics service for higher education where 12 universities are already using it (forming 300 million lines of data) and in the process to add more institutions and over 100 institutions have expressed interest to participate. By this, UK will have the world's first ever learning analytics big dataset, providing the opportunity to provide insight and improve learning and teaching. This indicates the importance of learning analytics and the enriching opportunity to explore such data.

Similar interest is also gradually building in the Middle East and North Africa (MENA) and the Gulf Cooperation Council (GCC) regions. Most MENA and GCC literatures cover general discussions of Big Data (Big Data is large and complex data sets collected from digital and conventional sources (Reyes, 2015)). Many of the papers focused on students' performance and engagement, often using qualitative data from surveys and interviews. There were not a lot of studies exploring behavioral theories such as self-regulated-learning and relating this to the analytics. In a time, where interest is building around the world in collecting learning analytics for the purpose of improving learning and teaching, the MENA and GCC countries have started to join the move to support and research LA. This will provide opportunities for innovation and development in higher education institutions in the region. The research interest is to examine LA in the Saudi Arabian higher education. Saudi Arabia shares with its neighbouring GCC and MENA countries many similar economical, institutional, and social characteristics (Kuncic, 2016). Such characteristics are visible in the countries' policies in politics, education, health, industry, infrastructure, tourism, and more. Strategic frameworks concerning education are highlighted in various MENA and GCC 2030 visions. Exploring the education theme in many of the different visions sheds light on the similar objectives toward improving and enhancing the education system in the region. Abu Dhabi vision 2030 focused on improving distance learning and e-learning (Abu Dhabi, 2008). Egypt 2030 vision focused on developing education through innovation, technology and emphasis on training and research (Egypt vision 2030, 2015). Similarly, the 2030 Saudi vision calls for improving higher education in Saudi Arabia by focusing more on Technology and innovation (Vision 2030, 2015). The opportunity to investigate learning analytics and dashboards in the Saudi context will help to provide an insight into applying these innovative tools that may help to achieve the higher education goals of the educational 2030 visions.

1.2 Aim of the Research

Using learning analytics has promising benefits in educational institutions such as Prediction on learning sequences, predictions on final learners' grades, or predictions on students' knowledge behavior, all that may enable students and lecturers making various learning and course decisions (Klašnja-Milićević, et al., 2017). Lecturers can make decisions based on the analytics to improve course design elements and understand students' behavior to better advise them to improve their engagement (Davies, S. et al., 2017). Lecturers may recognize students who are falling behind in a timely manner to advise them to catch up with their peers. Lecturers also may recognize what is not working in the course design and attempt to change it accordingly. Similarly, with students, they may benefit from dashboards that can empower them to adjust their own learning behavior and have a voice to reflect and improve their online engagement.

The aim of this research study is to explore learning analytics and dashboard usage by examining the educational environment in a Saudi Higher Education institution. The main objective is to investigate the effects of learning analytics on the educational experience for both students and lecturers. The research aims to uncover students’ behavior and attitudes when engaging online with LMS resources and dashboards. Would such an engagement have an effect on students’ performance? The research study will also examine lecturers’ usage of learning analytics and dashboards concerning course design options and students’ engagement. Would utilizing learning analytics and dashboards improve the current learning environment in a Saudi educational institution? Would providing analytical data improve lecturers’ instructional design? Would such data improve students’ engagement and performance? These are interesting questions to explore in this research study, see Figure 1-1.

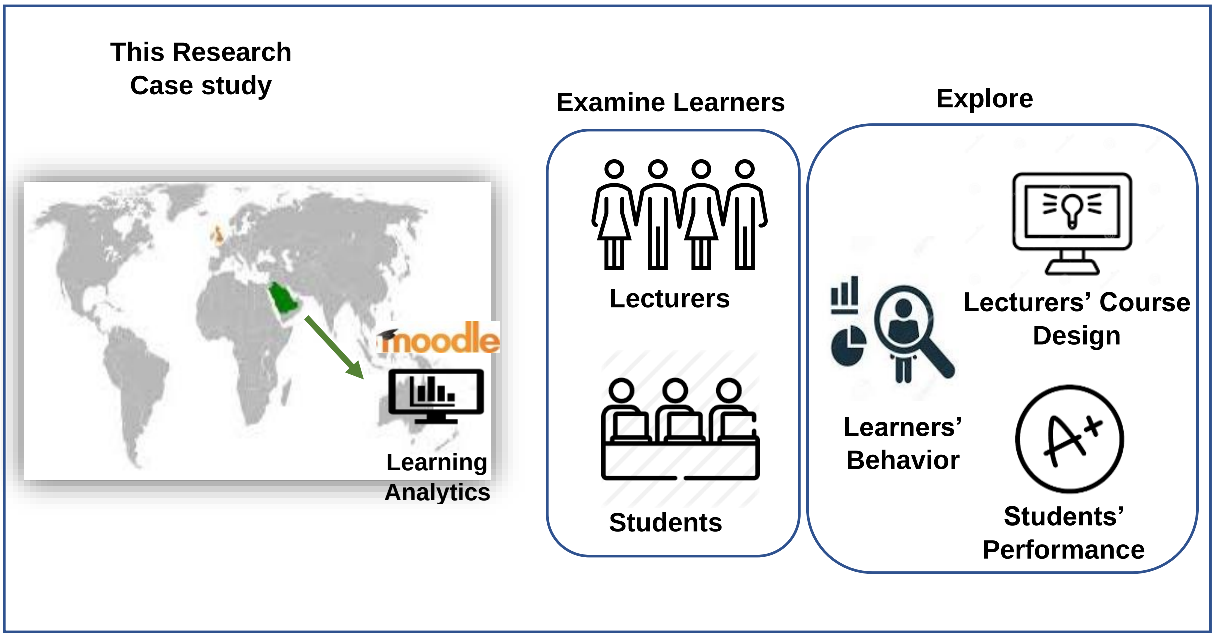


Figure 1-1: **Saudi Arabian Learning Analytics Research Interest Case**

Examining students' behavior and performance in the context of learning analytics is done repeatedly in a lot of literature. Researching learning analytics and dashboards in the Saudi Arabian higher education is fairly new. An opportunity for improvement to the current educational environment for both students and lecturers may be missed if the thousands of learning transactions stored in the Saudi learning management systems are not used. Making use of Data helps to provide insight and knowledge. Such data can be used to discover learners' behaviors and what patterns of engagement are observed? Would researching learning analytics in a Saudi context highlight any improvements or recommendations that may be helpful for educational institutions in the GCC and MENA region? Would exploring behavioral theories convey any new knowledge or highlight current behaviors? Exploring a Saudi context case will help to provide a glimpse of the current learning analytics status in the region and will help to provide insight into the challenges and recommendations that can be used by other educational institutions.

Learning analytics is a promising research field (Klašnja-Milicevic & Ivanovi, 2018). LA provides new and innovative methods, tools and platforms that influence researchers in Technology Enhanced Learning. Higher education institutions can apply LA to improve the facilities they provide for students and other educational stakeholders and it can improve learning outcomes and performance (Klašnja-Milicevic & Ivanovi, 2018). Such an opportunity would be missed if this research is not explored in the Saudi Arabian context.

1.3 Research Contribution

Examining behavioral theories in the Saudi context can help to highlight differences in learners' behavior, especially as learning analytics research studies and behavioral investigations have been done mostly in online or blended learning environments. This research starts the discussion of observing learners' behaviors and linking them to analytics in a traditional face-to-face learning environment that utilizes online resources. Conducting a case study in a traditional higher education setting helps to contribute to behavioral theories.

Furthermore, the research study outcomes can also help to contribute to learning analytics policy and practice in educational institutions. The research outcomes may help to define a successful learning analytics environment. By this means, recommendations can be made for best practice in analysis of students' behavioral pattern and lecturers' instructional design. Contributions to institutional policies may help Saudi educational institutions with the necessary policies, procedures and applications when applying learning analytics. It can help to highlight ethical concerns around learning analytics and students' privacy.

For the Literature and knowledge contribution, this mainly relies on examining learning analytics in an under-researched area, the GCC and MENA region. Conveying meaningful insight on learners' behavior and course design settings helps to build the learning analytics literature in the GCC and MENA region. More about the contributions are discussed in Chapter 7, conclusion.

1.4 Research Context

The research study is a unique study as it attempts to investigate learning analytics and dashboards in the Saudi Arabian higher education context. The objective of this study is to examine learning analytics to find patterns of students' engagement and understand students' behavior and performance in a traditional face-to-face educational environment that utilizes LMS system for online learning activities. The study also attempts to evaluate the course instructional design elements in LMS based on analysing the learning analytics data. The study also investigates students' behavior and lecturer's usage of learning analytics and dashboards. For this, the research study conducts an empirical study investigating learning analytics and dashboards in Saudi Arabian higher education by focusing on UBT, the University of Business and Technology in Jeddah, Saudi Arabia. The research study examines students' and lecturers' usage of Moodle learning analytics. The study also collects historic learning analytics data of past UBT courses to attempt to identify patterns of students' engagements in relation to Moodle course design elements.

Researching learning analytics at UBT helps to promote learning analytics research in the region and aims to add to the Technology Enhanced Learning (TEL) field. The use of LA dashboards by both lecturers and students is a unique opportunity provided by UBT where lecturers can monitor students' performance and help them to improve. Students will be able to directly track their own behavior and attempt to improve to do better in their courses. Both lecturers and students will witness the benefits and the outcome of using learning analytics and dashboard thought the academic term.

1.4.1 Saudi Arabian Higher Education Context

The Arab world, particularly the Gulf states, have worked on building their region's university systems, employing scientific research, international collaboration and projects, accreditation bodies both national and international, integrating current local culture, traditions, and laws, applying educational trends, globalization and more (Rupp, 2009). These characteristics help to define MENA universities including the researched Saudi case, the University of Business and Technology (UBT). UBT is a private university in Jeddah, Saudi Arabia. It resides mainly in the city of Jeddah. Jeddah is a centre for money and business in the Kingdom of Saudi Arabia and a major important port on the Red Sea (Municipality, 2020). The location of Jeddah as a main city in Saudi Arabia helped to target not only students from Jeddah, but from the various Saudi Arabian cities including major cities such as Makkah and Madina, Jazan and more. Not only regional students enrol in the university, but also international students whose families mainly reside in Saudi Arabia for work purposes. The student target covers all type of income students as the university also has different scholarship supported by the government and other private industries. UBT is a typical higher education institution in the Arab region as it shares similar structure characteristics with its MENA and GCC peers. The educational pedagogies adopted by UBT are similar to its peers in the region as it employs face-to-face traditional learning environment with the use of technology and internet in facilitating the learning experience such as using LMS, online libraries and databases and it has both female and male students. Also, like its peers, UBT employs national and international accreditation bodies to ensure the quality of its programs and international collaboration in research, teaching, partnerships and projects. (UBT, 2020). UBT shares similar objectives to its MENA peers, such as research, teaching, professional development and providing community services (Jaramillo & Zaafrane, 2014). The English language is the main language for teaching in UBT, similar to ts peers (in Saudi, GCC and MENA universities). It has a student population of over 5000 students and a variant qualified faculties staff both international and local, ranging from Saudi Arabia, Egypt, Jordan, Lebanon, Iraq, Algeria, Pakistan, UK, Canada, Italy and more.

1.4.2 University of Business and Technology (UBT)

UBT has two main campuses, Dahban (male) and Jeddah (female) with around 5000 students and 250 teaching staff (OPERA, 2020). UBT has several colleges: College of Business and Administration (CBA), College of

Engineering (CE), Jeddah College of Advertising (JCA) and College of Law (CL) (UBT, 2020). UBT started as a simple junior college in the year of 2000, offering business-related diplomas, and quickly progressed by 2003 into a full-fledged four-year college (CBA) offering six programs. In 2008, the College of Engineering was established, followed by the College of Advertising in 2011 and College of Law in 2017. Currently, UBT has successfully grown into large campuses spread in the city of Jeddah and the city of Dahban. UBT has a set of different computerized systems serving the research, academic and staff needs. UBT employs an Oracle based information systems for registration, grading, attendance, and advising systems (called *OPERA* systems), designed by UBT's own development team. UBT also uses Moodle, an open-source learning management system. The current UBT setup is to deliver face-to-face lectures but with heavy employment of Moodle activities. UBT lecturers utilize Moodle off-campus and in-campus as well. Most lecturers utilize Moodle resources and activities such as file uploads, discussion forums, quizzes and more. Feedback of assignments and quizzes are always accessed through Moodle. Moodle has been used for over ten years now with around 7000 courses and thousands of transactions being recorded and stored. This creates a large collection of learning analytics related to online activities stored in the LMS system. Such valuable data has never been used or examined yet. Mining these thousands of transactions may provide indicators of course design success. It gives information on what works and what does not work in the course structure. These mined data may also provide insight into students' behavior and what works for them and what does not.

The researcher is an MIS, Management of Information System, lecturer at CBA-Jeddah Campus. She also has managed e-Learning at the university, as she headed the eLearning section for 4 years, and has 8-year experience in administering the Moodle server, and earlier LMS systems: Blackboard and WebCT. The researcher is not affiliated with any of the courses in this study. Under the approval of the university, the researcher has sought the ethical and consent approval from both the lecturers and the students, and she has access to the Moodle platform as a system administrator to extract the needed analytical data and reports associated with the participant courses and the students who consented to the study. The researcher obtained Lancaster University ethical approval to conduct this research.

1.4.3 UBT – Learning Management System (Moodle)

Many colleges and universities are adopting technology to aid their teaching practice. This technological shift helps to integrate the traditional classroom environment with online course resources to enhance, replace, and effectively supplement face-to-face learning environments (Hart, et al., 2017).

Coijin et. al, (2017) share the same opinion as they explained that using the internet to provide content has transformed the face-to-face learning environment. Most educational institutions use internet in teaching, often through LMS. LMS can support student learning by providing content online such as presentations, assignments, forums, quizzes and more.

Moodle is an open-source learning course management system. It is a learning platform designed to provide educators, administrators, and learners with a single robust, secure, and integrated system to create a personalized learning environment (Yassine, et al., 2016). Moodle contains a set of different resources and activities. Activities include Assignments, Chat, forum, quiz, wiki, Turnitin assignment (integrated block) and more. Resources include file, folder, label, page, URL and more. In addition, it contains a set of different available blocks, reports, and statistics Data.

Moodle and other LMS systems collect extensive data on how staff and students are using the systems. The ability to track and store vast amount of data on students and instructional design is very helpful in educational institutions (Beer, et al., 2010) Such tracking in Moodle is conducted through various tracking tools and reports and through different analytic graphs and dashboards. Moodle has a wide list of analytical tools and graphs such as GISMO, Engagement Analytics, Course Dedication, Heatmap and more (Moodle Docs, 2017). Moodle offers several other learning analytics tools to assess students' performance such as MocLog, Learner Analytics Enhanced Rubric (Lae-R), smart Klass tool, Mindmaps course and engagement analytics tool. UBT currently has several Moodle analytical blocks installed such as GISMO, Lae-R, analytical graphs, completion progress dashboard and more. Since the aim of the research study is to investigate analytics tools used by both lecturers and students, the research study examines Moodle analytical graphs (used by lecturers only) and the completion progress dashboard (used by both lecturers and students) (Yassine, et al., 2016). This set of analytical tools and metrics available in Moodle are discussed next.

1.4.3.1 UBT Moodle Learning Analytics Metrics and Reports

There are a set of learning analytics sources found in Moodle. Each of these LA sources can be pre-collected or accessed through simple queries or through blocks, intended to be viewed, combined and calculated (Moodle Docs, 2017). A sample of a metric that can be used is the *Total-Activity* metric that includes counts of course access/views, activity/resources' views, reads, activity resource submission, postings and more. Other LMS metrics involve gradebook current grades, completion status, assessment feedback, view, pages visited, number of messages read and more. There are also a set of Moodle reports that tracks and collect actions of all Moodle users such as: Logs, activity reports, participation report, statistics, event monitoring, competency breakdown report and more (Moodle Docs, 2017).

1.4.3.2 UBT-Moodle – Dashboard and Analytical Graphs

Any educational institution can make use of the visual analytical tools in Moodle. For the purpose of the research study, the Moodle visual tools that are used are the Moodle completion Progress Block (Dashboard) and the block of Moodle Analytical Graphs (Moodle Docs, 2017). These tools and more are available for use by the UBT lecturers and students. Table 1-1 shows an example of the dashboard available in Moodle that is part of this study.

UBT MOODLE DASHBAORD	ACCESS	DESCRIPTION
Grades chart	Lecturers	Visualization for student participation: view students' grades
Content access	Lecturers	Visualization for student participation: display students' access to selected resources or tools
Active students	Lecturers	Visualization for student participation shows active students and active hours
Assignments submission	Lecturers	Visualization for student participation: display submission status
Hits distribution	Lecturers	Visualization for student participation: display students' access resource sand hours
Completion Progress Bar	Lecturers and Students	Time Management tool for students with overview for teachers

Table 1-1: Moodle Sample Dashboards and analytics (Moodle, 2018)

Moodle Completion Progress Block

The Completion Progress is a time-management tool for students to track and monitor their performance in the course in terms of submitting a Moodle assignment, taking a quiz, and posting a forum entry and such. The lecturers use the dashboard also to view the performance of all students. The dashboard visually shows what activities/resources a student is interacting with within the course. It is color-coded so students can quickly see what they have and have not completed/viewed (Moodle Docs, 2017). This tool requires pre-setup by the lecturer of the course. Tracking needs to be turned on in the course settings, depending on the Moodle institutional settings. Setting the tracking options is also needed to track which Moodle activities and resources have been used.

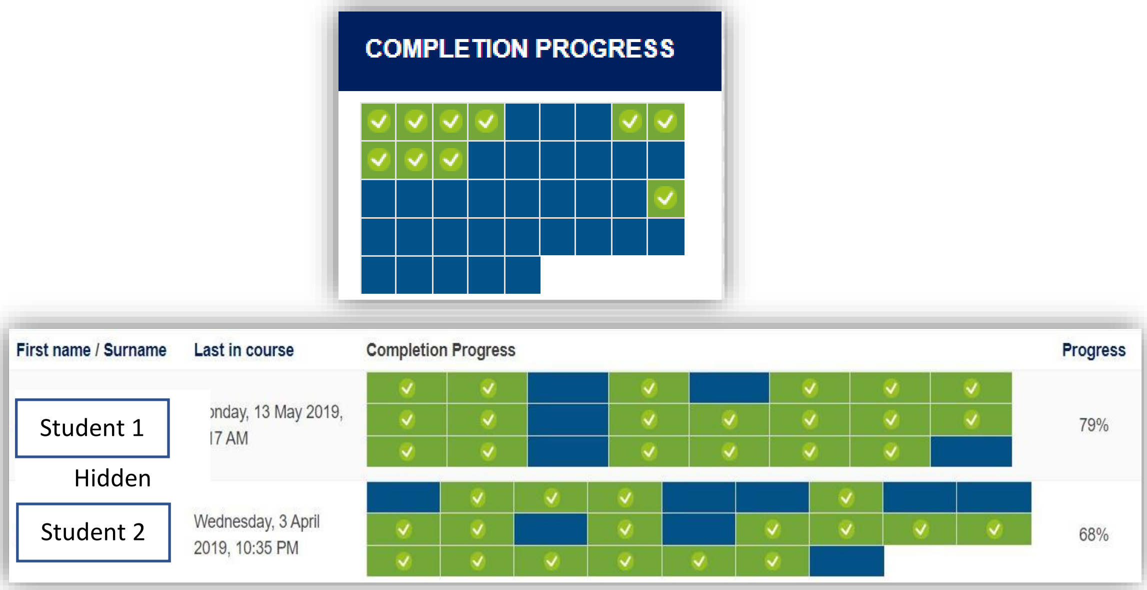


Figure 1-2: Moodle Completion Progress Dashboard, May 2019

The Green checkmark in the completion progress dashboard indicates that the student viewed this particular Moodle resource such as opening a syllabus, or any other file, taking a quiz, or posting a discussion entry. The blue cell indicates that no action was conducted in relation to this particular resource. There is also a red x mark for assessments such as quizzes failed. Students have access to their own completion progress dashboard. They can keep track of their progress during the academic term. Visual display of a sudden red x mark would trigger the students' attention to their performance. The course lecturer's dashboard is different as it contains the grid of performance for each student, so lecturers can monitor all the students and notice late or low performed students. Figure 1-4 for example, shows student 1 having a 79% completion progress for the current tasks whereas student 2 has 68%. The blue boxes are the items that were not used or opened in Moodle.

Moodle Analytical Graphs

The Moodle Analytical graphs block is a block that generates graphs intended to facilitate pedagogical decisions. The graphs have zoom capabilities and allow fast communication with students through email. This plugin provides five graphs that may facilitate the identification of student profiles. Those graphs allow the teacher to send messages to users according to their behavior inside a course (Moodle, 2018). Table 1-2 describes the different analytical graphs included in the block. These blocks were newly installed and running in the Moodle server in the summer of 2019.

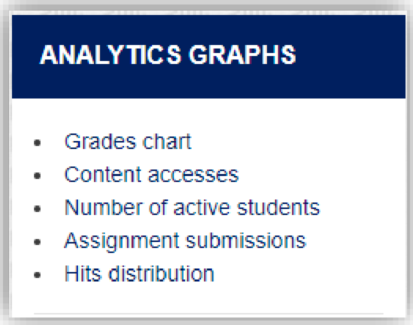
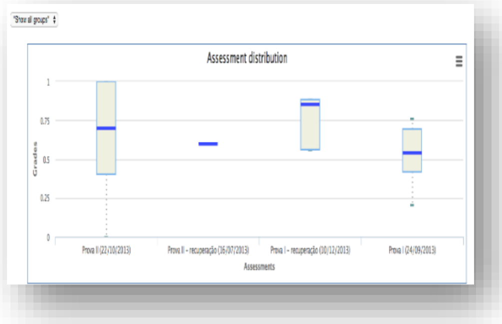
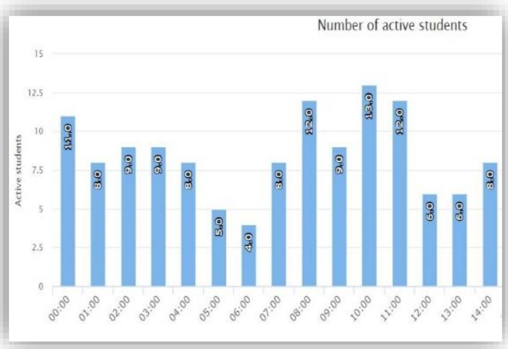
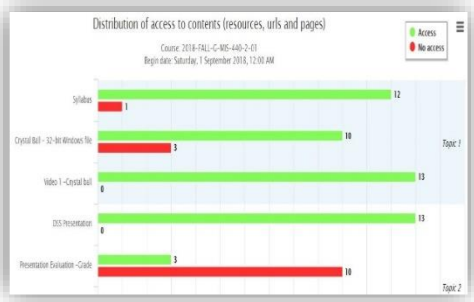
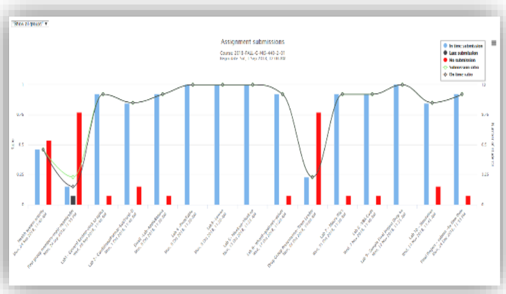
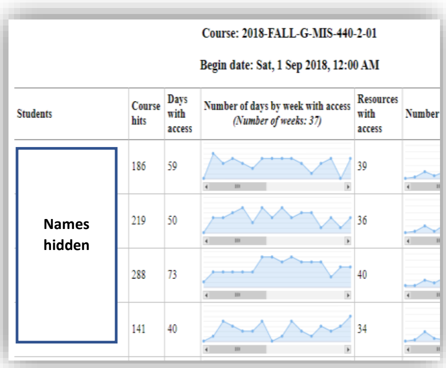
Moodle Analytical Graphs Block 	**Grades Chart** - A grades distribution that identifies the differences among evaluations and students with problems 
Content Accesses Chart - shows users accessed what resources. 	**Number of Active Users Chart** – who are the active users in a certain timeframe. 
Assignment Submissions Chart - Which users have submitted assignments on time or late. 	**Hits distribution** Chart - How each user is accessing the course and its resources in each course week 

Table 1-2: Moodle Analytical Graphs (Moodle, 2018)

1.4.4 UBT Students Information System (OPERA)

Along with Moodle, UBT has a main university information system, called *OPERA*. *OPERA* stands for Oracle Program for Education, Registration and Admission. The *OPERA* system is UBT's own Oracle based customized E-system, and it is the main academic system used by students, lecturers, and staff. It contains students' admission system, course registration, grading, attendance, advising, online portals and more(UBT, 2020). *OPERA* admission and registration system record students records in the system. The courses are created through *OPERA*. Any new course is created, or new students are added, this automatically is synchronized with Moodle because of Moodle-*OPERA* integration, check Figure 1-3. Lecturers use *OPERA* at start of the term with students advising, and registration exceptions. During the term, lecturers use *OPERA* for attendance and to insert students' grades as it is the official grading platform. Toward the end of the term, lecturers use *OPERA* to extract grading reports, evaluation, and quality reports.

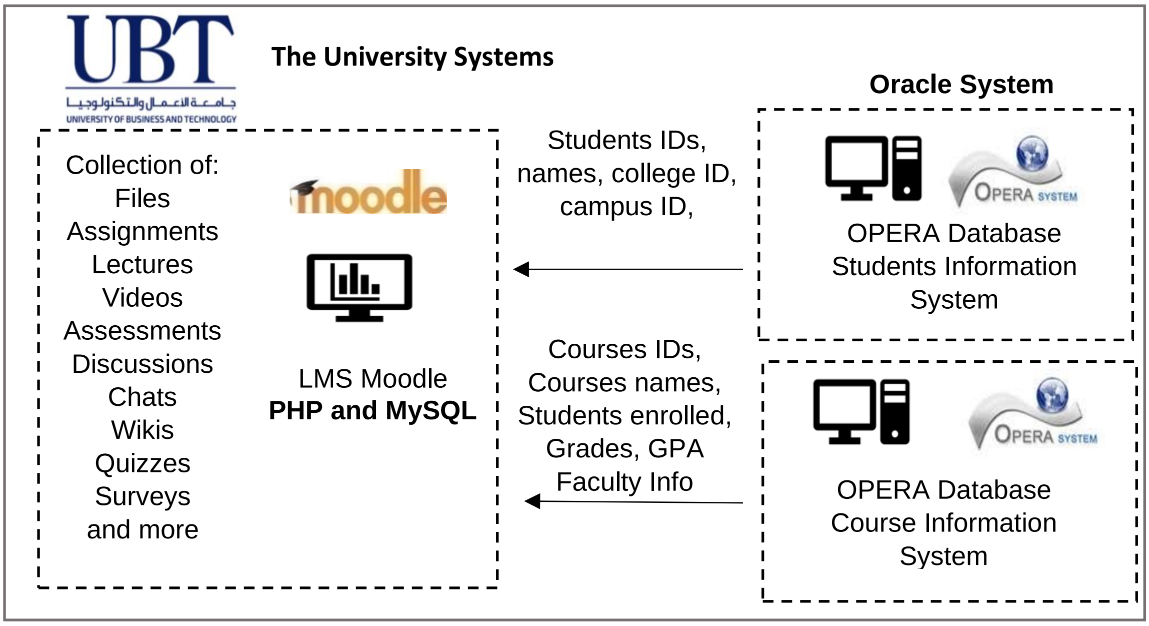


Figure 1-3: UBT Systems May 2019

1.5 Theoretical Framework

To examine learning analytics (LA) in the Saudi Higher Education context, the study uses 2 theoretical approaches to examine the data. In regard to examining students' and lecturers' behaviour, this study adopts the self-regulated theory (Pintrich, 2004). In regard to interpreting the analytics and examining its relation to course design and students' engagement and performance, this study applies LA data mining (Romero, et al., 2008) to process the analytical data sources and analyse them further. These two theories are outlined next.

1.5.1 Self-Regulated Learning (SRL)

Self-regulated learning (SRL) theory helps to provide insight on learners' behavior in an online setting. Self-Regulation is defined as setting one's goals and managing one's own learning and performance (You, 2016). Winne and Hadwin (1998) explained the SRL approach as learners constructing their own knowledge by using tools (e.g., Digital Moodle resources) to operate on raw information (for example, reading assigned online case) to construct products of their learning (information recalled from reading the online case). Students in a traditional course that utilize online learning resources in Moodle, may plan to dedicate five hours a week for accessing Moodle online activities. This is to define their SRL strategy and distinguish them from other students. This research study adopts four segments defined in a conceptual framework for SRL in the college classroom stated by Pintrich (2004), see Figure **1-4**. The four SRL segments, that the study examines, includes: planning and goal settings, monitoring, control and reaction and reflection.

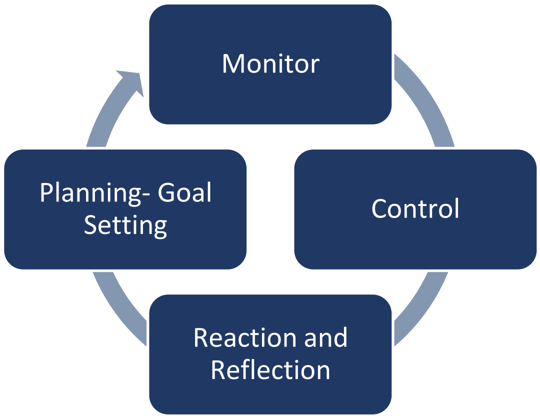


Figure 1-4: Pintrich Self-Regulated Learning, 2004

Pintrich's (2004) four SRL elements are used examine both students and lecturers in this research. Each SRL element was analysed and examined in the UBT academic settings. The students' SRL Planning and Goal Setting behavior include setting goals to utilize LMS, preparing a study plan for LMS activities, estimating time on LMS, dedicating set hours for LMS activities, setting up strategies to manage LMS usage. Students' SRL Monitoring behavior includes tracking LMS deadlines, knowing when grades are updated, periodically checking the LMS, and keeping up with the weekly readings and assignments. Students' SRL Control behavior includes knowing when one is behind of schedule, ability to lose attention online and managing to work even if LMS materials are dull. The fourth segment, the SRL Reaction and Reflection behavior, include changing strategies when needed, asking for help, and learning from mistakes. To examine UBT's students' SRL behavior, the four SRL elements are explored and examined.

Only a few studies investigated teachers as self-regulated learners. Kramarski & Michalsky (2010) highlighted teachers as learners, especially for technology use. SRL enhances understanding of developing teachers' knowledge in the field of educational technology, Adopting SRL elements help teachers design tasks such as tasks that require teachers to be active in deciding when and why to integrate technology into learning and how to engage students in such activities. The degree to which a teacher can do so makes the teacher more or less a self-regulated learner. This is commonly done with learning new knowledge. Having new digital technologies such as LMS tools and the use of online resources have the potential to facilitate SRL for both the lecturers and the students (Johnson & Davies, 2014).

Lecturer SRL Planning and Goal settings behavior elements concerning course learning design include preparing LMS content at start of the term and planning to make changes to future courses based on the analytics. The SRL Monitoring behavior elements include updating LMS periodically and checking LMS messages. The Control behavior elements include editing and changing LMS course design based on students' performance, peer observation and upon the analytics. The SRL Reaction and Reflection behavior elements include their reaction toward the effectiveness of the course design and the usefulness of the analytical tools.

1.5.2 Educational Data Mining (EDM)

Romero et al. (2008)'s data mining approach was followed to collect and analyse learning analytics data acquired from the analytical reports needed. LMS LA artifacts such as number of clicks, frequent login, total activities, time and more, all data that can be collected and analysed. Figure **1-5** shows the four main data mining steps (Romero, et al., 2008):

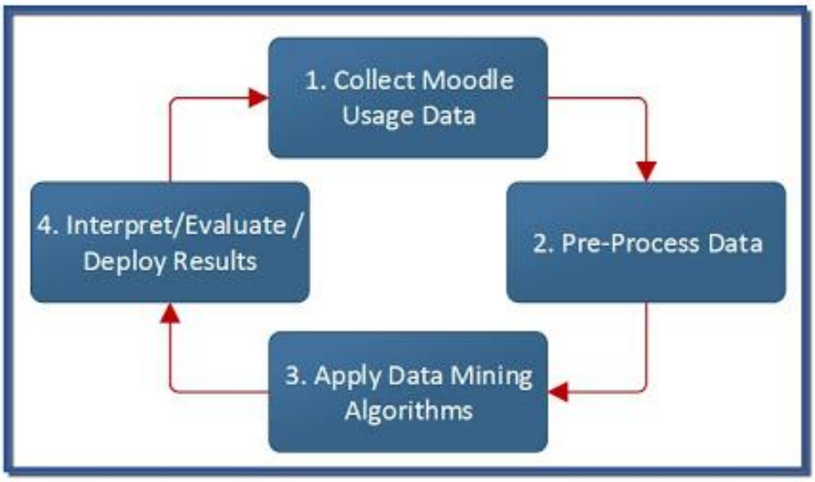


Figure 1-5: Romero, et al. Data Mining Process, 2008

Romero, et al.'s (2008) steps are conducted with each different type of analytics collected in this study. The process of data mining starts by collecting the needed reports and files that contain the raw data, for example, LMS log data files. Then, pre-process the data: This process requires organizing data, cleaning up and validate the data. This can be conducted by transforming the data into appropriate format in Microsoft Excel files and summarizing and categorizing the needed tables and cleaning and validating the organized data. This step involves also applying additional formatting. This is done mainly through applying Excel's own tools such as pivot tables, SPSS summarizing tools and charts. Step three involves conducting data mining techniques. These can range between using sophisticated software specialized in such as DBMiner, SPSS Clementine, Weka or more, to the use of other data mining techniques such as probabilities, statistics, clustering, visualization, and artificial intelligence. In this research study, a combination of SPSS analysis and Trend analysis using Excel Pivot table statistics, clustering, and visualization were used. The last step was to interpret, evaluate, and deploy the results. This involves finding the meaning and the knowledge behind the mined data.

A common analytics perspective that describes the data analytics results in also four stages (Minelli, et al., 2013): Descriptive stage, Diagnostic stage, Predictive stage, and a Prescriptive stage. The descriptive stage is the exploratory stage where the value is identified statistically. For example, this could be the number of participants or the number of courses. The diagnostic stage is where a resultant examination of the statistics is revealed. For example, stating a correlation between variables. The predictive stage is where the value has become known and future predication can be made. This involves further statistical analysis such as SPSS regression that can be used to predict future outcomes. The last stage, the prescriptive stage is when further actions can be recommended as what should be done with this discovered new knowledge, for example, further recommendations concerning the discovered relationship between variables. This usually involves recommendations to the institution's policy or stakeholders and such.

Both Pintrich's SRL theory and Romero, et al. (2008)' Data mining will be applied to examine the Saudi case study and will help in answering the research questions about the students' and lecturers' behavior and the course instructional design and students' engagement and performance. The research questions are outlined next.

1.6 Research Questions

RQ 1: To what extent, if any, does students' performance relate to their learning analytics.

RQ 1.1: To what extent, if any, does students' course final grade relate to their Moodle *Total-Activity* Metric?

RQ 1.2: To what extent, if any, does students' GPA relate to their logged events in Moodle log report?

RQ 2: To what extent, if any, does learning analytics affect students' engagement and course design choices?

RQ 2.1: What LMS course design elements generate the highest student engagement?

RQ 2.2: What patterns of student engagement, recognized from LMS course design elements, can be seen in historic Moodle data from the past 4 years?

RQ3: What are students and lecturers' self-regulated learning behavior and attitudes towards learning analytics and dashboards?

RQ 3.1: To what extent, if any, do students' self-regulated learning behavior elements affect the students' GPA?

RQ 3.2: What are students' SRL attitudes toward using Moodle dashboards?

RQ 3.3: What are lecturers' SRL attitudes toward Moodle learning analytics and dashboards?

1.7 Thesis Outline

Chapter 1 introduces the research topic and the aims of the research and the research contributions. It discusses the background of the researched case, UBT, the University of Business and Technology, in Jeddah, Saudi Arabia. Followed by Moodle, the LMS system adopted by UBT. Then a description of the research objective and the research settings is given, and the chapter ends with the theoretical framework and the research questions.

Chapter 2 highlights major literature studies, starting with some background information about Big Data, learning analytics & dashboards, and LA Ethical guidelines. This is followed by a review of studies focusing on Educational data mining, learners' behavior, performance and engagement, and the theoretical framework of SRL theory.

Chapter 3 discusses the methodology and the exploratory case study approach. Chapter 4 discusses the 3 data gathering methods used in the study: Data mining, questionnaire, and interviews.

Chapter 5 discusses all the methods used to analyse data and displays the resulted outcome. Chapter 6 discusses the findings of the data analytics and the answers to the research questions. Chapter 7 reflects on the research, particularly, case study generalization, and the contribution, limitations, and recommendations. It ends with suggestions for future studies. Appendix one and two contain the questionnaire and interview questions.

Chapter 2: Literature Review

The literature review explores various literature on learning analytics (LA) and dashboards. The search started with Big Data and learning analytics papers. Other searches followed for current and past literature on Learning analytics in Saudi Arabian higher education and the neighbouring GCC and MENA countries. After reading through the different literatures, a shift to exploring more topics about students' engagement and behavior was conducted. The review started then to explore past literature examining students' engagement and behavior in relation to learning analytics. It also explores past papers discussing self-regulated learning. The review also examines past literature examining lecturers' choice of instructional course design in relation to learning analytics. It also reviews the educational data mining process discussed in the various literatures.

A systematic literature review approach has been followed, where key terms are identified (inclusions and exclusions), using operands such as '*and'* and '+' (Creswell & Clark, 2014). Key terms (inclusion) that were included in the search: Learning Analytics, Big Data, Dashboards, students' engagement, Moodle analytics, motivation in online learning, learning behavior in online or blended learning, Educational Data Mining, Moodle dashboards, self-regulated learning and more. Combined terms such as analytics and performance, analytics, and achievements, SRL and learning analytics were also included. The online library of Lancaster University and Google scholar were used to access the various papers, articles, conference articles and books. The researcher's PhD supervisor has also recommended a set of papers, mostly recent published papers and articles and past theoretical papers. The literature studies are grouped into the following categories:

1. Background
    a. Big Data
    b. Learning Analytics & Dashboards
    c. Learning analytics Ethical Guidelines
    d. Learning analytics in the GCC And MENA region
2. Learning Analytics and Performance
3. Students' Engagement and Course Design
4. Educational Data Mining
5. Learning Behavior

2.1 Background

2.1.1 Big Data

Big Data is data that is large enough that it cannot be processed using conventional methods (Minelli, et al., 2013). Big Data triggers different diverse tools, mechanism, and software to handle capturing, storing, managing, and analysing its data. A typical Big Data dataset's size is usually measured in terabytes and petabytes. Big Data is usually defined by three dimensions: volume, variety, and velocity. Data volumes may consist of datasets, quantity of transactions, events, attributes, dimensions, predictive variables, and such (Minelli, et al., 2013). Unlike the traditional structured data, Big Data is becoming more unstructured containing text, audio, video, image, geospatial, and Internet data (including click streams and log files). This is referred as the Data variety. As for the Data velocity, it is the speed at which data is created, accumulated, ingested, and processed (Minelli, et al., 2013). While examining

Big data in education, one may argue that educational data is not Big Data. Does educational data have the 3 characteristics of Big Data? Lang, et al. (2017) argued that data collected within a MOOC is high in velocity and volume, but limited in variety, unless active measures are taken to achieve variety. Variety in educational data can include demographic information (gender, ethnicity, etc.) and prior knowledge measures (prior college enrolments, high school grades, standardized test scores, etc.). However, these variables are not collected automatically in MOOCs (Lang, et al., 2017) . Also, when comparing the volume of educational data to other industry data such as web data, retail and health care data, learning analytics may fall short on volume. The main differences between Big Data and Analytics are volume, speed, and variety (McAfee, et al., 2012). Despite these differences, a lot of research studies are exploring the application of learning analytics and educational data as large amounts of data are coming every day from eLearning resources which might give meaningful insight into students' performance, attention, and habits (Kvartalnyi, 2020).

2.1.2 Learning Analytics & Dashboards

Learning analytics is an emerging field in which sophisticated analytical tools are used to improve learning. Learning analytics is closely related to business intelligence, web analytics, academic analytics, educational data mining and action analytics (Elias, 2011). Learning analytics (LA) can be defined as the use of intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on Learning (Siemens & Long, 2011).

Another definition used by (Gašević, et al., 2016): Learning analytics (LA) is data collected by institutional student information system and from interactions with students' learning management system (LMS) such as Moodle, Sakai, Blackboard and more. The data collected convey an insight on the learning environment in the educational institution. The traced data (log data) recorded by LMS contain time-stamped events about usage of resources such as PDF and PowerPoint files and such and attempts of assessment such as quizzes or discussion's posts (Gašević, et al., 2016). Learning analytics enable data driven decision making while improving instructional productivity and resolving academic problems and enhancing students' performance in higher education (You, 2016).

Adopting and implementing learning analytics is fairly new in higher education institutions according to a survey conducted by the heads of e-learning Forum (HeLF) in 2015 (Shacklock, 2016). Nearly half of UK higher education institutions have not implemented learning analytics at all. Around only 1.9% have fully implemented and supported learning analytics. 17.0% have partially implemented learning analytics. 34.0% are working towards implementation and 47.2% have not implemented learning analytics yet. The interest to research learning analytics is shared in various literatures covering Europe educational institutions, US, Australia, MENA institutions and more.

The benefits of learning analytics are discussed greatly in most studies. Ifenthaler (2017) indicated that LA benefits usually concern multiple higher education stakeholders. Students benefits include understanding learning habits, analysing learning outcome, tracking progress, receiving intervention, increasing engagement, and increasing success rate. Instructors benefits include analysing teaching practice, increasing quality of teaching, monitoring learning progress, increasing interaction, modifying content to adjust students' needs, identifying students at risk and planning intervention. As for the benefits concerning course design, these include increasing quality of curriculum, comparing and evaluating learning designs, identifying, and adjusting difficulty levels and identifying learning preference (Ifenthaler, 2017). Kavitha and Raj (2017) share the same benefits such as identifying students at risk, recommending students reading materials and learning activities, improve learning pedagogies, and identify instructors who needs assistance and more.

An insight on students' behavior can be observed through learning analytics. A lot of research studies investigate students' behavior in relation to learning analytics. The self-regulated learning (SRL) theory is often explored in LA literature where students' behavior is examined. Learning analytics can provide direct intervention to help students develop their SRL skills. SRL behavior usually involves skills in planning, monitoring, action, and reflection (Pintrich, 2004).

Why the need for analytics? Evaluating the effectiveness of a course and checking if students' needs are met, and instructors' needs are supported along with evaluating the effectiveness of interactions, all are part of the reasons of using learning analytics (Elias, 2011). Traditional methods of evaluating such objectives usually rely on surveying students at the end of the term and self-evaluation, but these traditional methods may lack to provide full insight on the stakeholder's needs and the effectiveness of the course quality and interaction. For this, learning analytics can play a role in fulfilling such objectives.

Data on how students interact in their courses can be an indicator on how engaged the students are and how likely they may drop out. Learning analytics allow instructors to recognize the dis-engaged students from the start of the academic term. So, they can help to provide the needed feedback to the students and intervene to help students who are at-risk (Shacklock, 2016). This gives insight for the lecturer to redesign the instructional materials in the course content to better increase students' engagement.

Learning analytics enable educational institutions to track students' engagement, attainment, progression in real time, alerting instructors with students at-risk. Davies, S. et al. (2017) added also that the ability to identify students at-risk can enable intervention as the collected learning analytics data help to identify causes of disengagement and provide the needed help and support. The authors highlighted how Learning analytics will gradually become the key digital tool for forecasting students' success.

Learning analytic tools enable statistical evaluation of different data sources and identify patterns with the data (Elias, 2011). These patterns can help to guide in making decisions concerning course effectiveness and performance prediction.

Most common LMS contain a set of different metrics that measures certain criteria in LMS either concerning user attributes, course attributes, actions, resources, and setup and more. LMS metrics that are usually found in analytical systems are: LMS use, attendance, library use, assignments submission grades and more (Shacklock, 2016). To analyse the LMS data, additional students' and courses' information may be incorporated from the educational institution information systems.

To make use of learning analytics, LA data sources usually undergo a process of data mining to interpret the meaning behind them. Data mining techniques are commonly applied to identify patterns in these traced data. Gašević, et al. (2016). Educational Data mining (EDM) is a process that examine educational data and develop and use methods to explore the unique types of data that comes from educational context (Romero, et al., 2010). Learning analytics can be collected from various educational tools, reports, logs, Stats reports and visual dashboards and more. Dashboards helps educational institutions' stakeholders to make better decisions by visualizing data about the learners (Verbert, et al., 2020).

Elias (2011) describes dashboard as critical data visualization tools. Commonly presented as charts, graphs, dials, and maps. Meaningless data can be extracted from LMS and can be available for instructors and students in the form of dashboard-like interface. These graphical representations can guide and help instructors and students in the learning environment. dashboards are one of the most effective and attractive visual display techniques that are used as an informative tool that provides students, instructors view of the students' performance. They help to identify areas of challenges and strength in a course. Such findings can help to direct instructors to follow a specific instructional design and content updates. Students dashboards are a good example for an analytical tool that measures engagements in order to target early interventions and improve retention overtime (Shacklock, 2016). Students can have better understanding on their own progress. Dashboards promote students' self-reflection and encourage students' competition as students try to beat their own score or compare their scores to their peer's dashboards (Shacklock, 2016). Analytics displayed in students' dashboards can empower students to take control of their own learning and adjust their own behavior accordingly (Davies, S. et al., 2017).

There are a set of different dashboards available in most LMS systems. An example of a dashboard discussed in some literatures is GISMO. GISMO is an application that runs in conjunction with LMS. It contains 3 different panels: graph panel, list panel and time panel. It aims to help instructors to understand more about the behavior of the students and the resources accessed. GISMO uses the students tracking data as a data source and generate graphical representation that can be explored and manipulated by the course instructor. GISMO is used only by instructors.

There are other dashboards that can be used by both the instructors and the students such as Moodle completion progress dashboard, activity results, course dedication blocks (Moodle Docs, 2017), and Blackboard goal performance dashboard (Blackboard, 2019). Dashboards collect students traces for the purpose of self-improvement (Charleer, et al., 2014).

The different dashboards discussed here vary in purpose. The majority describes monitoring and transparency of students' performance. These dashboards contain symbols, graphics, numeric values for quantity of submitted assignments, top active students, lowest days accessed and such. All indicating behavior of students. If dashboards display students' performance concerning accomplishing course learning outcomes, then it can be very much associated with learning. Dashboards in this research study are more about monitoring and observing behavior. The case study in this research examines Moodle completion dashboard. This dashboard is accessible by both students and lecturers. Actionable information provided through the completion progress dashboard for the lecturers relates to reaching out to at-risk students whose progress is visualized with red and yellow alert symbols. This facilitates ease of detection of falling behind students. The same dashboard provides actionable information to the students that help them decide on monitoring their own performance and catching up with any delayed tasks and understand their actual progress in the class, triggering them either to reach out for help or adjust their performance accordingly.

With the use of learning analytics and dashboard in educational institutions, the issues of students' privacy and protection for students' data and students' personal information gets a major attention. Privacy and Ethics are main issues that usually are covered with learning analytics.

2.1.3 Learning Analytics Ethical Guidelines

Now days, there is already a set of ethical and privacy standards associated with technological research and data collection about human subject and learning analytics studies that need to pass the ethical approval in most western universities (Drachsler & Greller, 2016). They claimed that with the rise of Big Data and cloud computing, new ethical challenges emerged. Drachsler and Greller (2016) shared their definition of Ethics: ‘The philosophy of moral that involved systematizing, defending and recommending concepts of right and wrong conduct’ (p. 91). The authors define privacy as ‘a living concept made out of continuous personal boundary negotiations with surrounding ethical environment’ (p. 91).

Gašević, et al. (2016) followed the institution’s privacy and ethics process where they conducted the study. All students involved in the study were informed via email about their involvement in the study through the course interaction and the course interaction data (LMS). Data is collected for better understanding of students behavior to provide insight into the learning experience and improve course quality.

Shacklock (2016) indicated that one of the main issues raised by learning analytics are the ethical concerns around students’ understanding and consent to the use of their personal data in learning analytics. Shacklock (2016) outlined the eight data protection principles 1998 (DPA) concerning collecting personal data. This consists of:

> 1) Fairly and lawfully processed, 2) Be held for specific purpose, 3) adequate, relevant, and not excessive, 4) Accurate and up to date, 5) Not kept for longer than necessary, 6) protect the right of the individual, 7) kept secure, 8) No transfer without adequate protection. (Shacklock, 2016, p. 759)

Once the students give their consent, the educational institution needs to let students know what data they are collecting and how they intend to use it

(Shacklock, 2016). The private personal data cannot be used for any other purpose that is not collected for, unless specific consent is sought. Davies, S. et al. (2017) emphasized the importance of obtaining students' consent for the use of their learning analytics data. A survey of students in the UK in 2016 found that 71% of students do not mind if the university use students' learning activities information to help to improve students' performance. There are no reported students' objections in the National Union of Students (NUS) that is supporting developments in learning analytics. Davies, S. et al. (2017) called to protect the privacy of data and to take extra measures to prevent data leaking by securing and encrypting the data. Protecting students' data is discussed in most learning analytics research. Tsai, et al. (2020) examined the students' perspective toward the privacy of their learning analytics including engagement data as the physical and LMS attendance, logins and such, academic data as grades and background data as age, gender, ethnicity and more. The study showed that while students held protective attitudes towards personal data and high expectations of how the university should process their data, the majority are welling with the consent to allow access to educational data, have their data secure, and consent for further usages or identifying own data. The study highlighted key implications for learning analytics research and practice as identifying the key benchmarks of ethics and privacy: purpose, access, and anonymity and transparency and communication when adopting LA and information asymmetry.

Drachsler and Greller (2016) discussed the recommended privacy and data protection framework that needs to be applied with learning analytics collection and analysis in educational institutions. The eight foundation requirements of the framework are: data privacy, purpose of the data, data ownership, consent, transparency. Trust, access and control, accountability and assessment, data quality and data management and security.

2.1.4 Learning Analytics in Saudi Arabia

Learning analytics privacy and ethics concerns are also addressed in research studies conducted in Saudi Arabian higher education and the GCC educational institutions. Saqr, et al. (2017) conducted an empirical study at the college of Medicine in Qassim University, Saudi Arabia. The authors studied 133 students' online activities aiming to identify quantitative markers that correlate with students' performance and identify early warning signs for at-risk students (Saqr, et al., 2017). The university approved the research ethics of the study, and the author clarified this in the paper 'All users of Qassim College of Medicine sign an online privacy policy that detail possible use of data for research and user protection guarantees' (Saqr, et al., 2017), p. 759.

Hussain et al. (2017) handled privacy concerns differently at Zayed University in UAE. Students' IDs are sent anonymized to the researcher. This anonymized ID should match the anonymized ID in the dataset. It is an alternate solution to protect the privacy of the students. The study ensured following the ethical and privacy concerns. This approach can work also with past historic data where students have graduated and left the university and while following the privacy and ethical laws of the university, one can collect such data while maintaining confidentiality. For this research study, ethics and privacy issues were addressed by obtaining approval for any collected data whether current or past, applying best research ethical practice.

Aside from the privacy and ethical concerns, researching learning analytics in Saudi Arabia and the neighbouring GCC HE focused on giving a general overview of educational analytics and highlighted its benefits and advantages and exploring linking students' engagement and performance to the analytics. Moreover, there is a growing interest in researching Big Data and learning analytics in the region.

In a conference paper by Marks and Al-Ali (2016), a UAE study was conducted to examine the use of learning analytics within the learning management system. The study highlighted academic institutions' interest to collect data, analyse and measure course and program metrics, performance, alerts, and early warning systems. The study's findings indicated the challenge to find an effective approach to link the learning analytics functions to improve the decision-making process. What is interesting about Marks and Al-Ali's (2016) study (and shared by other studies as well) is that such research efforts are not an orchestrated effort by the university's body. These studies are self-initiated efforts by academicians that value the potential of learning analytics.

Aljohani et. al, (2019), proposed a framework for learning analytics that aimed to support integrated learning data by using an analytical dashboard AMBA (Analyse My Blackboard Activities), a tool that provides statistical and visual feedback for the students. The study examined the use of the Blackboard tool in relation to student performance and Blackboard accessibility.

Mukthar & Sultan (2017) discussed the current state of Big Data analytics in Saudi HE and identified possible applications and challenges of Big Data analytics. The paper helped to start the discussion about the importance of

Learning analytics and the challenges associated with it. The papers' findings indicated the lack of presence of Big Data in Saudi educational institutes as it is still in its early stage of implementation. Although, with the use of Moodle, Blackboard and other LMS system, Big Data in education can be detected in Saudi HE. Therefore, this is an excellent opportunity to conduct an empirical study examining Learning Analytics usage in one of Saudi Arabia's leading private educational institutions, the University of Business and Technology (UBT) in Jeddah, Saudi Arabia.

2.2 Learning Analytics and Performance

The analytical data usually collected in any active academic term in higher education institutions is usually very massive. This is because Clickstream data are recorded every time a learner clicks on any course resource (Douglas, et al., 2016). This generates enormous quantities of data that has to be aggregated and analysed and interpreted to provide meaning. Actions in LMS are monitored and stored and accordingly insight can be gained into students' online engagement, which can be used to improve learning and teaching (Conijn, et al., 2017). The need to collect thousands of analytic records from the Saudi educational institution can help to discover the learning analytics metrics residing in the system and can be used to convey the knowledge behind the analytics and furthermore the type of relationship that may exist between the analytics and the performance.

2.2.1 Learning Analytics Metrics

Learning analytics metrics are a set of functions or standards that can be used to measure and evaluate students' activities and performance (Purta, et al., 2018). Learning analytics metrics are used to monitor students' activities. Common metrics that are used in a lot of research studies are concerned with measuring frequency and durations. This is quite common as most studies are conducted in an online setting, or blended setting. Investigating duration and frequency would be slightly new in a traditional face-to-face environment, as in the researched Saudi context. The focus would be shifted to be more on examining frequency rather than duration. Since the Saudi student is not required to spend time online, due to the classroom traditional setting, it would be interesting to explore how often they do so. To help with this discovery, a Moodle analytical metric, *Total-Activity*, can be used. The *Total-Activity* metric is collected from students' statistics in Moodle. It counts the total clicks for a student online, so, it can be used as a measurement for student online engagement. It collects total posts and views of the LMS user.

To examine students' online engagement, analytical reports and log files can be explored to extract the learning analytics metrics. Furthermore, once the analytic data is extracted, it can be analysed and used to measure students' achievement. Tracing students' data to measure their behavior by observing computer log files, was examined in several studies. Hart, et al. (2017) examined online engagement variables along some attitude and cognitive variables in a flipped Math course, seeking to determine the best individual predictors of students' performance. The online engagement variables extracted from the log files were time to deadline for online workshop, time to deadline for grading peer students work, online quiz attempts, active and passive forum interactions. The study found out that out of the online engagement variables, both total amount of discussion forum posting and time for grading peer workshop, were both predictors of final course grade in combination with a couple of the attitude and cognitive variables.

The gap that can be investigated here in the Saudi context is what variables or learning metrics influence the final grades, specifically it is not a flipped environment, it is a traditional face-to-face one that utilizes an LMS. However, variables measuring time are not going to be collected and there are no cognitive variables examined.

More learning analytics are derived from LMS data. Gašević, et al. (2016) traced LMS data in a blended course model where they examined nine undergraduate courses. Variables derived included usage of the following: forums, course logins, resources, Turnitin file submission, assignment, book, quizzes, feedback, map, virtual classroom, lessons, and chat. Gašević, et al. (2016)'s study though, focused on other variables (non-related to Behavior in LMS) such as students characteristics: age, gender, nationality, living area, language spoken and more. The study also focused on the differences among students' levels and the diversity of the courses. The variables derived from LMS trace data were analysed based on usage. For example, discussion forums were visited most by Biology and Communications students. Mathematics students had the highest course login. There was also certain association discovered with the final grades for some of the variables. For example, students in Biology and Economy who accessed quizzed had about 0.7% higher grade than those who did not. Discovering the different analytics metrics is the focus of this research study. No other non-analytical variables will be explored. The need is to examine engagement triggered by students' movements and clicks. What are the learning metrics that are associated with high performance in the Saudi institution? For this, the research study is not collecting students' characteristics data, nor course discipline data. Instead, it is going to rely on students' movements.

There are certain learning metrics that show high correlation to students' final grades. Mogus, et. al, (2012) examined the activity logs and observed the LMS metrics: course view, assignment view, resource view, forum view, assignment upload, and project upload. Mogus, et. al, (2012)'s analysis revealed that the top log variables with the highest correlation with the final marks were: assignment view, course view, forum view, and resource view. Accordingly, this research study is intending to mine the Moodle log files aiming to discover what LMS metrics that trigger high performance.

To discover usage trends and obtain insights about user's usage of the system and their knowledge with the available resources and feature, Cruz-Benito, et al. (2015) explored educational data in a virtual environment (Second Life). Cruz-Benito, et al. (2015) indicated that tracking behavior patterns and measuring engagement in different LMS platforms enable determining users' interest in a specific feature or content. These measurements also enable managers to make decisions, promote specific content, perform actions to avoid dropouts, and improve system utilization.

To construct a predictive model for students' performance, Ashenafi, et. al (2015) examined several metrics such as number of tasks assigned, number of tasks completed and elements in homework assignments. However, Ashenafi, et. al (2015) had constructed and built a predictive model based on an automated peer assessment system that is built in the courses. The system depended on students assessing their peers and responding to questions and ratings asked by the teacher. The Use of additional examination tools is not part of the scope of this research study. Moodle existing log files and analytical reports will be used solely to collect the needed metrics recording the users' movements. Discovering what metrics have an association, if any, to the final grades will be examined in this research study solely based on the Moodle metrics collected and with no other non-analytical data examined such as students' characteristics or course disciplines and such.

2.2.2 Click Stream Data

Discussing the different LMS metrics in the different research literatures pointed out the total clicks of students as one measurement for students' online engagement. Clickstream data is triggered by students' clicks of posts and views of LMS resources and tools. A lot of research studies aimed to collect this clickstream data to analyse students' behavior. Furthermore, such collected data can be used to improve quality of online classrooms and eLearning.

The thousands of clickstream data collected in each academic term in most educational institutions have triggered an interest to research historic data. Beer, et al. (2010) summarized and aggregated 5 years of data from 2 LMS databases (Both Moodle and Blackboard) and students information system and grade database and examined the correlation of the number of clicks and students resulting grades. Beer et al. (2010)'s study resulted in a distinct positive correlation, despite other research not achieving similar outcome. Comparing this research case study to Beer et al. (2010)'s study, this researched case study is attempting to examine the correlation of the analytics with students' performance only in the Fall term because of the ethical approval needed to collect participants consent. It will though examine a 4-year historic Moodle data, acquiring the consent of only the lecturers, as the examination will examine only the instructional design of the course.

Benefits of analysing clickstream data is covered in most research. This includes students' intervention, improving instructional design and in some cases improve students' learning outcome. Lu, et al. (2017)'s study aimed to examine learning analytics by checking its effect on students' learning outcome. The study collected the learning analytics data by recording students' clickstream during learning activities (video or discussion). The captured data was collected from log files in a programming MOOC course and was mined. Accordingly, monthly reports were generated through a visual dashboard that instructors could access at any time, enabling instructors to intervein with any student with low performance.   Lu, et al. (2017)'s provided students intervention based on the analytics examined in an experimental group and provided intervention in another control group based instead on observations. The results displayed students with intervention based on the analytics achieved higher engagement and improved learning outcomes.

The objective of this research study, to research clicks, is not mainly to improve learning. It is more about understanding the engagement. For example, learning about students' online engagement can generate an outline for what triggers students to suffer or what triggers them to achieve high performance. In either case, such collected data can improve decisions on students' interventions or decisions to utilize certain resources or tools more in the LMS system.

Higher educational institutions are relying on LMS to generate academic analytics and make it available. While clickstreams are not a measurement of learning, learner access data can serve to identify groups of learners who utilize the materials differently. So, patterns of engagement can be discovered and analysed (Douglas, et al., 2016). Similarly, this research study aims to discover the relationships and explore the data collected to discover what information it conveys. It will take a step further in examining the relationship of course instructional design and students' engagement and performance, discussed all next.

2.2.3 Association of Analytics to Performance

Further decisions can be obtained from analysing the linkage of performance to learning analytics. The study of (Sclater, et al., 2016) reported how in the university of Maryland, US, students who obtained low grades used LMS 40% less than those students with C grades and higher. High GPA-students can be examined in this research study by exploring and mining the Moodle Log file. Upon the discovered knowledge, lectures can provide advice for under-achieved students with the recommended engagement pattern to perform better. Researching students' engagement patterns in LMS and predicting students' achievement was conducted also by Cerezo, et al. (2016). They separated students into groups with matching behaviors and analysed these different patterns and checked if any pattern relates to the final marks. However, this research study will not group students. It is aiming to analyse the pattern of engagement of all students and allowing the result outcome to explore or communicate any change in patterns.

Another way to examine the relationship of learning analytics to students' performance is to design and develop learning analytic tool that examines what effects students' performance. Mwalumbwe and Mtebe (2017) used an automated analytical tool database that is integrated with Moodle logs and forums and examined 2 blended courses. The study revealed 3 LMS factors that had a significant effect on student performance: discussion posts, peer interaction and exercises. Other LMS elements that had no significant effect were the time spent, number of downloads and login frequencies. Not all institutions have built-in customized tools to examine analytical data. A majority depends on LMS own reports and tools. This research study is going to utilize Moodle reports, analytical graph blocks and Moodle completions progress dashboard to examine behavior and learning analytics. In addition, this study is examining over 100 courses at UBT. But, since the current environment is a traditional face-to-face, variables such as login frequencies, and times spent on resources will not be examined.

There are few Saudi context cases where the level of activities to students' performance was examined. The study of Aljohani (2019) examined an analytical dashboard AMBA (Analyse My Blackboard Activities) in a Saudi Arabian university. The study divided an online Computer Science undergraduate course' students into two groups (controlled and experimental). The course was delivered using Blackboard. The LMS metrics used in the study were frequency of access to Blackboard, frequency of access to discussion boards, number of discussion posts and quiz results. Students had their own AMBA dashboards. There were several setups for the testing environment, one was that only the experimental group used the dashboard AMBA. The study resulted in that the more students used the AMBA dashboard, the more often they access Blackboard. There was a strong positive association between accessing AMBA and accessing Blackboard. There was also a strong positive association between accessing AMBA and students' final grades. This show that the use of dashboard has motivated students to access Blackboard more often and participate more in the discussion forum. There was also a strong desire to perform better than their peers. The enthusiasm of using visual boards will be explored in this research study.

Building on Aljohani (2019)'s study, this research is intending to do the same and examine LMS metrics and exploring more the usage of Moodle dashboard and the analytical graphs. An attempt to examine learning analytics will be a first step at UBT to make use of the thousands of learning analytics data available and discover what knowledge it conveys about students' online engagement and performance. Attempting to examine historic data does not seem to be covered in literature covering the Saudi context, so aggregating 4-year historic data will be a unique step done in this study and can convey more about engagement patterns. The study results can help other Saudi Arabian educational institutions to conduct similar examinations and compare results. Combined with further research can help to produce results that can be generalized to private higher education institutions or even all public and private institutions in the region that are mainly face-to-face environments.

2.3 Student Engagement and Course Design

Academic analytics can highlight the LMS features that gets high students' engagement. This can potentially provide teaching staff with an insight that they can reflect upon their practices (Beer, et al., 2010). For this, this research study is intending to investigate UBT's teaching staff's current practice and their current instructional design in Moodle. It will also examine students' engagement with the instructional design elements.

2.3.1 Instructional Course Design

Course design describes the sequence of learning tasks, resources and support that instructors provide for students during the academic term (Lockyer, et al., 2013). Lockyer et al. (2013) described it also as a series of planned pedagogical actions. It includes a set of LMS resources such as files, diagrams, links, tasks, assignments, quizzes and more. Conole (2012) defined learning design as a methodology for enabling instructors to decide on how to design learning activities (course design). Course Design indicates the various learning resources, assessments and communication tools used in LMS and the usage of these elements demonstrates students' engagement with LMS tools. LMS learning resources include PDF files, video tutorials, simulations, and such. Assessment tools include online quizzes, surveys, and such. LMS communication tools include discussion forums, chat, messages, and such. These LMS course design elements, if tracked, can indicate what students are spending their time on. Learning analytics can help to convey if students are using LMS resources or not using them at all. When are they using the resources? What are the most and least popular resources? By analysing the course analytics, this research study can provide a trail of students' interactions.

Learning design is focused on 'what students do' (Rienties, et al., 2018). Rienties et al. (2018) examined 151 modules with 111,256 students and found out that learning design strongly predicts virtual learning environment (VLE) behavior and students' performance. The study indicated that recent research investigated how learning design had a major influence on students' learning behavior, course satisfaction and grades. For this, the study of Rienties et. al (2018) attempted to examine the impact of learning design on students' engagement and examined the effect of learning design decisions made in four language courses. The learning design implemented a set of different taxonomy learning activities. The result of this implementation displayed a variation of 55% in students' utilization. Also, the time spent in each activity was influenced by how the instructor designed the learning activity. Exploring such utilization and what promoted better students' performance can help instructors design their future courses. This is similar to the aim of this research of investigating the course design elements of LMS and discovering the patterns that may help to guide UBT lecturers on how to build their Moodle course design effectively.

Linking between learning design and the usage of LMS and how the design impact students’ LMS engagement and performance was another interest of Rienties et. al (2015). Various learning activities were examined in 87 courses in The Open University (UK) - the largest online distance education institution in Europe. The learning activities included assimilative learning activities such as write, listen, find information, analyse, discuss and such. It also included communication activities such as debates and discussions, Productive activities such as creating and building, and assessment such as writing, reporting and more. The study used 2 LMS metrics: total LMS number of visits per week, average time spent on LMS. In terms of students’ engagement, the study results reported that LMS visits had positive relation on communication activities and negative relation to assessment activities. LMS visits also had positive relation to finding information activities. Thus, learning design decisions seems to strongly influence how students are engaged with LMS. In terms of students’ performance, productive and assessment activities had positive relation with students’ final grades. Assimilative activities, on the other hand, had a negative relationship to students’ final grade. In this research study, the priority would be to explore first the engagement numbers of students. This will convey what students engage with more. Based on this, the popular activities will be clear. A second examination will attempt to take a look at the high performing learners’ engagement patterns and what type of activities they utilize. By doing this, both high and low performance achievements can indicate the engagement pattern on the course design elements.

To transform teaching and learning, Davies, S. et al. (2017) discussed the opportunity of using technology to enhance curriculum design. To make instructional design and curriculum changes, key learning elements visited by students need to be examined. These visits indicate students' engagement. Davies, S. et al. (2017) indicated that sustained students' engagement is important in any curriculum redesign. Every time, students interact by logging into an LMS or submit assessments online, they leave a digital footprint behind. Learning analytics takes care of examining these footprints. This data measures learners' engagement with the course design elements.

2.3.2 Students Engagement

Student engagement refers to the involvement of students in their learning process as the time user spent learning and the number of activities conducted. Evidence of engagement can help explain how users engage with certain learning tools, enabling any needed improvement of any aspect of the tool that is not utilized enough, also preventing dropout and helping users to reach their learning goals (Cruz-Benito, et al., 2015). Hew (2016) investigated the factors related to MOOC design and the MOOC resources that are well received by the students and needed for promoting students' engagement. Hew (2016) described the structure of the MOOC courses containing course description, syllabus, reading list, accomplishment statement by the instructor, and signature profile. The resources used varied: videos, discussion forums, quizzes, and assignments. The special factors related to the MOOC design include problem-centric learning using interactive games, instructor accessibility using emails, weekly live discussion and humour, peer interaction, active learning with the self- assessment, resources that address the participant needs. This research investigates the current structure of the UBT courses and checks which resources have an impact on students' engagement with the difference that these courses are not online courses and there are other factors that may affect students' engagement other than course interaction.

There are different indicators of engagements in the LMS various systems. Data from LMS can be used as an indicator for students' engagement and data patterns changes can be examined (Beer, et al., 2010). Class attendance and participation have been used as a metric for engagement in many studies (Beer, et al., 2010). The engagement is positively linked to a set of desired outcomes such as high grades. Accordingly, this research case study is attempting to investigate if online engagement with Moodle resources relates to high grades, and if this association is positive or negative.

Students' clickstream data can be an indication of students' engagement. Though repeated clicks on an online activity does not necessarily indicate learning, amusement, or confusion. But it does convey an engagement level with an activity. There are few research studies that have used students' trace data as an indication for students' engagement. Jovanović, et al. (2019) needed to learn about students' engagement by collecting students' trace data of online class activities. The study acknowledged the ambiguity of the meaning behind the collected learning traces and behavior; What would a high number of page views be a sign of? Is it high confusion, motivation or productive engagement? The study though refers to the collected trace data as engagement and this included descriptive statistics that offered insight into the students' engagement in activity evaluation patterns. The study recognized events such as clicking to replay, pause, and repeat videos, quiz interactions, frequency of clicking an activity, all as engagement with an activity. There was also an examination of engagement with a 2D self-evaluation Canvas that included descriptive statistics that offered insight into the students' engagement in activity evaluation. The study aimed to collect the trace data and collect students' self-reporting of the difficulty of the online activity conducted to examine associations of various elements of engagement and performance. The study is similar to this research study as it had 2 perspectives, the students self-reporting perspective (Questionnaires here) and the trace data (Moodle analytical reports here) as a reflection of students' engagement with the online resources.

There are a set of benefits for examining learning analytics. Cruz-Benito, et al. (2015) indicated that such exploration of users' engagement in a learning platform is useful because obtaining knowledge about user's usage will help instructors better plan and design the deployment of educational content and resources inside the learning platform, enhancing the personal experience and learning process for students. Similarly, this research study shares the same objective of improving course design elements based on the educational data analysis conducted at UBT. By understanding students' online engagement, Mogus, et. al, (2012) indicated that instructors can design more appropriate activities and materials either prior to start of the course or during. They can also design individualized learning materials that may assist students in better understanding and can help them to improve their performance. Ifenthaler (2017)'s study indicated that instructional design used learning analytics to evaluate learning materials, adjust difficulty levels and help to facilitate a plan for interventions and improve curriculum planning. This research study is aiming to investigate the current capabilities of learning analytics at Saudi higher education institutions and gain an understanding of perceptions of LA. Feedback provided by learning analytics to instructors can help to evaluate their teaching strategies. For example, if an instructor can see no one is downloading a particular file, or student heavily relying on some other type of files, then this information can be helpful when updating current instructional designs or in designing new modules (Shacklock, 2016).

2.4 Educational Data Mining

In order to collect the learning analytics data and to analyse it to understand students' engagement, performance and learn course instructional designs best practice, there is a data transformation process that the analytics need to go through in order to acquire the stated knowledge; this can be done through educational data mining (EDM). The different learning analytics acquired from LMS log files and reports need to undergo the process of data mining to discover the knowledge behind them. Within the e-learning field, data mining can be used to explore, visualize, and analyse the data with aim to identify useful patterns to obtain students' learning behavior or feedback that instructors can use when designing instruction and materials. Data mining includes tasks and methods for statistics, visualization, clustering, classification, association rule, text mining and so on (Mogus, et al., 2012).

2.4.1 What is EDM?

Ali (2013) explored the various definitions of data mining with a focus to examine the role of data mining in the educational sector. Ali (2013) defines data mining as an exploration data analysis and a process for discovering patterns. Ali (2013)' study stated some of the benefits of data mining in the educational sector. These include identifying students' needs, predicting students' enrolment, predicting students' performance, course compiling, students course selection, students' performance and dropout and instructors' teaching performance and more.

Data mining can be used to explore, visualize, and analyse data to identify useful patterns and predict needed actions (Romero & Ventura, 2007). Romero & Ventura (2007) discussed some aspect of educational data mining concerning data discovery methods used in e-learning as the purpose is specifically to guide students in learning. Mining involves capturing meaningless data, then reporting information, enabling prediction based on knowledge and actions (Elias, 2011). The pattern of discovered data investigated uniquely here in this research study will focus on both current interval data (Fall 2018) and historic data for the period of 2015 to 2018. A comparison will be conducted among these two intervals for the purpose of revealing more about learning analytics.

Various LMS systems such as Blackboard and Moodle accumulate large log data of students' activities and usually, these systems have built-in student monitoring tools (Romero & Ventura, 2007). These tools can record students' activities such as reading, writing, taking quizzes, communicating with peers and such. This is done a lot in most LA research. This research study will take a step further in collecting more analytics, other than the log files. Students' statistics of the study participants and course activity reports will be collected and examined. The aim is to gather as much data as possible to analyse students' engagement and performance and course instructional design decisions. The diversity of the collected analytical reports will help to strengthen the findings.

Further benefits of educational data mining include helping instructors identify students with poor performance or low interaction (Hussain, et al., 2017). LMS records the time students access course pages, records the files they upload, and other actions the students conduct. Hussain, et al. (2017) indicated that papers researching EDM want to mine data to find set of variables that correlate to the students' final grades. EDM and learning analytics rely on collecting large amount of data about students' interaction with LMS and they apply mining and analysis to extract information that will help educational institutions to learn about students' retention and program completion. Instructors' role in this research study is different as they will be surveyed and their participant courses will be examined and analysed, providing insight on both their instructional design and the level of their students' engagement. Such insight would be interpreted further to reveal any correlation elements to final grades or elements of students' interactions and retention.

2.4.2 EDM Process

Collecting learning analytics and analysing the collected data to interpret the meaning, mostly follow similar processing paths. Hoel and Xiao (2018) discussed the ISO/IEC 20748:2016 learning analytics process model. They describe 6 processes: learning activity, data collection, data storing and processing, analysing, visualizing and feedback and actions.

The process starts with a learning activity, then data is collected from various educational environments and systems. The collected data may be too large and may include many attributes which may call for data storing and processing. This also involves transforming the data into a suitable format. Other tasks may follow such as data clean-up, data integration, data transformation, data reduction and user identification. After pre-processing the data, it is analysed, visualized, and actionable feedback is generated. This data exploration and hidden patterns discovering can help to provide a more efficient learning experience.

There are other different frameworks for the EDM processing that are used by many studies. Davies, R. et al. (2017) examined a framework for learning analytics, a modified version of Campbell and Oblinger (2007) educational data mining framework that included five steps: data selection, data capture, data visualization and system refinement. Similarly, Elias (2011) discussed Campbell and Oblinger (2007)'s five steps of analytics: capture, report, predict, act and refine.

Similar frameworks for EDM processing are followed also in e-learning (Romero & Ventura, 2007). Educational data mining involves data pre-processing steps. Data pre-processing allows the transfer of an original raw dataset into an appropriate shape so that it can be used by a particular data mining algorithm (Romero & Ventura, 2007). Before applying a data mining algorithm, a few general data pre-processing steps must be addressed such as data cleaning, user identification, data transformation and integration and more (Romero & Ventura, 2007). This research study adopts Romero et al. (2008)'s 4-step data mining process for how Moodle data is collected, pre-processed and cleansed, interpreted and evaluated and how results are deployed. The study of Mogus, et al. (2012) used the same Romero et al. (2008) four steps data mining process. Similarly, this research study will follow in the same data mining steps, except that in the data mining phase, instead of using a specialized data mining tool (Weka) as in Mogus's study, a combination of statistical and trend analysis will be used instead.

2.4.3 EDM Tools

Some of the data mining techniques used in educational systems, discussed by Romero and Ventura (2007) are statistics and visualization. A set of specific statistical tools can be used such as Synergo/CoIAT, AIWBES, Weka and Keel and more. This research study is relying on SPSS for using complex statistical tests such as regression and correlation analysis. Other than statistics, Romero and Ventura (2007) listed some other samples of how to apply data mining techniques in educational systems. These include sequence patterns, prediction, association, text mining, clustering, and visualization.

Some of these patterns can be used through SPSS and Microsoft Excel. Excel can be used for the process of organizing and refining the data and analysing patterns of data such as cubes of selected data by applying Pivot Tables.

Moodle exports its data from log files to spreadsheet format (Excel), through which the user can feed in data and create pivot tables. The graphic results of pivot tables are a summative table report that helps to organize great volumes of data and calculate certain attributes emerging from the data. Using Excel in exploring analytical data is quite common in research studies. Dierenfeld and Meceron (2012) used Excel pivot tables to perform analytical processing with the educational data and help to answer questions related to the LMS resource usage. “A pivot table is a highly flexible contingency table. The table can be created from a large dataset and offers the possibility to look at one section at a time” (Dierenfeld and Meceron, 2012, p.117).

Pivot tables were used in Heinrich (2015)’s study to investigate if learning analytics can provide useful insight at a course level in a blended format to examine the LMS resource usage. Top resources used were course homepage, resources (text, video, and PDF), forums, assignments, and the course information. Even though this research study is intending to do the same, and conducts trend analysis using Excel pivot tables, to provide insight and examine LMS resource usage, the main focus though is on discovering patterns of engagement in both the Fall 2018 data and a 4-year historic data.

Elements of engagement can be counted, sorted, and clustered in groups of users, relating each user with their performance (Cruz-Benito, et al., 2015). This research study will use Excel to examine the engagement by following the same path of counting the elements of engagement, sorting them, filtering them, creating clusters and more. Clustering involves GPA clustering, course type clustering, event type clustering and more, all to provide an insight on LMS utilization and students' engagement.

2.5 Learning Behavior

Most studies on learning analytics are largely data driven and not explicitly based on theories (Conijn, et al., 2017). Some studies use different theories such as the interaction theory of Moore or the self-regulated learning (SRL) theory. In this research study, SRL is adopted as the theory to examine learners' behavior.

2.5.1 Self-Regulated Learning (SRL)

To exercise control in online learning, learners have to develop SRL (Yamada, et al., 2017). SR learners are those who can prepare a learning plan, adjust it, and apply self-control and self-evaluation. Skilful SR learners tend to plan their final goals and the needed steps to accomplish them. They tend also to be motivated, and they constantly monitor their learning process and evaluate it and adjust it when needed (Yamada, et al., 2017). In this research study, the researcher will attempt to evaluate the current UBT students' SRL behavior in a traditional face-to-face setting that utilize Moodle heavily.

Self-Regulated Learning (SRL) emphasizes how learners select, organize, and plan the form and the amount of their own instruction (Zimmerman, 1990). You (2016) indicated that a lot of SRL research studies have indicated that learners who frequently use self-regulated learning strategies exhibit better academic achievements. SRL behavior can distinguish between successful and unsuccessful learners. Successful learners are active in the online learning environment. They regularly access course news, they study and review course materials, they submit assignments in a timely manner, and they self-evaluate their learning, asking questions when they need help and constantly communicating with others. Unsuccessful learners on the other hand, do not manage their time well, they produce less efforts to complete assignments and lack life-coping skills. You (2016) indicated that online learning requires high degrees of initiation, organization, and studying. Examining such learning behavior in the UBT traditional settings will be one of the objectives of this research study. What are the SRL elements that stand out in both UBT students and lecturers when interacting with the analytical tools in Moodle. Students are commonly examined in a lot of SRL research studies, but there is a gap as lecturers are not considered mainly SRL learners. For this, the research study will examine this non-common aspect.

Regarding SRL learner profiles, Self-regulated learning tends to have certain patterns (Roll & Winne, 2015). SRL learners tend to follow the following pattern: identify factors that may influence the tasks they need to do, then they frame goals and design plans to approach these tasks, then they implement actions to fulfil the tasks and monitor them, and lastly, they construct strategic revision to understand the actions taken. Roll and Winne (2015) indicate that tracing learning analytics helps in evaluating the types of actions students choose to perform. These actions reflect the students' knowledge, experience, and habits. The SR learner profile does not necessarily apply to this research case's students. An opportunity though to discover SRL behavior and analyse it further and associate it with performance is provided in this research study.

2.5.2 Trace SRL Behavior

Self-Regulated Learning, in an online learning environment, can be traced because students' learning behaviors are automatically recorded by LMS (You, 2016). LMS provides the tools to monitor students' learning participation and progress. By this, the collected data help instructors to identify at-risk students to provide help for them and adjust any needed instructional strategies (You, 2016). You (2016)'s study aimed to identify significant LMS indicators, including self-regulated learning indicators to predict course achievements. LMS systems, such as Moodle and Blackboard, provide analytical functions summarized to instructors, and tracing usage data from LMS capturing students' self-regulated behavior. While You (2016)'s study relied on examining the LMS content and the learning analytics associated with accessing course information to discover the students' SRL behavior, this research study will rely instead on surveying students about their SRL behavior by questioning them about their style when using the LMS resources and the analytical dashboards. This research study is going to incorporate SRL elements when building the surveys and the interview questions aiming to survey both students and lectures about learning analytics and dashboards.

Examining and tracing behavior with learning analytics involves sometimes different frameworks. Winne (2017) discussed a framework called COPES: Conditions, operations, products, evaluations, and standards. The framework explored the type of activities done by the learner and talked about how learning analytics are linked to the SRL elements. Linking learning analytics to SRL can be done using log files. Log files can be traced by examining exact details of each user's log file elements (Kim, et al., 2018). Details such as frequency, time spent, seeking help and such. The use of SRL questionnaire helps to get further insight on students' behavior. This is also conducted by Kim, et al. (2018) to relate the analytics to the students' SRL behavior. Following the same path of Winne (2017) and Kim, et al. (2018) to link the analytics to SRL, this research study would need to collect extensive data for each individual user. Collecting the details of each user's usage is not within the scope of this research. Understanding learners' SRL behavior by surveying the learners' usage and their exposure to the analytics is what this research study is intending to do. Furthermore, this research study is intending to link the grades to the students' own self-regulated learning testimonies. This can provide meaning to which SRL elements affected grades the most.

Chapter 3: Research Design

3 Methodology

3.1 Case study Objective

The study conducts an exploratory **case study** at UBT, Jeddah, Saudi Arabia. It researches the use of Moodle analytics and dashboards. It focuses on exploring students' engagement with the Moodle completion progress dashboard and examines students' behavior and performance when utilizing Moodle in their courses. The case study also explores lecturer's behavior toward Moodle analytical graphs and Completion progress dashboard and how it can influence their Moodle course design choices and students' monitoring and advising. **Exploratory case studies** are used when there is no pre-determined outcome (Yin, 2014). Since this research is exploring "What" questions, an exploratory case study is appropriate, especially that case studies also work best for exploring complex data that a survey cannot acquire.

The exploratory case study explores what is happening with the analytics in the participating courses and discovers usage patterns of behavior in past historic courses. The case study answers the research questions seeking to understand the relationship between the analytics and the students' performance, engagement, and course design. The case study collects both primary and secondary data from the 2 colleges CBA and CE.

The case study collects **primary data** that consists of learning analytics transactions recorded in the Moodle system during the academic term of Fall

2018, along with surveying both lecturers and students and interviewing lecturers towards the end of the Fall term. This requires lecturers to use the completion progress dashboard and Moodle analytical graphs during the Fall term. The students are exposed only to the completion progress dashboard as it is transparent to each student and they can observe and monitor their own performance through it, during the Fall term. The primary data includes quantitative data (collected from UBT analytical and performance Data and questionnaires) and qualitative data collected from interviews.

The case study also collects **secondary data**, thousands of learning analytics data collected from the past four-year period. This secondary data does not include any student performance data, it mainly focuses on the analytics and what patterns it conveys about students' engagement and the Moodle course design elements. The historic data covers year 2015, 2016, 2017, and 2018 (Spring). The secondary data contains quantitative data collected from UBT's Moodle analytical reports.

3.2 Mixed Methods

Considering the nature of the primary and the secondary data needed for this study, a mixed method of data collection and analysis is implemented (Creswell & Clark, 2014). The **mixed method** follows convergent parallel mixed method, where both the quantitative and qualitative data are collected and analysed in parallel, but they are integrated and related during the discussion of the analysis results. The problems researched in this study explore the use of learning analytics and dashboards among students and lecturers and examine the relationship between using this new technology and students' behavior, performance and engagement and lecturers' course design elements. Quantitative data includes statistical data of students' movements in the course and students' and lecturers' LIKERT based questionnaires. The quantitative data provides facts about the current learning behavior, and further analysis reveals the association of the analytics and course design to the performance. Qualitative data on the other hand conveys more about the reasoning behind the facts. Qualitative data includes lecturers' testimonies on their own course instructional design style and the behavioral patterns they follow preparing their course materials and their feedback about students behavior. The qualitative data helps to provide the interpretation behind the behavior. Why students act in a certain way, can be conveyed from the lecturers' perspective. Why lecturers have certain design pattern or why it differs from year to year. The level of interaction among the quantitative data and the qualitative data indicates the need to apply a convergent parallel design (Creswell & Clark, 2007). The purpose of the convergent design as indicated by Creswell & Clark (2007) is to obtain different but complementary data on the same topic to better understand the research problem. It also helps increase the validity of the data. Data collection was conducted in Fall 2018, where analytical data got built during the Fall term, and soon after the courses are completed, data collection started for both the quantitative data and the qualitative data. Data mining is conducted on the analytical reports. Students' questionnaires are finalized at the end of the term, and interviews start also at end of the term. The challenge faced is to maintain focus on each phase because of the complexity of the data mining process. Questionnaires are also challenging as many of them are collected manually also at end of the term. Interviews also take time to plan and conduct with each individual. The advantage is the massive gain of discovered knowledge through using these multiple methods that result in rich data.

3.3 Ethical Guidelines

Many educational institutions incorporate a broad statement about the use of student data in their student-contract, or in the policies and forms the student sign at enrolment. At UBT, electronic signatures are available in the students' portal when they sign-in for UBT's students' policies. Consent for personal data is currently in-progress to be finalized to facilitate more research opportunities at the university concerning students' analytical and personal data. The purpose for collecting learning analytical data is to support students learning and success. Concerning collecting students' personal data is not something that students object to. Shacklock (2016) indicated that students nowadays are relatively comfortable with the use of their data in learning analytics. This may be because, nowadays students are more technology savvy and are more open to new digital trends. Students are growing up in digital world dominated by Google, Amazon, Facebook where the young students' generation do not mind exchanging their personal data for access to products and services (Shacklock, 2016). UBT students have been helpful in past research and this research study provides the needed information sheets and consents forms to welcome the students to be part of this unique study as they are part of an investigation of an under-researched area in Saudi Arabia higher education.

To ensure that the needed learning analytics ethical guidelines are followed, the researcher has followed Lancaster University's Ethical approval process to ensure the protection and privacy of students' and lecturers' data. Information and consents forms are shared with the participants to clarify all the needed information about the study, the data collected and the analysis process. The researcher has also ensured to follow UBT's own policies in regards of students' and lecturer's privacy and data protection to conduct this research study.

Lecturer's approval was sought through signed participation forms during the summer of 2018. Orientation about the research requirements, expectations and orientation with the Moodle analytical graphs and dashboard were all conducted in a 2-week period at start of the Fall of 2018 academic term. Stop-by visits, phone contacts and emails were conducted throughout the Fall academic term to ensure a smooth process of applying the analytics in the classroom and to ensure to answer any concern lecturers may have.

Students' approval was sought through signed participant forms posted in each participant Moodle course homepage. They were asked to participate voluntarily in the study. They were also provided with an information sheet explaining what data is collected and what and how it is used. Students' approval to the study was indicated by signing their Student ID in the consent forms. The consent form explained all the needed information about collection of the students' analytical data in Moodle and their final grades and GPA data needed at the end of the term. Students were encouraged to ask their lecturer or contact the researcher if they have any questions about the new dashboard that showed up in their participant courses. Lecturers oriented the students about the simple-to-use dashboard. Section 3.4 and 3.5 discuss the selection of the participant UBT lecturers, courses, and students.

3.4 Participants

Out of the four major colleges at UBT, only 2 colleges are selected for the study. Data is selected from: College of Business Administration (CBA) and College of Engineering (CE). The Advertising college (JCA) is not part of the study because it relies on a practical projects approach. It does not have heavy Moodle transactions built because of their course delivery structure. College of Law (CL) was established a year before the start of the research in 2017, so, it does not have enough Moodle transactions built by the start of the research.

To effectively examine the rich analytics in the case study, careful screening was conducted to nominate the participant lecturers. The study needed lecturers who utilized Moodle resources effectively and have active students' engagement online. The study aimed to include lecturers who post materials, use discussions, online quizzes, and other Moodle resources, and have high communication within the academic term in the Moodle platform. So, a query was conducted in the Moodle server to extract top active courses in a past two consecutive terms (Fall 2017 and Spring 2018). To determine active courses in Moodle, a list was composed from using the Moodle admin tool: Course overview Report. It displays the top active courses. So, 20 lecturers were selected and contacted based on their performance in Moodle to seek their approval to participate in the research study. UBT selected lecturers were very cooperative and enthusiastic and approved their participation in the study.

There were 20 lecturers selected for the Fall 2018 term: 8 male lecturers from CBA and CE colleges and 12 female lecturers from CBA. 15 lecturers were selected for the historic 4-year data, with 5 males and 10 females. They all signed the official consent approval and information form that was sent in the summer of 2018. In addition to orienting the lecturers with the newly installed dashboards, video tutorials were also provided, and contact was available for any help needed. Three meetings were conducted for each campus at the start of the Fall term to help the lecturers get started and ask questions and get acquainted with Moodle analytical graphs and Moodle completion dashboard. Short sessions were also conducted based on the request of some lecturers during the first 2 weeks of the term. The researcher explained her role in regards of protecting the privacy of the course and explained the timeframe that is needed to access the courses' and students' analytics.

The total students who were enrolled in the participating courses was 1425 students (this included repetitive students). The unique list (after removal of all duplicates) included 925 students, with 370 male students and 555 female students. All students of the participating courses had a welcoming message in their Moodle page displayed throughout the term explaining the research study and providing contact information for any queries. There was a video tutorial and a PDF help file provided as well. Students can only view the completion progress dashboard; they do not have access to the analytical graphs. Out of the 925 students enrolled students, around 711 students consented to the study. The valid participant list with valid IDs was 419 students. see Table **3-1** for the participant list. Section 4.2 discusses the students' selection. The lecturers explained the role of the completion dashboard to the students and kept track of them during the term.

Student participants	Numbers
Total enrolled in participant courses	1425
Unique students	925
Total Students participant	**925**

Lecturer participants	Numbers-Fall	Numbers-Historic
Male campus	8	5
female Campus	12	10
Total	**20**	**15**

Table 3-1: Participants

3.5 Courses

The study focused on both the Fall 2018 courses and a 4-year historic data set to make use of the thousands of Moodle learning transactions available. Courses were selected based on the voluntary participation of the lecturers selected as participants in the study. The Fall 2018 participatory courses covered 60, out of approximately 200 courses from CBA and CE colleges. 41 courses from the female campus, and 19 courses from the male campus, this yielded around 120 course analytical reports, plus 100s of students' analytic data statistics. The study covered courses that have consistently high levels of Moodle usage. The lecturer participants of the study were approached to approve selecting a past course that they happened to teach for four years in a row. So, the historic data did not include newly joined lecturers and it included CBA and CE active Moodle lecturers. The study aimed to track the learning analytics in each course in the past 4 years (2015, 2016, 2017, and 2018). Selected lecturers gave consent also to allow examining their past courses. But some courses, were dropped because they did not have enough years. For this, the list was shorter and only 15 courses were selected (historic data) (10 from female campus, and 5 from the male campus). The 15 lecturers signed an additional consent and information form to proceed with collecting the historic data. Only summarized descriptive analytics concerning the course analytics were collected for the historic data. 15 courses in a 4- year period yielded only around 59 analytical reports.

3.6 Data Sources

There are different types of data sources collected in this research case study:

- Analytical data collected from 3 Moodle analytical reports.
- Students Grades and GPA.
- Student testimonies collected through questionnaires.
- Lecturer testimonies collected through questionnaires & Interviews.

3.6.1 Analytical Moodle Reports

There are 3 different types of Moodle analytical reports that were examined: "***User Statistics***", "***Activity Reports***", and "***Log Reports***". Moodle user statistics help to highlight the relation of students' hits with their grades. Both Moodle logs and activity reports help to highlight pattern of students' engagement in the course, what resources were mostly used and what Moodle events were visited the most, especially by high GPA students. The log file also highlights the patterns of students' engagement for a historic 4-year data. Table **3-2** summarizes the 3 types of Moodle analytical reports used in the case study. A description for each type follows, along with the needed mining steps to collect and prepare the data for analysis. Data mining process and details are discussed in the methods section 4.1.

Moodle Analytical Report	What Data?
Moodle User Statistics	Track total hits of the student in a time interval in each course.
Moodle Activity Report	Track each activity's hits in each course such as access to resource, file, or use of a Moodle tool. Compared to the Log files, activities in the activity report are indicated by type of files such as a PowerPoint, PDF, Image, video. There may be around 20+ different types of activities in the course.(after mining)
Moodle Log Report	Track all type of events in Moodle for all users who access the course, including instructor, student, administrator, and guest. Log files may contain 80+ different events.

Table 3-2: Data Sources

3.6.1.1 Moodle User Statistics

Each user in Moodle has their own descriptive statistics data. The statistics graphs and tables display how many hits the user has on various parts of the course site during various time frames (Moodle Docs, 2017). The Total-hits is a calculated total metric that is calculated for the purpose of this research study. I am calling it the *Total-Activity* Metric. The *Total-Activity* metric collected from students' statistics counts the total clicks for a student online, so, it can be used as a measurement for students' engagement. As discussed in the students' engagement, Literature Review section 2.3.2, clickstream data can be used to examine engagement, similar to Jovanović, et al. (2019) who collected trace data of students' interaction with online activities and also engagement with a 2D Canvas evaluation tool for the purpose of examining associations of engagement and performance. The *Total-Activity* metric in this research study collects total posts and views of the LMS user. Views in Moodle indicate user accessing a Moodle resource or activity to read or download. Moodle posts on the other hand means a more interactive action such as submitting a quiz, assignment, or add an entry to a discussion forum. The total activity combines both views and posts of the user, which indicate the hits of user visits in Moodle (Moodle Docs, 2017). It sums all the activities done in each course for each student. A student may have a total of 1340 hits in one course, where another student may have 640 total hits. In either case, these total hits (*Total-Activity* metric) are mapped to the students' final course grade to attempt to examine the relationship between the hits and the performance.

Teachers and non-editing teachers can access their students' statistics through accessing participant list → choose any student, the student profile is displayed, then click statistics. Moodle user statistics display a table grid for a set timeline displaying the total number of views and posts conducted by the user. This requires examining each student's statistical information grids. The study yields a potential 925 statistical grids to examine (this is equal to the number of student-participants in the course).

3.6.1.2 Moodle Activity Report

Each course in Moodle contains an activity report. A Moodle course activity report shows the total number of views for each activity and resource used in the course. This includes file uploads, Discussion forums, quizzes and more. The report can be viewed by managers, teachers, and non-editing teachers. The report tool can be accessed in Administration > Course administration > Reports > Activity report (Moodle Docs, 2017). Activity Report lists all resources and activities used in the Moodle course and list total number of views and how many users accessed each resource along with the day and time it was last accessed. For this study, this yields around 60 Fall 2018 activity reports and around 59 historic activity reports to examine. Both Moodle activity reports and Moodle log files (followed next) attempt to examine the pattern of students' engagement with Moodle different resources and events.

3.6.1.3 Moodle Log File

Each course in Moodle contains a log file. A log file in LMS generally allows educators to collect and review statistical data in how students approach and use the different LMS events, how long, and what time and more (Mogus, et al., 2012). A log file records all actions (from start of the course, till the end) conducted by course users, including the lecturers, students, administrator, and others. The collection of data includes time, event name, description, user full name, effected user, IP address, and such. Moodle log data can be accessed in course level (data available for each course lecturer, students do not have access to this data). The report can be viewed by managers, teachers, and non-editing teachers. The report tool can be accessed in Administration > Course administration > Reports > Log. Once a course is created in Moodle, a log report starts to record every action conducted in the course from any user. These set of actions are called events. Sample of events includes quiz-attempt-is-viewed, a-file-has-been-uploaded, user-list-viewed, grade-user-report-viewed, message-sent, subscription-created, wiki-history-viewed, add-Turnitin-Assignment, and more.

Table 3-3 displays sample similarities between a mined Moodle activity report and a Moodle log report. The study yields around 60 Fall 2018 log reports and around 59 historic log reports to examine.

Sample Activity in Moodle ***Activity Report***	Sample events in Moodle ***Log Report***
Discussion Forum	*Discussion viewed* *Discussion created* *Discussion subscription created* *Discussion subscription deleted* And more….
Assignment	*Add submission* *Submission form viewed* *A submission has been submitted* *The submission has been graded* *Submission updated* And more….

Table 3-3: Activity Reports vs Log Report

3.6.2 OPERA Final Grades and GPA

Another source for data is students' performance data. Students' final grades are recorded at end of the Fall academic term by the course's lecturer in the *OPERA* grading system. Only the course lecturer has access to their own course grading system. Because of the confidentiality of students' grading records, this data is requested confidentially using only students' IDs (who have consented to the study). The request is sent to the *OPERA* Grading Database administrator and the grades are sent in Excel format directly to the researcher. Final grades are inputted as values (100 to 60). Any value less than 60 is considered failed, and failed students earn the letter grade F instead of a value number. Another grade letter that students may get is 'DN' Absent Fail who lacked in attendance and are considered Failed and GPA is affected. There are other grades as 'W' Withdrawn and 'IP' In-Progress that do not affect the GPA and are not part of the research study and students with these grades are removed from the research study.

3.6.3 Questionnaire Data

The students' questionnaire contains a combination of self-regulated learning (SRL) and attitudes questions. The objective is to check students' learning behavior and attitudes toward Moodle resources and the Moodle dashboard. The questionnaire also makes use of students' GPA as it is mapped to their SRL behavior. Students with self-regulated learning characteristics can stand out with their time planning, monitoring efforts and self-observation, and choice behavior (Pintrich, 2004). It is interesting to survey the UBT student-participants and highlight what elements of SRL they have and if it effects their GPA or not.

To construct the questionnaire, several SRL questionnaires were visited such as the SRL questionnaire produced by the centre for research on learning at the university of Kansas (Erickson, et al., 2015). The rest of the questions were attitude questions about using dashboards, understanding the purpose, and believing if it is helpful and useful. To check the questionnaire, see Appendix one.

For the planning and goal setting SRL element, associated questions for these elements included setting goals to help utilize Moodle, planning a study plan for Moodle activities, ability to estimate task duration, dedicating set of hours for Moodle activities and the ability to set strategies to manage studying the Moodle online resources. For the monitoring SRL elements, questions included: ability to keep track of Moodle deadlines, knowing the grades updates, check Moodle news periodically and keeping up with the weekly reading and assignments. Control SRL element questions included: knowing when falling behind schedule, loosing attention online, and managing to work even if material is dull. Reaction and reflection SRL elements Questions included: changing strategies when needed, asking peers for help, asking the lecturer for help, and learning from mistakes when failing occur.

Lecturer's questionnaires contained a combination of SRL behavior and attitude questions that check lecturers' usage and attitudes to learning analytics and dashboards. The SRL elements can highlight if a lecturer is capable to design course content effectively, self-reflect and react upon discovering information from the analytics. Planning and goal setting SRL element questions included setting Moodle content at start of the term and planning future course design changes upon the discovered analytics. Monitoring SRL element questions included updating Moodle content periodically and checking Moodle messages. Control SRL element questions included changing course design upon students' performance, observation, and analytics. Reaction and reflection SRL element included questions about identifying students at risk, reaction to the Moodle analytical graphs and the completion progress dashboard and the usefulness of these tools. Other questions sought the lecturer's attitudes toward these tools. Questionnaire Analysis approach is discussed in the methods section 4.2.

3.6.4 Interview Data

The objective of the interview is to seek lecturers' course instructional design habits and their perceptions and attitudes toward the use of Moodle learning analytics and the newly implemented LA dashboard. Following the same path of the questionnaires, the Interview questions are structured around the elements of Pintrich (2004)'s SRL. The purpose of this is to associate the SRL behavior elements with lecturers' testimonies as they are considered technology learners when they interact with the Moodle analytical graphs, and the completion progress dashboard. The objective of the interviews is to get further insight on both students' behavior from the perspective of the lecturers and also get further insight on lecturers' behavior in their approach to Moodle instructional design. Reasons for the behavior are better explored through the testimonies. Follow-up questions help also to explain more about the behavior, Check Appendix 2 for the interview questions. The interview analysis approach is discussed in the methods section 4.3.

3.7 Research Design Framework

All the different data sources that are used in the research case study are highlighted in Figure 3-1 and mining these files and discovering the knowledge behind them. Figure 3-1 highlights how each research question will be answered. The figure starts with the theory involved in answering the research question. Then, it states the objective of examining this Research question. Followed by stating the data source file examined. Then, the number of records or participants needed to answer this RQ. Then, the process used to analyse the data source. Finally, the figure states the analysis used to answer this RQ. For example, to answer RQ 3.1, the theory in use is Pintrich's Self-Regulated Learning. It is used to examine students' behavior. The data sources that will are used are the questionnaire data and the GPA data. The analysis is conducted using SPSS regression.

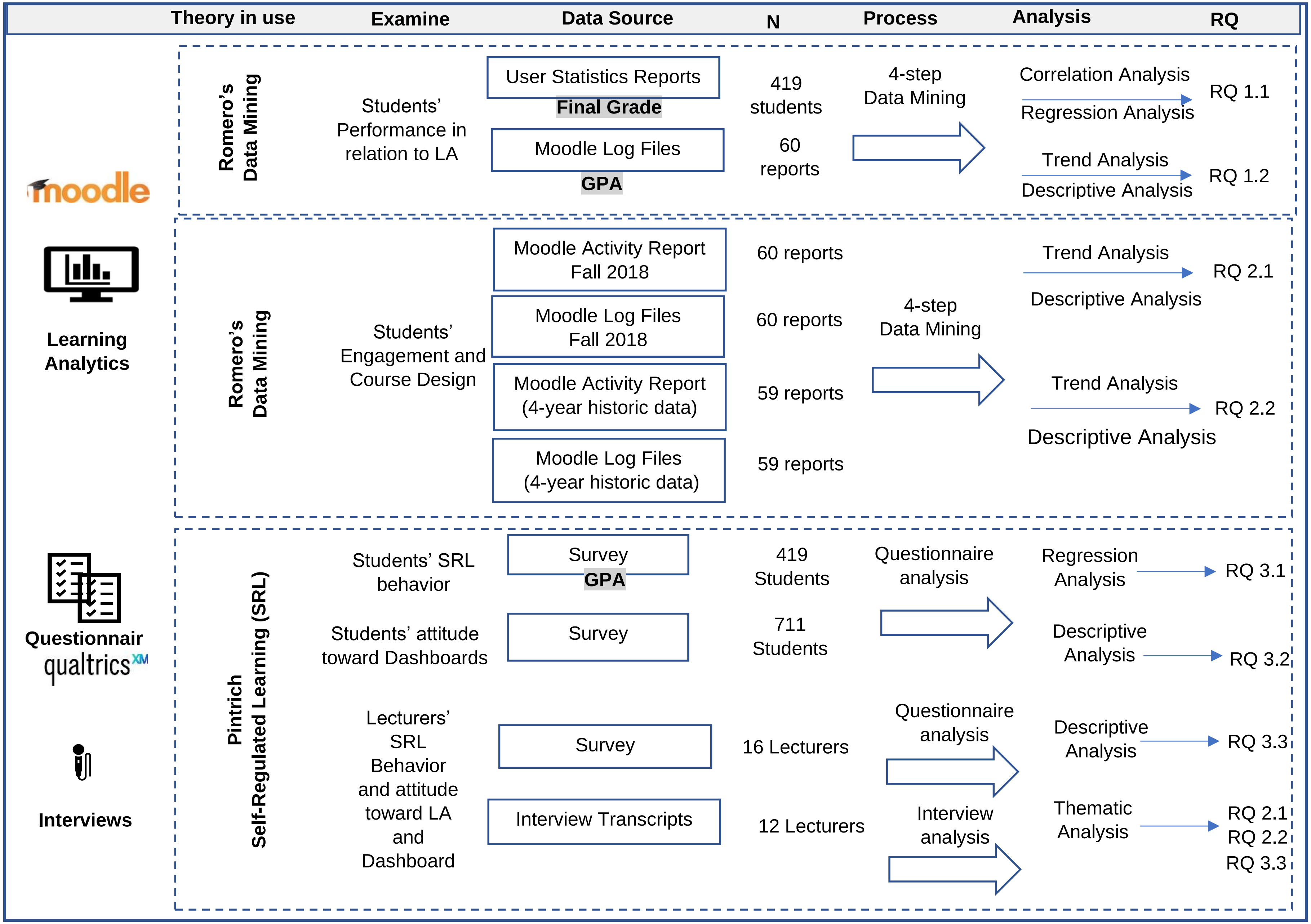


Figure 3-1: Research Design Framework, May 2019

Chapter 4: Method

The primary data collects quantitative data through extracting descriptive statistics from Moodle learning analytics (LA), and questionnaire responses. Also, it collects qualitative data through semi-structured interviews. The secondary data collects quantitative data through extracting the descriptive statistics from Moodle LA of the historic 4-year data. The data collection is done in parallel as the UBT case study is employing a parallel convergent mixed method. Each data is collected separately for the purpose to strengthen the validity of the data obtained. For example, information about what tools the lecturers use to design the course; This information can be obtained quantitatively from mining the course's analytical reports in Moodle, or from the lecturers' questionnaires, or obtained qualitatively from the interviews. The methods to collect the data discussed in this chapter consists of:

- 4.1 Data mining of:
  - Moodle students' statistics
  - Moodle activity reports
  - Moodle log files
- 4.2 Questionnaires for
  - Students
  - Lecturers
- 4.3 Semi-structured Interviews to
  - Lecturers

4.1 Data Mining

Both primary and secondary data undergo data mining analysis. Moodle tracks students' movements and actions in a course. Moodle data mining start by applying Romero's (2008) data mining process by first **collecting** the raw Moodle analytical data. This includes collecting data from the 4 different resources: The student statistic data, the course activity Report, the course Log file, the students' GPA, and final grade in the course. Then the **process** of cleaning up the data and transfer it to the needed format is applied. Each source data has been processed and formatted to prepare its data for analysis differently. Data is then mined and analysed. Follows is interpreting the data and **evaluating** it using different measurement is applied. Results are then deployed and discussed. The **data mining** process is discussed for each data source below. Data mining and analysis started at the end of Fall 2018 and took around 7 to 8 months to complete (Spring 2019 and summer 2019). It was finalized at start of Fall 2019.

There are a set of challenges associated with collecting and implementing analytical techniques to analyse learning analytics in higher education. Klašnja-Milićević, et al (2017) lists some of these challenges as the challenge of converting complex, often unstructured data into actionable information, which is usually very time consuming. This was apparent from day one of collecting the learning analytics from the Moodle system at UBT and figuring out the best way to handle each LA report and the time it took to process the data mining and reach the last step of providing the meaningful data. The time took for the data mining process, including the data capturing, refining, interpreting, and deploying and predicting results for the UBT case was around 7 to 8 months. The data was automatically recorded during a 4-month period prior for the data collection period. So, it took around 1 year to collect and mine the data.

Other challenges indicated by Klašnja-Milićević, et al. (2017) is the complex associations available in educational data as a very large number of variables and parameters to be considered. These may reside in different systems. So, Importing and integrating of institutional data systems and combining data sets from across a variety of unconnected systems can be challenging. Data may not conform to one standard and combining such data requires intensive transformation and organization. In the UBT case, there are multiple sources of data such as *OPERA* system, the institutional registration system and Moodle system. Exporting tables to Excel format and merging data and use of SPSS to transform and integrate data, all complex steps that require proper planning and execution. This is explained in each of the data mining process discussed next with each data source used.

4.1.1 Data Mining: Moodle Students Statistics

Data mining for the Moodle students' statistics was conducted on the Fall 2018- 419 students who consented to the study. This yielded manual insertion to 419 records of data combining students' statistics data and students' grades and GPA data. The statistics data mainly focused on one learning analytic metric: ***Total-Activity*** metric, a count for all the hits (both views and posts) of all Moodle resources in the specified course. The researcher has collected each student information in each course and appended the information into one Excel file. The Excel file is further organized, appended, and formatted. The below mining steps clarify the process needed to acquire students' statistics data.

4.1.1.1 Collect

The researcher, having admin Moodle access to the Moodle system, collected the students' user statistics data. For each of the 419 valid students who consented to the study, the researcher accessed the student user statistics in Moodle administrative site. To access each student statistics data, the researcher searches for the student by ID, once the student is found, the profile is clicked. Statistics is one of the actions links available in the profile. In the statistics window (Figure 4-1), a table of some views and posts and a total of all activities in specified time frame is displayed. The researcher manually records the calculated total number of all activities in an ID-sorted student paper sheet. This data collection process was conducted immediately after the end of the Fall-2018 term and lasted till the end of the Spring 2019 academic term. This was a steady data collection process done gradually, multiple days every week.

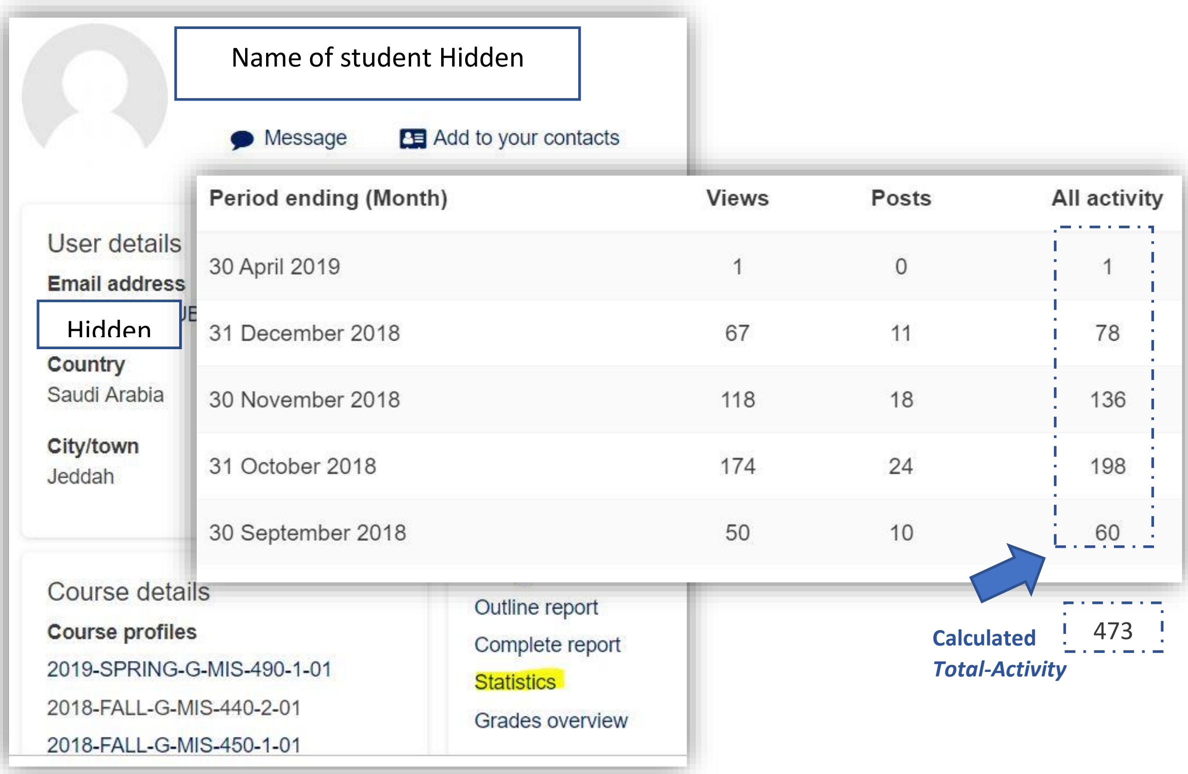


Figure 4-1: Moodle Sample Student statistics, May 2019

4.1.1.2 Pre-Process

4.1.1.2.1 Data Organization

Once all 419 students' records are recorded into the ID-sorted sheet. Data is inserted into an Excel sheet. This process also took some time to append the courses, *Total-Activity* (TA), GPA and grades to the students list. This was done in alphabetical order. So, for each student ID, the courses were listed and accordingly, the TA was appended for each course along with the final course grade. The Administrator of the *OPERA* registration system sent the students GPA along with all the Fall courses final course grades. A separate process cleansed the grades data in a separate Excel file. A removal of any non-participant course and keeping only the participant course for each student listed in alphabetical order was conducted. Once this was ready, inserting the final grades manually was conducted to each students' registered course. A final step was merging of the GPA data, check Figure **4-2**.

Campus	IDs	GPA	Course 1 TA	Course2 TA	Course3 TA	Course4 TA	Course5 TA	Course1 Grade	Course2 Grade	Course3 Grade	Course4 Grade	Course5 Grade
Jeddah	Hidden	2.42	174					60				
Jeddah		2.25	209					0				
Jeddah		4.58	272	206				92	81			
Jeddah		2.5	236	301				63	72			
Jeddah		3.63	252					85				
Jeddah		4	195					88				
Jeddah		2.8	153	179				0	62			
Jeddah		3.25	269	208				77	81			
Jeddah		4.88	255					97				
Jeddah		4.15	880					90				
Jeddah		4.63	178					85				
Jeddah		3.63	468	433				73	82			
Jeddah		4.94	166					97				
Jeddah		2.42	172					60				
Jeddah		3.58	393	473	239			75	72	71		

Figure 4-2: Mined Excel -Students (TA) -GPA and Grades, May 2019

4.1.1.2.2 Data Cleanup

The data table contained only students' IDs and course ID and campus name. The term name (Fall 2018) was removed, students and Lecturer names were also removed. Course names is not addressed in the research paper, so, it was listed alphabetically, but with the names course1, course2, accordingly. The merged data of the Final course grades that was merged with the students' total number of activities were visited and cleaned up. 'F' grades (Fail), or 'DN' (Absent fail) were all converted into Zero for the purpose of grade analysis as they affect the GPA and performance in the course. Grades as 'W' withdrawn and 'IP' in-complete were removed as they do not affect the GPA.

4.1.1.2.3 Data Validity

Data was validated in several steps: Students list validity, then course list validity, then merging GPA and Final course data validity was conducted. For students list validity, the process of ensuring only the 419 students, who consented to the study are the one recorded in the list. The Original 925 students’ IDs are extracted from *OPERA* course registration system. These Excel tables contained all students who registered in the participant Fall 2018 courses. Survey exported the 711 students’ IDs list. Only valid IDs were collected in a separate list. Comparison has been conducted between the 419 students and the full students list. Course names were mapped to the students’ ID using Pivot tables. Summarized IDs and removal of duplicate data were helpful to ensure of the students’ ID list. Appending course and information to the students list required careful manual mapping. Each student record had the associated courses listed in alphabetical order. This helped when appending manually the course final grade. Merging GPA data was done through using SPSS merge data that was ensured alphabetical order of Students IDs and matching of IDs to add the GPA. Final course grades were added manually with care and through a wide timeframe during the 3-month period of data collection. A revision process was conducted at time of the daily data insertion.

4.1.1.3 Apply Data Mining

The produced ready to be process Excel file was opened in SPSS format and accordingly, a simple data mining process using SPSS statistics such as correlation analysis between variables and regression analysis were conducted to specify the correlation between the final course grade of the students and their *Total-Activity* movements in the course.

4.1.1.4 Interpret, Evaluate and Deploy

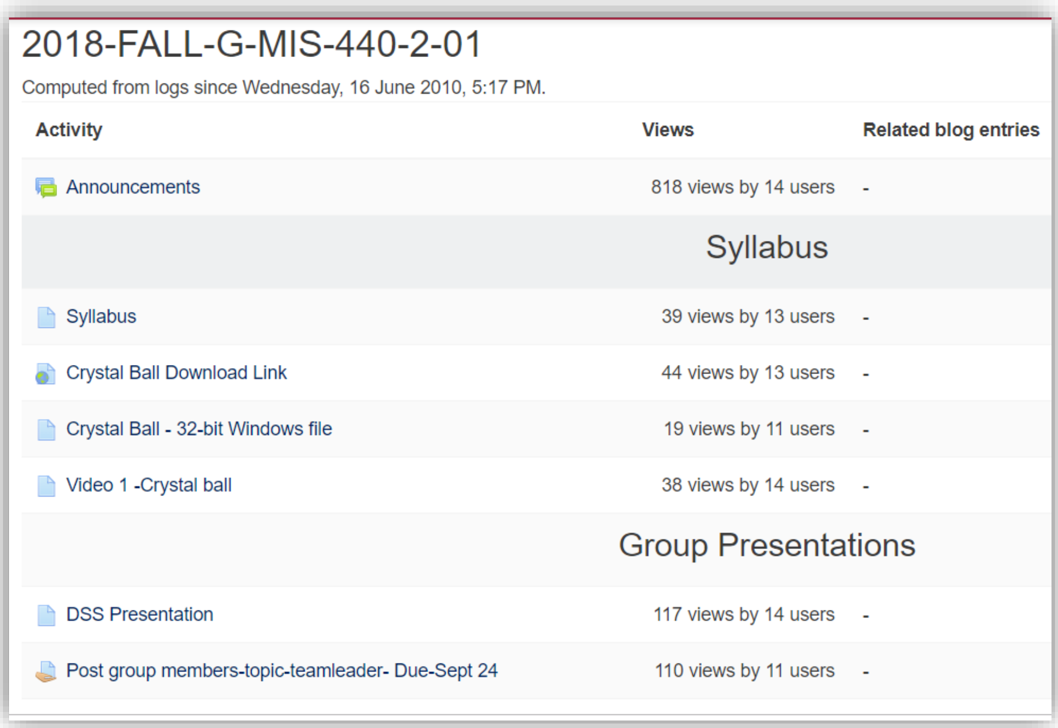
This is the knowledge discovery resulting for data mining, where the results are interpreted and used for further actions. Information discovery is done here. For this research's purpose, the resultant formatted mined data of students' statistics are used to discover its relationship to the students' performance. This is discussed in the analysis section 5.1.1. Lecturers can now have a further look into students' performance and can even use the discovered knowledge to predict future students' performance in relation to their Learning analytics *Total-Activity* metric.

4.1.2 Data Mining: Moodle Activity Report

Data mining for the activity report is done for both the primary data (Fall 2018) and the secondary data (4-year data). The Fall 2018 yielded 60 activity reports, and the 4-year data yielded 59 activity reports. The researcher has collected each course activity report and saved it in Excel format. The objective is to come up with the learning activities used in the UBT courses. This communicates the course design decisions that UBT lecturer follows when designing their learning materials. Mining the activity report is not an easy task as it is complex. As stated by (Rienties, et al., 2015), classifying learner activity can be subjective and consistency is important when mining these data from the different 60 activity report files. For this, examining all the 60 reports and organizing them to be in a uniformed format was challenging. This took a long time to accomplish to ensure accurate and consistent end results. For example, the term PowerPoint was represented differently throughout the 60 reports. Some lecturers used names such as: Lectures, Slides, Power Point, PowerPoints and so on. In order to count all the occurrences of PowerPoint files, the mining process had to organize a unified term: PowerPoint, and counts the total hits for this term, eliminating any other different occurring term.

4.1.2.1 Collect

The researcher with the Moodle admin access visited each participant course and accessed its activity report through Course administration → Report → Activity Report. The researcher manually saved content of each activity report in a single Excel file. For the 60 Fall 2018 courses, 60 files were collected and stored. For the historic data,15 courses were examined, yielding 59 files of a 4-year data to be collected and stored. Check Figure **4-3** for a sample of Moodle activity report.



2018-FALL-G-MIS-440-2-01

Computed from logs since Wednesday, 16 June 2010, 5:17 PM.

Activity	Views	Related blog entries
Announcements	818 views by 14 users	-
	Syllabus	
Syllabus	39 views by 13 users	-
Crystal Ball Download Link	44 views by 13 users	-
Crystal Ball - 32-bit Windows file	19 views by 11 users	-
Video 1 -Crystal ball	38 views by 14 users	-
	Group Presentations	
DSS Presentation	117 views by 14 users	-
Post group members-topic-teamleader- Due-Sept 24	110 views by 11 users	-

Figure 4-3: Sample Moodle Activity Report, May 2019

4.1.2.2 Pre-Process

4.1.2.2.1 Data Organization

A visit is conducted by the researcher to the course and copying the Activity report into a separate Excel file, Figure 4-4.

	A	B	C	D	E	F	G	H	I
1	2018-FALL-B-FIN-410-2-02								
2									
3	Computed from logs since Sunday, 13 June 2010, 11:03 AM.								
4	Activity	Views	Related bl	Last access					
5	Announcements	67 views by 25 users	-	Wednesday, 26 December 2018, 8:30 PM (25 days 15 hours)					
6	Syllabus	195 views by 36 users	-	Thursday, 27 December 2018, 3:50 PM (24 days 20 hours)					
7	PowerPoint Chapter	95 views by 30 users	-	Wednesday, 26 December 2018, 4:43 PM (25 days 19 hours)					
8	Professional certificate Exam Mat	41 views by 24 users	-	Wednesday, 26 December 2018, 4:07 PM (25 days 20 hours)					
9	PowerPoint Chapter	63 views by 26 users	-	Wednesday, 26 December 2018, 4:43 PM (25 days 19 hours)					
10	Professional certificate Exam Mat	62 views by 26 users	-	Monday, 14 January 2019, 11:09 AM (7 days 1 hour)					
11	PowerPoint Chapter	104 views by 30 users	-	Wednesday, 26 December 2018, 4:43 PM (25 days 19 hours)					
12	File Download	-	-						
13	File Download	56 views by 21 users	-	Monday, 14 January 2019, 11:09 AM (7 days 1 hour)					
14	PowerPoint Chapter	120 views by 29 users	-	Wednesday, 26 December 2018, 4:44 PM (25 days 19 hours)					
15	File Download	1 views by 1 users	-	Wednesday, 26 September 2018, 1:22 PM (116 days 22 hours)					

Figure 4-4: Excel Raw Data-Moodle Course Activities, May 2019

A process of data organization was conducted for each of the 119 files (60 Fall + 59 Historic) to have a unified format of the activities' terms and to calculate the number of views they acquired during the timeframe studied. Since all courses have various names for the activities, a process of unifying and summarizing the activities to maintain organized entries was conducted. For example, all Word files related to the syllabus were renamed Syllabus. All different chapter presentations were renamed to PowerPoint. The resultant activities were 28 terms: Access File, Moodle Assignment, Moodle Choice, class activity, Discussion Forum, Excel File, Executable file, External Tool, External Link, Moodle Feedback tool, Final exam, Final Project, Folder, image, midterm, Announcement (Moodle Label), PDF file, Moodle peer evaluation, PowerPoint, Questionnaire, Quiz, Syllabus, Unique file (any other format), URL, video, Wiki, word file and finally a zip folder.

Once the files are unified and edited to use the same activity terms, a process of organizing the data and combining all Excel files into one Excel file was conducted. 60 files (Fall Data) were compiled into one Excel file. The same for the 59 files (Historic Data) were compiled also into another Excel file, check Figure 4-5

	A	B	C	D	E
1	Campus	Course ID	Teacher	Activity	Total Views
2	Jeddah	2018-FALL-G-HRM-301-1-01		Announcements	366
3	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	43
4	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	31
5	Jeddah	2018-FALL-G-HRM-301-1-01		Syllabus	113
6	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	196
7	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	121
8	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	154
9	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	186
10	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	40
11	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	52
12	Jeddah	2018-FALL-G-HRM-301-1-01	Hidden	PDF	37
13	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	165
14	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	154
15	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	141
16	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	102
17	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	108
18	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	103
19	Jeddah	2018-FALL-G-HRM-301-1-01		PowerPoint	87
20	Jeddah	2018-FALL-G-HRM-301-1-01		Quiz	535
21	Jeddah	2018-FALL-G-HRM-301-1-01		PDF	25
22	Jeddah	2018-FALL-G-HRM-301-1-02		Announcements	309
23	Jeddah	2018-FALL-G-HRM-301-1-02		Discussion Forum	65
24	Jeddah	2018-FALL-G-HRM-301-1-02		PDF	76
25	Jeddah	2018-FALL-G-HRM-301-1-02		PDF	22

Figure 4-5: Mined Excel - Course Activities, May 2019

4.1.2.2.2 Data Cleanup

Clean-up process to clean the data in the Excel files was conducted to remove any extra column of data and ensured unique activity names were kept and edited if inconsistent terms showed up. For example, PowerPoint differ from Power Point, so clean-up must ensure consistency. Pivot Table summary, filter and find tools, all helped to ensure this. Once data clean-up was conducted, the resultant formatted 60 and 59 Excel files followed the data mining process of transfer and were compiled into two Excel files. Additional fields were added to identify campus and course ID in the fall data and identifying campus, courses ID, year, and term for the historic data.

4.1.2.2.3 Data Validity

To ensure validity of data, processing of data entry was conducted with care and with no rush and a period of 3 month was available to collect and prepare and mine the data. A revision process was conducted to review the total views of the activities. Once the 60 and 59 files were combined into 2 Excel files, pivot tables were used to ensure validity of the unified activities' terms. The pivot table helped to summarize the 1000 records and detected mistakes and misspelled terms from the summarized table. This helped to fix any misspelled term for all the other activity terms.

4.1.2.3 Apply Data Mining

The produced ready to be processed Excel files for both the Fall 2018 and the 4-year historic data were analysed using trend analysis by applying additional Pivot table analysis to categorize the activities and to summarize its total usage hits. Clustering and visualization of the Pivot table analysis were conducted to mine the activity reports data.

4.1.2.4 Interpret, Evaluate, and Deploy results

The resultant 1612 and 1712 records of Excel summarized pivot tables were conducted in the analysis section 5.1.2. Trend Analysis was used to evaluate the deploy the results that helped to determine the UBT Moodle activities and resources pattern and the resources and activities with highest students' engagement.

4.1.3 Data Mining: Moodle Log File

The log file analysis is conducted for each of the 60 Fall courses (with around 614, 824 records of data) and for the 4-year historic analysis of 15 courses (with around 297,608 records of data). Moodle Log files are available for instant download at any time. Data mining for the log file requires further processing for the data and combining any additional data to extract further information. The data mining process started by collecting the statistics descriptive log data from each course as explained next.

4.1.3.1 Collect

The researcher accessed each of the participant course and ran each standard log and exported the content into an Excel file though: Course administration → Reports → Logs. Total 119 files (60 Fall + 59 Historic).

4.1.3.2 Pre-Process

4.1.3.2.1 Data Organization

All Fall 2018 course logs were combined into one Excel file. The same for the 4-year log files, were also combined into another Excel file. Female and male campus courses were combined in the file and accordingly additional fields had to be added to identify the campus information. The fall log file contained 614,824 records of data. The Historic log files contained 297,608 records. Additional process was done to map students' IDs and add their GPA and appended it to the Excel files.

4.1.3.2.2 Data Cleanup

The data clean-up was needed when merging the GPA data with the log file data. Only students who have consented to give access to their GPA were added to the file. This process required editing to the Students' names in the log file. Because the log file did not record the student ID and only recorded the student first and last name, it was difficult to conduct the GPA mapping. The original list of students exported from the *OPERA* system contained the Full Name of student with long multiple names, as in *Halah Osman Mohammed Nasseif*. The log file, on the other hand, contained just *Halah Nasseif*. So, to use the SPSS merge data tool, the name had to be identical and sorted alphabetically. The original student list was cleaned up to have only first name and last name, then the process to merge the students ID and GPA data was conducted.

4.1.3.2.3 Data Validity

Since the log file is already set and ready with its set fields and columns, additional effort was needed to append all the log files into one Excel file and appending new columns to the list such as course ID, teacher name and more, causing a lot of empty cells. Since it is an exceptionally large file with thousands of records and to avoid empty cells throughout the document, a tool was needed to fill the course IDs and such repeated throughout the spreadsheet. So, an Excel short cut key was used to copy and paste Course IDs and other course information to the log file to fill the empty cells. Other validation included merging the GPA data using SPSS and reviewing the students' names along with the GPA.

4.1.3.3 Apply Data Mining

The produced ready to be process Excel files for both the Fall 2018 and the 4-year historic data were analysed using trend analysis by applying additional

Pivot table analysis to categorize the event logs and summarize its total usage hits. Clustering and visualization of the Pivot table analysis were conducted to mine the activity reports data.

4.1.3.4 Interpret, Evaluate, and Deploy results

Evaluating the lengthy log file (614,824 records of data for the Fall 2018 and 297,608 records for the historic 4-year data) and exploring its various field names took some time. The analysis will focus on the event type and its relation to GPA in the analysis section 5.1.3.

4.2 Questionnaires

Questionnaires (5-scale Likert) were distributed to the primary data's participants (20 lecturers and 925 students) at the end of the academic term of Fall 2018. Around 300 surveys were filled online as students accessed the survey link through their Moodle course page. (The researcher displayed the link toward the end of the Fall academic term, 4 weeks before the final exams). The other 400 students filled the survey manually through hardcopies provided after their final exam. The researcher inputted the survey entries manually. Some of these papers were eliminated on the spot, as they were filled recklessly with lots of empty answers. Out of the 925 students, around 711 students consented to the study and filled the surveys completely. The valid participant list was 419 students. The invalid list of students' records included some misspelled IDs and missing IDs. There were also some records that were eliminated from the analysis as some had withdrawn from the courses ('W' grade) or had in-complete grades ('IP') as they did not have final course grades. As for the lecturers' survey, out of the 20 lecturers, only 16 filled the survey. 1 lecturer had left the university by the time of the final exams; the other 3 lecturers were occupied and could not fill the survey.

Descriptive analysis of questionnaires statistics was applied to interpret the self-regulated learning behavior for both students and lecturers. Descriptive analysis was also applied to test attitudes and reactions of students toward the Moodle completion progress dashboard. It was also applied again to interpret the attitudes and reactions of lecturers toward Moodle analytical graphs and Moodle completion progress dashboard. Regression analysis was applied to test the relationship of students self-regulated learning variables to their GPA. Check Questionnaire questions for both students and lecturers in Appendix One.

4.3 Semi-Structured Interviews

The interviews were conducted with 12 lecturers out of 20. Braun and Clark (2006) interview protocol of a qualitative method with a thematic analysis was used. The interviews started at end of Fall 2018 and continued through the Spring 2019 term. There were also follow-up questions through additional face-to-face discussions and phone contacts and emails. This was done during the analysis period of the analytics to relate the lecturers' input to explain some of their courses' analytics behavior for both the Fall term and the 4-year historic data. For the interview questions see Appendix Two. The analysis approach taken with the interviews followed the six-phase approach to thematic analysis by Braun and Clark (2006):

1. Getting familiar with the data
2. Generating initial codes
3. Searching for themes
4. Reviewing potential themes
5. Defining and naming themes
6. Producing the report.

ATLAS-ti software was used to analyse the 12 interview scripts. Another tool that was used was Word cruncher to ease the process of finding a theme by analysing the common repeated words. Interview analysis is discussed in the analysis section 5.4.

Chapter 5: Data Analysis

The data analysis section provides the results analysis of the data collected from:

- The Data Mining of the 3 Moodle analytical reports
- The Questionnaires of the students and the lecturers
- The Lecturers' Interviews

Since the UBT case study utilizes a convergent parallel mixed method approach collecting both the quantitative data (data mining, questionnaires) and qualitative data (interview), the analysis approach will incorporate any needed data found in any of the methods to support the analysis. For this, some interview testimonies and statistics data are merged into the analysis discussions to provide more strength and clarifications to the analysis findings.

5.1 Data Mining Analysis

Data mining techniques are commonly applied to identify patterns in the traced data. The interpretation of these patterns can be used to improve understanding of learning and teaching processes to predict the achievement of learning to support intervention and aid various decisions. This process has been described as Learning analytics (Gašević, et al., 2016). Mining the collected data aim to highlight the discovered knowledge behind the data mining analysis conducted.

This section visits the data mining process and results conducted in section 4. In this research, the level of significance applied alpha = 0.01 and hence the significant results considered are p <= 0.01. Data mining analysis continues in this section to reveal further information or knowledge discovery that resulted from the different data mining done to the different analytical reports. User statistics analysis and activity report analysis and Log report analysis are discussed highlighting each analysis outcome and what further insight it conveys.

5.1.1 User Statistics Data Mining Results

The Moodle user statistics report contained all students' total number of activities in all their participant courses. Data mining was conducted to prepare the resultant data for evaluation and interpretation. Part of the data mining process, students' course final grades were mapped to the learning analytic metric data (*Total-Activity*). Table **5-1** below displays the Number of students examined. All 419 students took at least one course, where the minimum number for activities obtained was 13 and the highest total number of activities was 880, with a mean of 252.56 and standard deviation of 167.76. About 166 students of the 419 were registered in 2 participant courses with a minimum of 45 total activities and a maximum of 1522, a mean of 293. 73 and a standard deviation of 178.47. 60 students out of the 419 were registered in 3 participant courses, with a minimum of 65 of total activities and a maximum of 839 total activities, with a mean of 304.28 and a standard deviation of 178. 476. 13 students out of the 419 were registered in 4 participant courses with a minimum of total activities of 112 and a max of 639, a mean of 331 and a standard deviation of 146.36. Only 3 students out of the 419 were registered in 5 participant courses, with a minimum of 156 total activities and a max of 639, a mean of 266.67 and a standard deviation of 95.887.

Total activities Descriptive statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Course1 TA	419	13	880	252.56	167.769
Course2 TA	166	45	1522	293.73	193.410
Course3 TA	60	65	839	304.28	178.476
Course4 TA	13	112	639	331.00	146.367
Course5 TA	3	156	325	266.67	95.887

Table 5-1: Activities Descriptive Statistics

Table **5-2** displays the statistics data for the course final grades earned by the students. All Students who are registered in at least one course earned a final course mean of 81.50 with the lowest grade earned was zero and highest was 100. Students who are registered in at least 2 courses earned a final course grade mean of 84.24 with a minimum grade of zero and a highest of 100. Students who are registered in 3 courses earned a final course grade mean of 87.25 with a minimum grade of 60 and a highest of 100. Students who are registered in 4 courses earned a final course grade mean of 92.08 with a minimum grade of 80 and a highest of 100. The 3 students registered in 5 courses earned a mean of 88.67 and lowest grade of 80 and highest of 95.

Grades Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Course1 Grade	419	0	100	81.50	17.761
Course2 Grade	160	0	100	84.24	13.641
Course3 Grade	60	60	100	87.25	11.859
Course4 Grade	13	80	100	92.08	7.588
Course5 Grade	3	80	95	88.67	7.767

Table 5-2: Grades Descriptive Statistics

To analyse the relationship between the total number of activities and the final course grade earned, a number of SPSS analysis was conducted.

Correlations analysis was conducted to test the relation and Regression was conducted to predict future grades based on the total activities' analytics.

5.1.1.1 Correlation Between Total-Activity and Final Course Grade

Hypothesis H_1 is examined to test the relation between the students' *Total-Activity* and their course final grade:

> **H_1:** There is a significant relationship between students' course final grade and their *Total-Activity* metric in the course.

The data mining resultant file of the students' statistics was analysed using SPSS correlation. The objective was to examine if there is a relationship exist between a student's learning analytics metric (Total-activities) and the students' final course grade. Because a student may be enrolled in more than one course (up to 5 courses), the average of the total activities of for a student was calculated. The same was done for the grades students got in their multiple courses. The correlation was conducted between the average activities and average grades of a student.

The 419 students' analytics were analysed. A Pearson's r data analysis revealed a significant positive correlation, ($r(417) = 0.265$, $p<0.01$ (2-tailed)). It is a significant positive correlation. Though, it is a weak correlation, assuming that weak is where $r < 0.3$, moderate is between 0.3 and 0.7, and strong >0.7. Students who were more active in Moodle displayed slightly higher Final course grades. This association does not prove causation. An association of 26% is a weak association but, this maybe contributed to the UBT's setting as it is a traditional face-to-face environment that utilize Moodle for the online activities. Further variables can be examined to discover more about this relation.

For this, hypothesis H_1 is accepted as there is a significant relationship as $p<= 0.01$. In the several literatures discussed in the Literature review chapter, all had stated similar correlation values when examining different LMS variables against the students' performance.

5.1.1.2 Final Grade Prediction Model

A further SPSS analysis was conducted to determine the model that can be built to predict future students' performance based on their *Total-Activity* Metric. To learn more about this association, SPSS Curve estimate regression was conducted to examine further this relationship. In Gašević, et al. (2016)'s paper, the authors discussed that regardless of the data source examined, the prediction of student grades is generally determined by applying logistic regression.

A simple curve regression was calculated to predict students' final course grade based on the students' *Total-Activity* movements in Moodle. Table **5-3** displays SPSS Curve estimate regression resulted models. Models of (Linear and quadratic) resulted with high Significance of .000. But the Quadratic got the highest R^2 value of 0.83. Figure **5-1** displays both the linear and quadratic models' observations. So, the quadratic model can be used here to predict the performance of students based on their *Total-Activity* Metric. Investigating learning analytics association with learner's interaction helps to create a prediction model for the performance as displayed next.

Model Summary and Parameter Estimates									
Dependent Variable: Avg Grades									
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.070	31.524	1	417	.000	76.217	.025		
Quadratic	.083	18.724	2	416	.000	72.513	.054	-4.025E-5	
The independent variable is Avg Activities.									
a. The dependent variable (Avg Grades)									

Table 5-3: Regression Model Summary- Analytics

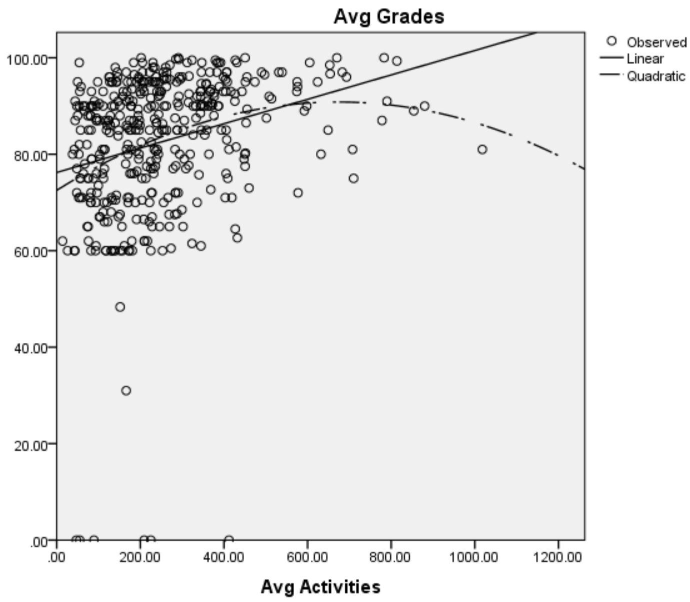


Figure 5-1: Quadratic and Linear Model, May 2019

Table **5-4** displays a significant regression equation found ((F (2,416) = 18.724, $p < .01$) with an $R^2 = 0.083$). Student's predicted final course grade equals to 72.513 + 0.054 * (*Total-Activity*) in marks. Final Course Grade mark increased 0.54 for each input of *Total-Activity* and decreased 0.000004025 for each Total activity square.

Model Summary and Parameter Estimates								
Dependent Variable: Avg Grades								
	Model Summary					Parameter Estimates		
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2
Quadratic	.083	18.724	2	416	.000	72.513	.054	-4.025E-5
The independent variable is Avg Activities.								

Table 5-4: Regression Model- Predict Final Grade -Analytics

Predication of students' grade, where the dependent variable is the final grade, has been a reported task in the learning analytics and educational data mining literature (Gašević, et al., 2016). So, this research study attempted also to examine the same, through applying the constructed Model for Quadratic:

$y = a + b_1x + b_2 x^2$

Predicted Final Grade = 72.513 + 0.054 * (*Total-Activity*) -0.00004025 * (*Total-Activity*)^2

So, for a UBT student with a total activity metric of 70, we can estimate the Final course grade as follows:

Predicted Final Grade = 72.513 + 0.054 * 70 -0.00004025 * (70)^2

Example for a low-level activity student TA = 70

= 72.513 + 0.054 * 70 -0.00004025 * (70)^2
= 72.513 + 0.054 * 70 -0.00004025 * 4900
= 72.513 + 0.054 * 70 -0.00004025 * 4900
= 72.513 + 3.78 -0.197
= 72.513+ 3.5
= 76

Another Example for a high-level activity student of TA = 1018

= 72.513 + 0.054 * 1018 -0.00004025 * (1018)^2
= 72.513 + 0.054 * 1018 -0.00004025 * 1036324
= 72.513 + 54.9 -41.7
= 72.513 + 13.2
= 85.7

Mwalumbwe and Mtebe (2017) suggested further studies to incorporate interviews or focus groups to get more insight on why some LMS elements have more effect on the students' performance than other tools. For this, in this research study, interview questions follow-up was scheduled to talk to the lecturers and gain more feedback on any reasoning or justification for actions.

5.1.1.3 Correlation Between Total Activities and Students GPA

Additional correlation examination conducted with students' GPA. It turns out that GPA also had a significant positive association with the *Total-Activity* Metric. The 419 students' *Total-Activity* metrics were analysed in relation to the students' GPA. A Pearson's r data analysis revealed also significant positive correlation, ($r = 0.293$, $p<0.01$ (2-tailed). Students who are more active in Moodle displayed slightly higher GPA than others. An association of 29% is a weak association but, this maybe contributed again to the UBT's setting as it is a traditional face-to-face environment that utilizes Moodle for the online activities. Further variables can be examined to discover a significant relation to the GPA.

5.1.1.4 GPA Prediction Model

Similar to the Final Exam prediction SPSS analysis conducted, another model is constructed to predict students' GPA based on their *Total-Activity* Metric. A simple curve regression was calculated to predict students' GPA based on the students' *Total-Activity* movements in Moodle. SPSS Curve estimate regression resulted in several models and the quadratic model was used because it resulted with high Significance of .000 and with the highest R^2 value of 0.103, Check Table **5-5**. So, the quadratic model is also used here to predict the students' GPA based on their *Total-Activity* Metric. Figure **5-2** shows both the quadratic and linear model of associating the GPA with the *Total-Activity* metric.

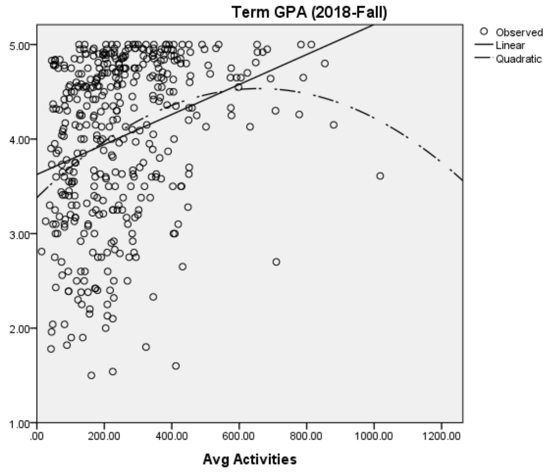


Figure 5-2: Linear and Quadratic Model -GPA and Activities, May 2019

Model Summary and Parameter Estimates								
Dependent Variable: Term GPA (2018-Fall)								
	Model Summary					Parameter Estimates		
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2
Quadratic	.103	23.828	2	416	.000	3.381	.004	-2.663E-6
The independent variable is Avg Activities.								

Table 5-5: Regression Model- Predict GPA -Analytics

A significant regression equation found here ((F (2,416) = 23.828, $p < .001$) with an $R^2 = 0.103$). Students' predicted GPA equals to 3.381 + 0.004 * (*Total-Activity*) – 0.00000663 * (*Total-Activity* metric)^2 in points. GPA points increased 0.004 * for each *Total-Activity* and decreased 0.000002663 for each *Total-Activity* square.

Predicated GPA = 3.381 + 0.004 * (*Total-Activity* metric) -0.000002663 * (*Total-Activity* metric)^2

So, for a UBT student with a total activity metric of 70, we can estimate the term GPA as follows:

Example for a low-level activity student of TA = 70

Predicted GPA = 3.381 + 0.004 * 70 -0.000002663 * $(70)^2$
= 3.381 + 0.28 -0.000002663 * 4900
= 3.381 + 0.28 -0.013
= 3.6

Another Example for a high-level activity student of TA = 1018

Predicted GPA = 3.381 + 0.004 * 1018 -0.000002663 * $(1018)^2$
3.381 + 0.004 * 1018 -0.000002663 * 1036324
=3.381 + 4.0 -2.75
=72.513 + 13.2
= 4.6

5.1.1.5 User Statistics Summary Analysis

The statistical association examined is similar to other research conducted that tested relationship between students' specific behavior elements and their final grades. For example, Leon (2018) attempted to investigate the relation between students' attendance and students' performance by employing relatively advanced statistical modelling. Leon used Linear modelling to estimate the relationship between absences and grades. So, examining the relationship between students' analytical movement in Moodle and their final grades can follow the same statistical analysis. To compare between the 2 studies, Leon (2018)'s study examined 2 numeric elements (absences and final grades). This research study examined total activities and final grades. In Leon (2018)'s study, absences contributed only 32% to class performance. In this research study, the analytical engagement (*Total-Activities*) contributed to around 26% to the Final course grade. Other variables may contribute further to the performance. That is why this relationship does not prove causation as the relationship is weak and other variables are needed to be examined further.

So, in conclusion, the last phase of the data mining process for the students' user statistics report, verified the knowledge discovered in regards to the relationship between a learning analytics metric (*Total-Activity*) and the students' performance. The *Total-Activity* Metric has a positive association with the performance metrics such as Course final grade and GPA and prediction for future performance can be conducted using the following Quadratic models:

$$\text{Final Grade} = 72.513 + 0.054 * (\textit{Total-Activity}) - 0.00004025 * (\textit{Total-Activity})^2$$
$$\text{GPA} = 3.381 + 0.004 * (\textit{Total-Activity}) - 0.000002663 * (\textit{Total-Activity})^2$$

5.1.2 Activity Reports Data Mining Results

The Moodle Activity reports for both Fall 2018 term and for the historic data of the 4 consecutive years: 2015,2016, 2017 and 2018 highlighted each Moodle activity and resource that was used by the students. **Fall** Activity reports resulted in an Excel file with **1611** records of summarized Moodle activities along with the total number of students' hits. The **historic** 4-year data contained **1712** records. Excel Pivot tables were used to help produce a summarized resource usage data. Dierenfeld and Meceron (2012) indicated that Excel Pivot Tables are used to construct useful overview of resources access over time. The resultant used Moodle activities in the **Fall** term were **26** Moodle activities including resources and tools. The resources were: Access files, Excel, final exam, Final Project, Midterm, Note files, PDF, PowerPoint, Project, syllabus, Word files and Zip folders. As for the tools, they were Announcements (Label), Assignments, Class activities, Discussion

Forums, External tool, File Download, Folder, Image, Peer evaluation, Questionnaires, Quiz, Turnitin, Unique files and URL.

The 4-year **historic** data included **28** activities with some different tools such as Moodle Choice, Wikis, Feedback, and the video resource. For the following analysis section, some testimonies from the lecturers' followed-up interviews are used to explain the variations of tools usage among the years. Follows is the 2 activity reports analysis: The fall 2018 activity report analysis and the 4-year activity report analysis.

5.1.2.1 Fall 2018 Activity Report analysis

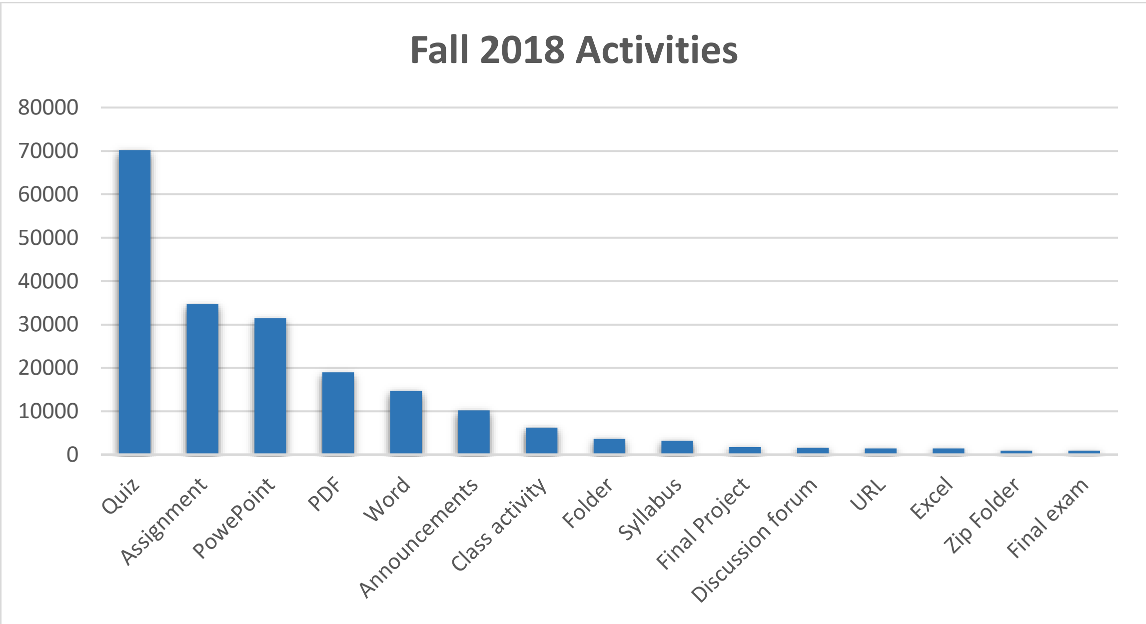


Figure 5-3: Fall 2018 Moodle Activities, May 2019

With the various Moodle tools and resources available for all lecturers to use, fall 2018 participant courses demonstrated a specific pattern usage of the Moodle tools. The data mining process conducted for the 60 course-activity reports displayed the top highest activities used by the UBT lecturer. Figure **5-3** displays the top 15 activities used the most. From mining the activity reports of Fall 2018, the highest top activity used in the fall was the Moodle Quizzes with a 35% usage of all activities. Moodle Assignments followed next with a 17% usage. Popular downloads were for the PowerPoint, PDF, and Word files with 15%, 9% and 7% usage accordingly. Class activities were any files that were used specifically during class hours, these earned 3% of usage of all activities. Both syllabus and Moodle folder got 2% of lecturers' usage. The lecturers had equally 1% usage for Final project, Discussion forums, URL, and Moodle external links. Comparing the results to past literature as (Raadt, 2015), it is quite similar. The study of (Raadt, 2015) surveying 238 higher education institutions in 57 countries (including 39 from UK, and 1 from Saudi Arabia) about Moodle usage and this resulted in user percentage of 90.3% using Quizzes and 89.9%, using assignments, followed by 86.6% using discussion forums and 86% using files.

Course patterns discovered are similar to what lecturers stated in the surveys and interviews. The lecturers usually use Moodle uploads to upload the syllabus, PowerPoint slides, Project requirements. They also make use of the communication medium using Label announcements and Moodle discussion forums. Other lecturers use Turnitin Assignments, Moodle quizzes and some use the Backup and restore tool to re-use the course materials in new academic terms. Some lecturers try to be creative and add video links and external links. To examine this in future research, different data collection and data integration is needed to build the Excel file with each student's total access for each resource is recorded.

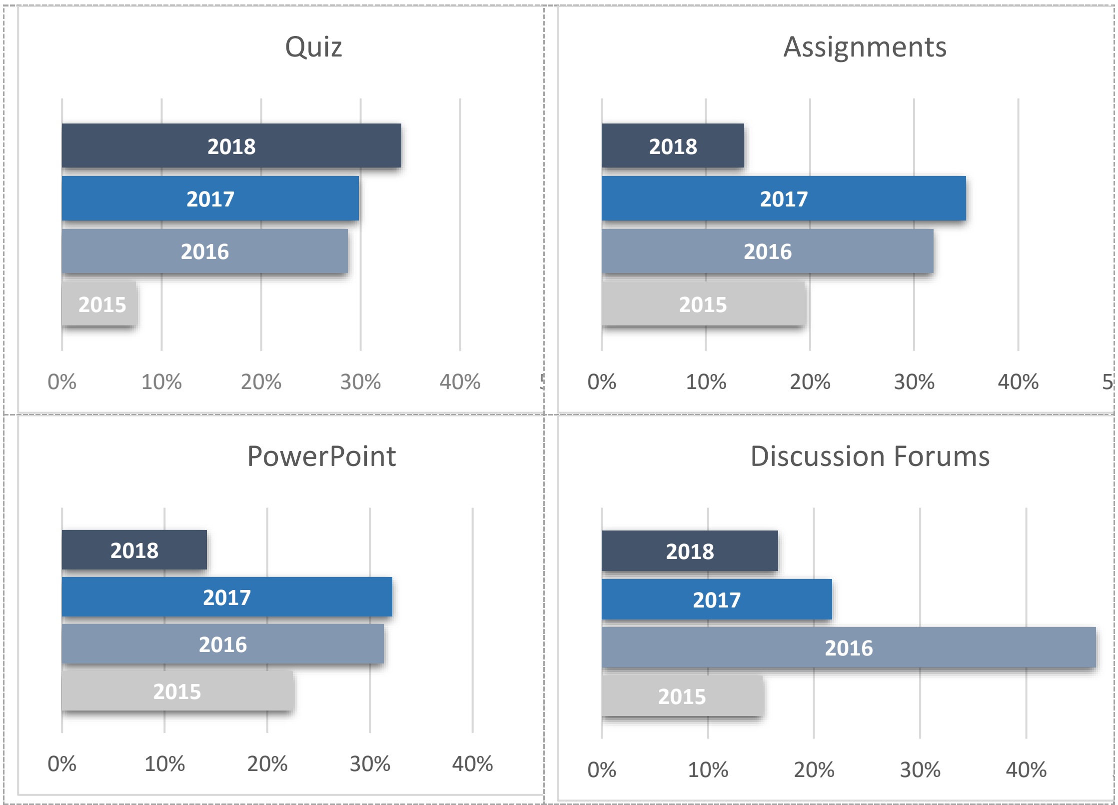
5.1.2.2 Four-Year Historic Activity Report analysis

The same process of mining the fall activity reports was followed to mine the 4-year historic data. Table **5-6** displays the percentage of utilization in each year for the top activities used within the 4-year timeframe. The activities are ranked based on the number of hits. The table displays the list of top active activities during the 4 years and it displays the percentage usage of each activity in each year. For example, we took the Quiz activity and examined its utilization throughout the 4 years. In year 2015, quiz utilization was only 7%. Quiz usage percentage increased in the proceeding years, reaching 34% in 2018. Thus, this section highlights the various changes in the activities during this 4-year period.

To understand the year variation changes, there were some major institutional and software changes that occurred during this 4-yeat period. According to lecturers' testimonies, the major changes included major Moodle software upgrade in year 2016 that fixed issues related to importing test banks to Moodle. Other changes were mainly administrative changes to the academic section where new administration was assigned in 2016 and more institutional changes occurred in 2018. Academic administration has a role in encouraging and guiding lecturers and supporting Moodle utilization. Table **5-6** shows the utilization changes for activities during the 4-year period. Then, Table **5-7** highlighting the usage of activities in graph.

Activity	2015	2016	2017	2018	Total activities
Quiz	7%	29%	30%	34%	100%
Assignment	19%	32%	35%	14%	100%
PowerPoint	22%	31%	32%	14%	100%
Word	16%	30%	34%	20%	100%
PDF	10%	13%	43%	34%	100%
Discussion forum	15%	47%	22%	17%	100%
Excel	2%	21%	23%	54%	100%
Syllabus	23%	35%	27%	15%	100%
Folder	31%	24%	19%	26%	100%
Final Project	28%	20%	35%	18%	100%
Zip Folder	34%	31%	24%	11%	100%
Class Activity	0%	37%	44%	18%	100%
Final exam	6%	9%	5%	81%	100%
News forum	35%	0%	65%	0%	100%
URL	15%	41%	21%	23%	100%

Table 5-6: Activity percentage viewing per year



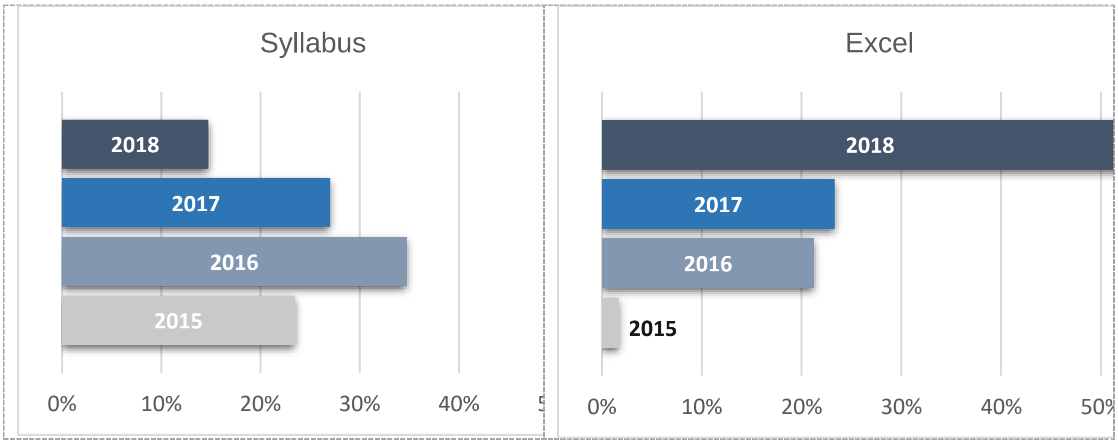


Table 5-7: 4-year Sample Charts of Activities Utilization

Quiz

Table **5-7** shows the various changes of activities among the years. Quizzes have increasingly become popular each year. The highest increase was in 2016 with a jump from 7% to 28%. The highest usage was in year 2018 with a 34% usage among the years. As indicated earlier, the reason behind the changes was the new upgrade changes to the Moodle version in year 2016. What also helped to explain the continuous increase percentage throughout the year was the increased awareness of Quiz benefits and the high utilization among the UBT lecturers. This is due to several peer advice recommending the use of quizzes.

> *Lecturer 9*: “Now, that I talked to my peer Lecturer 2, she mentioned that I can convert the Test bank directly to Moodle quiz, so, I can do this now”.

Assignments

Moodle Assignments had an increasing pattern where it had a steady increase during the years and suddenly a drop of -19% usage in 2018. As indicated in the follow-up lecturers' interview, the reason behind this sudden decline is the increase usage of another e-learning merged tool in Moodle, which is Pearson MyLab. Lecturers depended on assignments from MyLab and used less Moodle assignments. Other reasons included less academic support to Moodle in 2018.

PowerPoint

PowerPoint resources had also steady increase during the years, but suddenly had a drop of -15% in the year of 2018. This is due to a university administrative decree asking the lecturers to stop using PowerPoint and remove them from Moodle part of encouraging the students to use the Books more. All lecturers interviewed indicated that they all removed immediately their PowerPoint slides upon the University decree. Other Microsoft applications had different variations. Word reacted similarly to PowerPoint with a decline of usage in 2018 of -13%. In contrast, Excel had a 25% increase in 2018. The use of Word and Excel different pattern is not justified for a specific reason. From the interviews, Finance lecturers indicates that their Excel usage had increased, which explain its high usage in Fall 2018 (Finance students are the largest students' group at UBT).

Discussion Forums

Year 2016 exhibited sudden increase in usage in some Moodle activities as in the Discussion forums and class activities. There were administrative changes in the academic section at UBT in year 2016, where new administrator was assigned, more e-Learning workshops were conducted. An increase of 37% meant higher usage for the discussion forums, this included the announcements conducted using the news forums as there was encouragement at that time for lecturers to utilize Moodle to communicate class news to the students. The drop in 2018 may contributed to another new change in the administrative academic section at that time.

Syllabus

Syllabus usage was slowly active during the years but had a sudden increase in year 2016. Similar to the discussion forums case of having new administrative changes, syllabus uploads were encouraged to be done and known to all students in Moodle. Lack of support to e-learning administrative wise, could be an indication for the drop in 2018- syllabus upload.

5.1.2.3 Four-Year Historic Activity Reports Data vs Fall 2018 Data

A comparison is conducted to compare the 4-year historic data to the fall activities data. A percentage of usage is used for the comparisons. Figure **5-4** compares the Fall 2018 to the 4-year historic activity data.

Activtiy	Fall 2018 usage	4-year usage
Quiz	35%	23%
Assignment	17%	17%
PowerPoint	15%	16%
PDF	9%	12%
Word	7%	14%
Annoucements	5%	0%
Class activity	3%	1%
Folder	2%	2%
Syllabus	2%	2%
Final Project	1%	2%
Discussion forum	1%	6%
URL	1%	0%
Excel	1%	2%
Zip Folder	0%	1%
Final exam	0%	1%

Figure 5-4: Comparison Activities Utilization - Fall & 4-Years, May 2019

To compare between the two timeframes, Quizzes usage was higher in Fall 2018. This is due to the increase awareness of Quizzes in Moodle among the lecturers according to their interviews. Assignments, folders, and syllabuses utilization is the same. Figure **5-4** shows a drop in using PDF and Word in the recent Fall 2018. This can be due to the adoption of Pearson MyLab with materials ready to be used by the students. Lecturers indicated that MyLab software is filled with lab exercises and assignments that caused less usage in the assessment Moodle resources. A 5% drop in use of Discussion forums in Moodle in Fall of 2018 term. The difference between the 2 timeframes is mainly because courses examined in the Historic 4-year data were Business courses and the Fall data contained additional Engineering courses. This may indicate the reason as business courses tend to use Discussion forums more according to a fellow-up interview questions to one of the Engineering lecturers.

Announcements usage in Fall is higher, as the label tool is mostly used by the lecturer to add announcements as indicated in the lecturers' interviews. Lecturers prefer to communicate to students through Moodle especially that majority of the students do not use the university's email. Part of the peer discussions, lecturers tended to use labels heavily and they even thought about other creative ways to add their announcements with the use of colours, animation, and video.

> *Lecturer 12*: "Students tell me that Lecturer x course design is very appealing, why you do not use similar design tools like her? But I do not have this capability".

Lecturer 12 after peer discussions sought to learn how to add animated objects and marquees in her labels to attract students' attention. Similar reactions are shared among the lecturers trying to improve their label communication to announce latest news to the students.

Mining the activity reports helped to highlight the course design pattern that UBT lecturers follow. In terms of type of Moodle activities and resources, the approach that the UBT lecturers is following is utilizing the assessment tools in Moodle. Moodle Quizzes and Moodle Assignments are the top active activities utilized in Moodle. Less utilization was for the communication tools in Moodle. According to one of the UBT lecturers, lecturers rely on a one-way communication rather than a 2-way communication. Moodle does have the tools to facilitate 2-way communication as the use of Discussion boards, wikis, chats and more. None of the 2-way communication tools are highly utilized. Assessments are heavily utilized in the fall term with Moodle quizzes and Moodle assignments. Compared to Gašević, et al. (2016)'s study, this research study focused on the type of Moodle activity that is utilized the most regardless of the course type. Analysing the fall log data helped to provide an insight on what UBT students mostly engage with in Moodle such as quizzes, assignments and Turnitin.

5.1.3 Log file Data Mining Results

Moodle log reports share similar objectives with the Moodle activity reports. Both convey information about the students' list of used resources and activities. The mined activity report has customized activity terms, depending on the different lecturers' usage. The log report is not customized; it is already set in every Moodle course and can be exported at any time to an Excel file. The resultant Moodle log file analysis for both Fall 2018 term and the historic data of the 4 consecutive years highlighted a lot of different Moodle logged events usage by the course lecturer, the students, and the Moodle administrators. Fall log reports mining resulted in an Excel file with **614,824** records of events information. The historic 4-year data contained **297,608** records. The resultant log file contained entries as event name, Description, IP address, time, user full name, affected user, and course name, campus, full course name, year, and term. An additional merging for GPA data was added to the fall log file appended only to those students consenting for the study. Similar to the previous activity report analysis, some testimonies from the lecturers' interviews were used to explain the variations of logged events usage among the years. Follows is the 2 type Log file analysis: The Fall 2018 log file analysis and the 4-year log data analysis. Both used Excel Pivot tables to segment and analyse the data and interpret the resultant data. Dierenfeld and Meceron (2012) indicated how Excel Pivot tables can convey data from the log file as how lecturers can get information if students are learning regularly during the semester or only just before exams. Also, analysing the log files can indicate the most utilized Moodle events.

5.1.3.1 Fall 2018 Log Data Analysis

The Fall log files of 614,824 records contained various rich information about the different events conducted by the students, lecturers, administrator and more. For the purpose of this research, Fall Log reports were used to analyse students' engagement. Examining which Moodle course elements and resources that got the highest students' hits. What course resource design elements were used the most in all Fall courses and which lecturers utilized more. In addition, a further look into students' type of log event and their GPAs. Moodle top logged events of Fall 2018 are displayed in Figure 5-5 below.

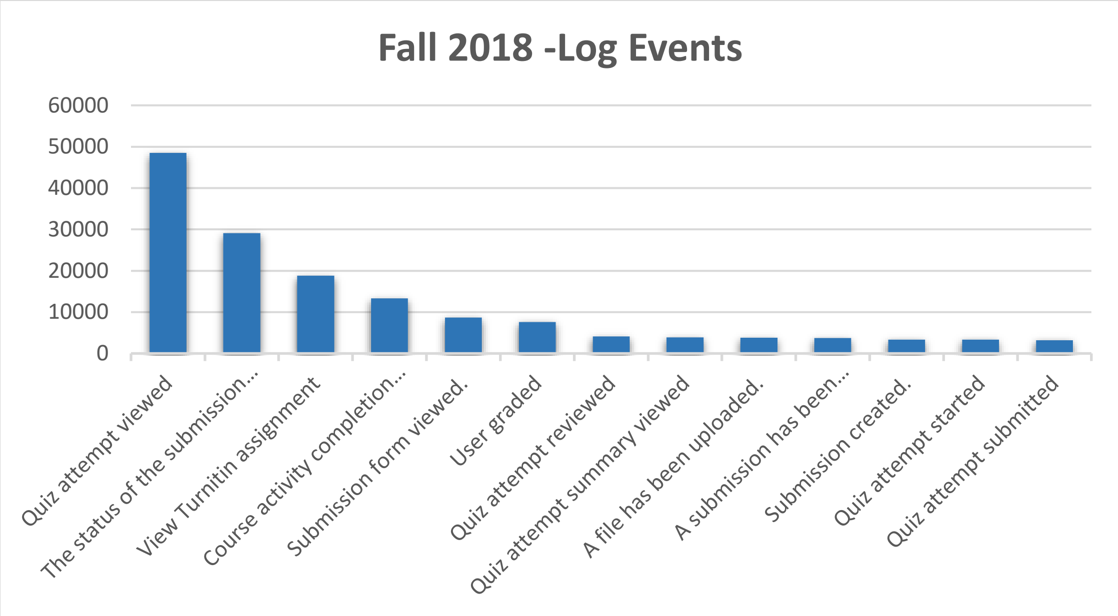


Figure 5-5: Fall 2018 Events Log, May 2019

Aside from viewing the course and the course module, Figure 5-5 shows the highest events conducted in the Fall term associated with the student users. The events were viewing-Quiz-attempt, viewing-the-status-of-a-submission, viewing-Turnitin-Assignment, Quiz-attempt-reviewed, quiz-attempt-started and more. To make further discovery of the resultant log file, further examination to relate GPA to the type of events to build a pattern of events expected from UBT students is discussed next.

5.1.3.2 Log Data and Students' GPA

Part of the discovery of knowledge from mining the log reports is to discover any association between patterns of the events types and students' GPAs. As indicated by Gašević, et al. (2016), Lecturers can use Pivot tables to check exams performance and examine average grades in relation to students' attempts of taking the exams. Similarly, in examining UBT log files, GPA data can help to analyse which type of learning resources are associated with high GPA students. This can provide insight on how to help to advise lower GPA students to improve their performance by providing more attention to which learning resource. So, a further analysis was conducted to check the pattern of high GPA students and what type of activities, they mostly utilize. For the purpose of this analysis, the GPA is categorized in Table **5-8**:

GPA	Total # students	Category
(4- 5)	229	A
(3-3.99)	99	B
(2-2.99)	83	C
(1-1.99)	8	D

Table 5-8: Fall 2018 GPA Student Data

High GPA students refer to 'A' students, and low GPA students refer to 'D' students. A comparison of log event utilization among the different students' GPA is listed in Table **5-9**. From examining the usage of the log file, the characteristics of usage of the different events earned the following: 74% of discussion viewing was done by the 'A' students, where only 1% of discussion viewing was done by the 'D' students. Discussion viewing mostly indicated the use of announcements, so, 'A' students tended to follow up with course news and updates. 72% of user profile viewing was done by the 'A' students, where 0% of user profile viewing was done by the 'D' students. Viewing profiles usually is done to know the lecturer's contact and message him/her, or to check their peers in the class to attempt to contact and communicate. So, 'A' students tended to communicate more than D students. 'D' students had no activities at all in submitting or uploading files, which means they do not submit course work. They had also 0% viewing of user profiles which means they lacked interest to communicate with their peers or lecturers. So, the actions associated with the 'A' students included following up with the course news and updates through the announcements, reviewing quiz attempts, submitting by deadlines, uploading files, and viewing Turnitin assignments. This can indicate that these high usage of these LMS events are associated with students' high performance. A closer look into the events highlighting high- and low-level activities is followed.

Event Name	D %	C %	B%	A%
Discussion viewed	1%	9%	16%	74%
User profile viewed	0%	7%	20%	72%
Quiz attempt reviewed	1%	8%	19%	72%
A submission has been submitted.	0%	6%	23%	70%
A file has been uploaded.	0%	6%	23%	70%
Submission created.	0%	7%	23%	70%
View Turnitin assignment	1%	9%	21%	69%
The status of the submission has been viewed.	1%	6%	24%	69%
Add Submission	1%	9%	22%	68%
Submission form viewed.	0%	8%	25%	67%
Quiz attempt submitted	1%	9%	24%	66%
Course activity completion updated	1%	7%	27%	65%
Quiz attempt started	1%	10%	24%	65%
Quiz attempt summary viewed	1%	10%	25%	65%
User list viewed	1%	11%	23%	65%
User graded	1%	10%	24%	64%
Quiz attempt viewed	1%	11%	23%	64%

Table 5-9: Logged Moodle events' Percentage viewing per GPA

In Mogus, et al. (2012)'s study, similar examination was conducted to check percentage of usage of the LMS activities by the A, B, C, D and F students. In Mogus, et al. (2012)'s study, 'A' students tended to have the highest activity in viewing the assignments with a percentage of 27%, followed by resource view and assignment upload with 24% of each. The least viewed activities were for discussion viewing and project uploads as both earned 21%. This contrast the UBT students' case, where the highest utilization by the 'A' student was for the discussions, user profiles and quiz attempt reviewed. Quizzes were not part of Mogus, et al. (2012)'s study to explore. But this is the case with most studies, as some variables are examined, and some are not. Next, the top six UBT's 'A' student's activities highlighted in red in Table 5-9.

Discussion view

Table **5-9** displays the percentage usage of Discussion forums among the different GPA students. The 'A' students made a 74% utilization of Discussion forums, compared to the 1% 'D' students used. High GPA students tended to use the discussion forums more often than other students. Discussion forums in the UBT case were mostly used to communicate course news and any updates or changes to the course. Students seemed to view the discussions a lot during the term. So, a characteristic of UBT high GPA students is that they are keen to follow up with class news and updates during the academic term. This can be a helpful hint for students with lower GPA to try to catch up with course news and be acquainted with the course updates during the academic term.

Quiz attempt review

The table also shows a high 72% quiz attempt viewing by the ‘A’ students. To review a quiz attempt, means to view the quiz after it was conducted. This indicates that students may view the attempt to learn of their mistakes or view the quiz content to prepare for upcoming exams or review their answers. So, this is an indication of attempting to learn and seek knowledge by viewing the stated knowledge or learning from own mistakes. So, another characteristic of UBT high GPA students is that they are keen to prepare well for exams by studying well and learning from their mistakes. They attempted to prepare well from past assessments. Lower GPA students can try to start reviewing their quiz attempts and learn from past quiz contents during the academic term.

Submission has been submitted

Another high percentage of 70% was for submitting assignments. The ‘A’ students seemed to submit most required submissions during the academic term, which shows their commitment to follow deadlines and submit required assignments. So, being keen to submit the required tasks in Moodle is another characteristic that lower GPA students may try to do in an attempt to raise their GPAs.

A file has been uploaded

70% of the Fall 2018 uploads was conducted by ‘A’ students. Students uploaded files when lecturers request submission of assignments and tasks. So, high GPA students tended to upload required files during the academic term. Lower GPA students had zero % upload. If they can try to commit to uploading all requested files during the term, it may help to raise their GPAs.

Turnitin Assignment is viewed

High GPA students had 69% viewing of the Turnitin Assignments where lower GPA students had 1%. Viewing the Turnitin assignment indicated clicking the assignment and viewing it. It did not indicate adding or submitting. So, high GPA students at least clicked on the Turnitin assignment and viewed it, where lower GPA students did not. This indicated once again that high GPA students tended to be keen to view Turnitin Assignments and their requirements. For Lower GPA students to improve their GPA, they can try to be keen and attempt to use Turnitin.

User Profile is viewed

Viewing a Moodle user profile indicates the interest to view user information such as contact email. When students click user-profiles, this indicate either their interest to customize their own profile or check other profiles to attempt to contact. So, a high percentage of 72% of user profile viewing was done by the high GPA students. This indicated the interest of the ‘A’ students to be innovative and edit their profile, and interest to communicate with either the lecturer or peers. Lower GPA students can try to communicate with the lecturer or peers more to improve their performance.

In a similar study of Mwalumbwe and Mtebe (2017) that examined type of LMS activities that effect the students’ grade, students who obtained higher grades were mainly active in discussion forums and interacted more with peer students and students who completed exercises got better grade than those who did not. Comparing Mwalumbwe and Mtebe (2017)' study to this research findings, UBT students with high performance had high activities in discussion forum usage (74%) and user profile viewing (72%) which is an indication of attempt of communication with lecturers or peers, and quiz revision (72%).

Discussing the benefits of this research findings of examining GPA students' certain pattern of LMS activities was unique compared to other research studies. Examining the mined data of the log file helps to give an insight on recommendations for the course design LMS features as well. The insight gained from Gašević, et al. (2016)'s study can trigger solution to the lecturers when designing their LMS course features. For example, Gašević, et al. (2016)'s study results showed negative association between assignments and grades in Mathematics courses, where in contrast, there was a positive association in the marketing courses. This may indicate that there is lack of alignment of the assignment with the course expectations or there is weakness in the face-to-face classroom integration, where both are not an issue in the marketing course. Similarly, in this research study, examining the association of high GPA student in the UBT context triggered an advisory list of Moodle resources to include in the UBT course design. More emphasis on assessment tools such as quizzes, assignments and discussions can be incorporated in future UBT LMS design and encourage students to utilize these features to improve their GPAs. Now, that the fall log data was examined, a further look into the 4-year Log data and a comparison are conducted in the following section 5.1.3.3.

5.1.3.3 Historic 4-Year Log Data

Historic data displayed the different patterns of Moodle events engagement. Events concerning course design elements and the extent of their usage were examined. Similar to the historic activity report analysis, Table **5-10** shows top events of all the years and the percentage of usage of each event in each year and it displays the variations in events log utilization among the 4-year period.

Log event	2015	2016	2017	2018	Total count
Course viewed	19%	26%	32%	23%	100%
Course module viewed	16%	25%	33%	26%	100%
Quiz attempt viewed	5%	32%	31%	32%	100%
The status of the submission has been viewed.	21%	31%	33%	15%	100%
View Turnitin assignment	12%	23%	36%	29%	100%
Calendar event updated	7%	30%	37%	26%	100%
Grade deleted	8%	46%	45%	1%	100%
User graded	10%	33%	34%	22%	100%
Course module updated	23%	30%	34%	13%	100%
Submission form viewed.	22%	35%	31%	12%	100%
A file has been uploaded.	19%	30%	35%	16%	100%
A submission has been submitted.	19%	30%	35%	16%	100%
Discussion viewed	22%	31%	30%	17%	100%
Submission created.	23%	35%	31%	12%	100%
Role assigned	40%	24%	21%	16%	100%

Table 5-10: Moodle Logged events' utilization percentage per year

To compare the events utilization in the different years, Table **5-11** displays a brief description about the top events utilized and the discussion of the variations is discussed next.

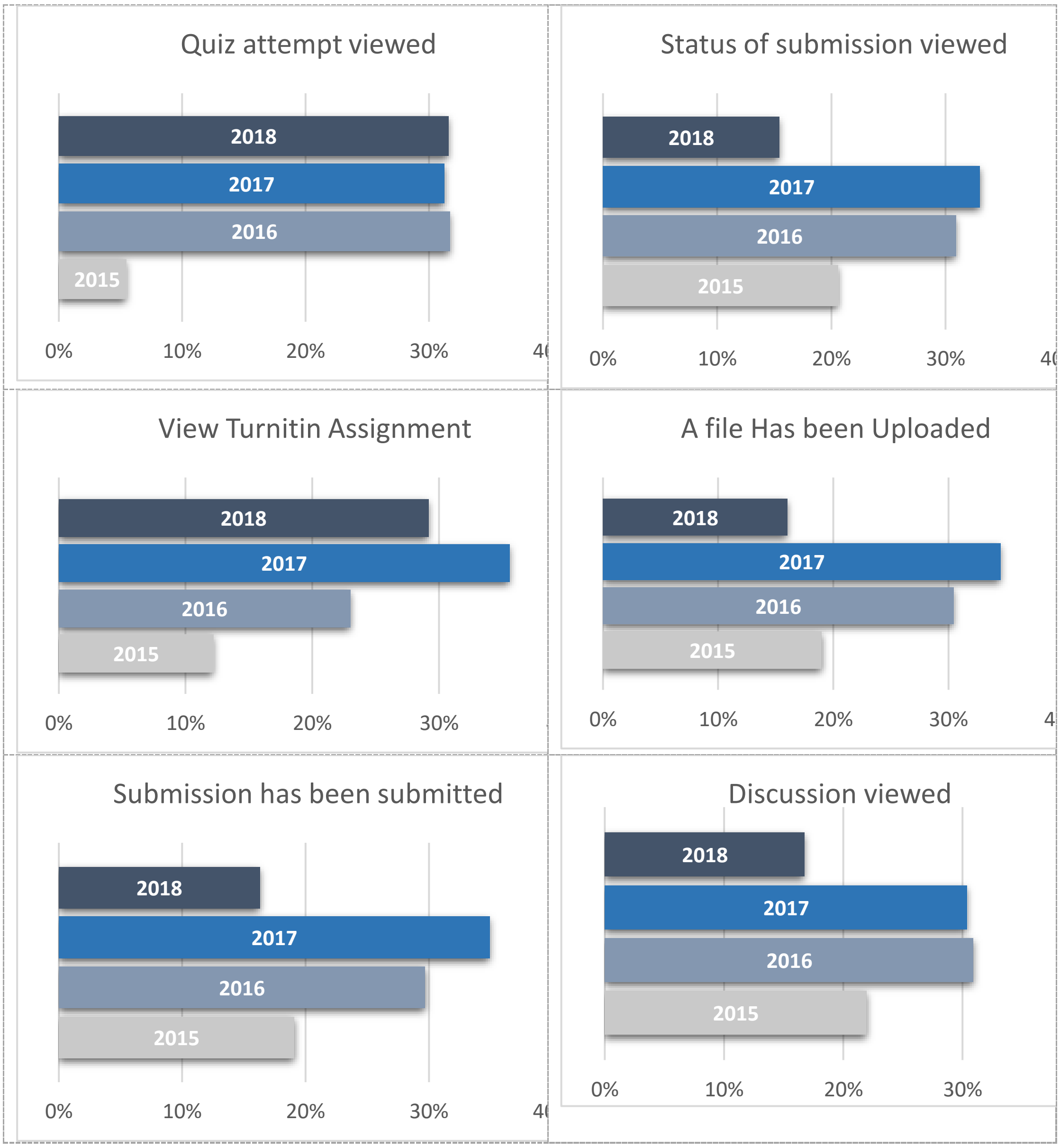


Table 5-11: Events utilization- 4-year Period

Quiz attempt view

Year 2015 experienced the lowest quiz percentage usage. This is similar to what stated earlier in the activity report analysis. Year 2016 experienced the Moodle upgrade-fix that allowed more quizzes to be created. This explains the very low percentage of quiz attempts view as there were not many quizzes created because of the difficulty of importing test banks. It seems lecturers who created quizzes in 2015 relied on adding quiz questions manually.

Status of submission is viewed

Also as indicated earlier in the activity report analysis, with the adoption of Pearson MyLab, a drop on use of assignments was noticed in 2018. This explains this drop also in the event logged -viewing status of submission.

Turnitin Assignment is viewed

Logged events allowed to explore more information about additional add-on blocks added to Moodle such as Turnitin assignments. This was not easy to detect in the Activity Report, but it is easier here as log reports automatically record all actions in Moodle. The percentage of using Turnitin assignment and viewing it was highest in 2017, then a slight drop occurred in 2018. When interviewing the lecturers and asking about Turnitin, few indicated the need for support and workshops to use Turnitin.

> *Lecturer 11*: "if I want to use it, I have to make sure that I have explained how Turnitin works to the students. When I attempted to do that with the master students, I felt that it may cause confusion or fuss. So, I found myself on the due date, I only received 10 out of the 15, so, what happened to the 5 students who did not submit? So, when I contact them, a long list of excuses and complains are shared as they I was pointed out that I did not explain enough about Turnitin. So, I think at some point, we need to provide the necessary support in order to cope with the Moodle requirements. So, we have to give enough support of the faculties and the students and workshops".

This may justify the lower numbers in 2018, where more support was needed.

A file has been uploaded

This is similar to the submission of assignments as a drop in percentages occurred in Fall 2018. This is again as indicated earlier in the activity report analysis, is due to the adoption of Pearson MyLab. This is also the same reasoning behind the pattern of usage for this submission event.

Discussion Viewed

Discussion forums in the activity report analysis experienced high usage in 2016 and lower usage in the proceeding years. The event itself of viewing the discussion experienced similar drop, but with steady decrease. The reason can be similar to the one provided in the activity report analysis which is the change in the administrative academic section in 2016 which involved encouraging lectures to use Moodle effectively and communicate with the students through Moodle.

Now, that the 4-year log data has been examined, a comparison between the 4-year log events and the Fall 2018 log events are discussed next.

5.1.3.4 Fall 2018 Log Data vs Historic 4-Year

Similar to the comparison of the activity reports in the 2 timeframes, a comparison is conducted here as well for the logged events. Figure **5-6** displays the comparison chart. There are no major variations between the event logged among the years especially for students' related events. The major difference is related to system events such as updating course calendar which is done automatically. Calendar events are automatically recorded by the system when lecturers assign deadlines to assignments and quizzes (Moodle Docs, 2017).

Log Event	Fall 2018 usage	4-year usage
Course viewed	29.6%	32.0%
Calendar event updated	23.8%	2.6%
Course module viewed	19.0%	24.0%
Quiz attempt viewed	8.1%	10.2%
The status of the submission has been viewed.	4.9%	8.1%
View Turnitin assignment	3.1%	3.4%
Course activity completion updated	2.2%	0.2%
Submission form viewed.	1.4%	1.6%
User graded	1.3%	2.0%
Quiz attempt reviewed	0.7%	0.7%
Quiz attempt summary viewed	0.6%	0.7%
A file has been uploaded.	0.6%	1.6%
A submission has been submitted.	0.6%	1.5%
Submission created.	0.6%	1.1%
Quiz attempt started	0.6%	0.6%
Quiz attempt submitted	0.5%	0.5%
Course module updated	0.5%	1.9%
User profile viewed	0.4%	0.3%

Figure 5-6: Comparison Logged Events - Fall and 4-Year, May 2019

Comparing the 2-time periods, all events seem reasonably close. An interesting finding though, is the event of the calendar-event-updated. It is 21% higher than the one in the 4-year period. This implies that more lecturers are assigning deadlines to the assigned students' activity. This can be a quiz, assignment, or even a forum. This proves higher number of dedications to assignments and projects and enforcing calendar deadlines to ensure students submit their tasks. The quiz-attempt-viewed is higher in the historic period. This is mainly due to 2016's Moodle upgrade that improved the quiz test bank feature and the general low e-learning usage in 2018 due to the change in administration.

Mining the log file reports of both Fall 2018 and the 4-year historic data, helped to highlight the course design pattern that UBT students are engaged with. In terms of type of event logged recorded, quiz attempts being viewed was the top logged event recorded. Followed by viewing the submission of assignments status and viewing Turnitin assignments which all relate to assessments. So, students' engagement in the Fall and the 4-year consecutive year was mainly related to students' assessments.

The analysis of the 2 Moodle reports "Activity Reports" and "Log Reports" revealed the various resources mostly used by students and the top-most Moodle events triggered the highest engagement among all students and a pattern of resources usage was revealed for high GPA students. These resources are mainly assessment tools such as assignments, quizzes, and discussion forums. The data mining analysis of the current Fall term and the 4-year data highlighted the same type of resources. There are not many variations among the different types of resources, as all mainly relate to assessment. There were some variations though among the different utilization of the resources. These mainly related to either institutional new polices factors or administration changes factors and software related factors. These may explain why certain resources were used less in one year and were suddenly highly unitized in the proceeding years. The resulted high engaged resources along with the discussions of the factors affecting the 4-year pattern data can help to guide lecturers when designing their future course instructional design elements. To explore the students' own perspective about their engagement while using these Moodle resources and the analytical dashboard will be discussed next.

5.2 Students Questionnaire Analysis

5.2.1 Students' SRL Behavior Highlight

This section reports the questionnaire analysis of the students' responds to questions aimed to discover the students' learning behavior towards Moodle usage and the completion progress dashboard. 5-LIKERT 16 questions were used in the survey to address students' SRL behavior. SPSS was used to produce the descriptive statistics for the 16 SRL elements that are internally reliable (Cronbach's alpha .816). The 5-LIKERT scale used (Strongly Agree – 5, Agree-4, Neutral-3, Disagree-2, Strongly Disagree-1). Based on the 5-LIKERT, the level of agreement (Attitude), Table 5-12, was used to summarize the attitude of each question:

Weighted Mean	Attitude
4.20 – 5.00	Strongly Agree
3.40-4.19	Agree
2.60-3.39	Neutral
1.80-2.59	Disagree
1.00-1.79	Strongly Disagree

Table 5-12: Attitude

The questions applied Pintrich (2004) conceptual Self-Regulated Learning framework where it has four phases: Planning and goal settings, monitoring, control, and reaction and reflection. The distribution of the 16 questions was distilled based on the use of SPSS Factor analysis, the questions were grouped into 4 categories as shown next. Having a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) value of .848, a value higher than 0.5, support the validity of the questionnaire (Chan & Idris, 2017).

For the descriptive analysis of the questionnaire, since these are anonymized surveys and the results of the descriptive analysis are summarized with no indication of students' data, the 711 survey entries were all examined.

Phase 1: Planning and Goal settings

- Q1-1: I set goals to help me to utilize Moodle.
- Q1-2: I plan out a study plan for Moodle activities.
- Q1-3: I can estimate how much time a Moodle task needs.
- Q1-4: I dedicate set of hours for Moodle activities and resources.
- Q1-5: I set strategies to manage my studying that includes Moodle usage.

Phase 2: Monitoring

- Q2-1: I keep track of Moodle deadlines.
- Q2-2: I know my grades when they are updated.
- Q2-3: I periodically access Moodle to check any new news or updates.
- Q2-4: I make sure I keep up with the weekly readings and assignments.

Phase 3: Control

- Q3-1: I know when I am behind of schedule.
- Q3-2: I lose attention easily online.
- Q3-3: I manage to work even if Moodle materials are dull.

Phase 4: Reaction and Reflection:

- Q4-1: I change strategies if I am not making progress.
- Q4-2: I ask my peers when I need help.
- Q4-3: I ask the lecturer when I need help.
- Q4-4: When I fail at something, I try to learn from my mistakes.

Table 5-13 displays the descriptive data of the 5-LIKERT answers for the SRL Planning and goal settings behavior. All 5 elements of the Planning and goal settings earned an attitude of Agree. UBT students believed that their planning and goal setting skills are solid. All agreed on having the ability to set goals, prepare a study plan, estimate time for tasks, dedicate the needed hours and setting the needed strategy.

Planning and Goal settings	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Setting Goals to use Moodle	1.5	6.3	14.9	51.3	25.9	3.94	0.89	Agree
Planning a study Plan	1.8	7.9	19.7	44.9	25.7	3.85	0.96	Agree
Estimate time for Moodle Tasks	0.4	5.8	19	51.6	23.2	3.91	0.83	Agree
Dedicate hours for tasks	1.8	12.7	20.3	43.7	21.5	3.7	1	Agree
Set strategies to use Moodle	1.5	9.7	15.6	45.9	27.3	3.88	0.97	Agree

Table 5-13: Students SRL-Planning-Goal Settings

Table **5-14** displays the descriptive data of the 5-LIKERT answers for the SRL monitoring behavior. UBT students strongly indicated keeping track of deadlines, with a mean of 4.22 and keeping up with the readings and assignments, with a mean of 4.2.

Monitoring	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Keep Track of Moodle Deadline	1.1	4.5	10.4	39.7	44.3	4.22	0.88	S Agree
Know Grades when updated	4.2	12	14.2	34.7	34.9	3.84	1.15	Agree
Periodically access Moodle to check news	1.5	4.5	11.5	40.6	41.8	4.17	0.91	Agree
Keep up with readings and assignments	0.7	3.5	12	43	40.8	4.2	0.83	S Agree

Table 5-14: Students SRL-Monitoring

Table **5-15**Table **5-15** displays the descriptive data of the 5-LIKERT answers for the SRL control behavior. UBT students believed that they know when they are behind of schedule with a mean of 4.01 and managed to work with dull materials with a mean of 3.51. Though, UBT students conflicted on the loss of attention. Some indicated they lose attention easily online and some do not.

Control	S disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Know when Behind of schedule	0.7	6.8	14.2	47.8	30.5	4.01	0.88	Agree
Loss of Attention easily	6.5	29	24.5	27.8	12.2	3.1	1.14	Neither
Manage to work with dull Materials	3.4	13.6	26.6	41.5	14.9	3.51	1.01	Agree

Table 5-15: Students SRL- Control

Table **5-16** displays the descriptive data of the 5-LIKERT answers for the SRL reaction and reflection behavior. UBT students strongly believe that they learn from their mistakes when fail with a mean of 4.37.

Reaction and Reflection	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Change strategies when no progress	0.3	2.3	21.7	51.5	24.3	3.97	0.76	Agree
Ask peers for help	0.8	4.8	12.5	50.1	31.8	4.07	0.84	Agree
Ask lecturer for help	1.1	4.5	10.7	47.4	36.3	4.13	0.86	Agree
when fail, learn from mistake	0.4	1.7	5.9	44.3	47.7	4.37	0.71	S Agree

Table 5-16: Students SRL- Reaction and Reflection

Students' testimonies showed their confident in all the 16 self-regulated behavior elements. The testimonies showed highest agreement on keeping track of deadliness and reading and assignments (Monitoring SRL behavior) and learning from mistakes (Reaction and reflection SRL behavior). UBT students viewed themselves as self-learners who managed their own learning and adjusted and controlled their learning when needed. Table **5-17** displays the 4 SRL elements statistics with highest mean 4.13 for the reaction and reflection skills and mean of 4.10 for the monitoring skills. The lowest SRL skills was for the control behaviors.

Students 4- SRL Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Planning and Goal Settings	711	1.00	5.00	3.8560	.67022
Monitoring	711	1.25	5.00	4.1048	.68440
Control	711	1.67	5.00	3.5401	.68169
Reaction and Reflection	711	2.00	5.00	4.1371	.55602
Valid N (listwise)	711				

Table 5-17: 4-SRL Elements Descriptive Statistics -711 students

Figure **5-7** displays both strong SRL students' behaviors: Monitoring and reaction and reflection. The lowest SRL behavior was for the control behavior. Students can work on improving their SRL control behavior by keeping themselves engaged in learning, increasing their attention, knowing when they fall behind and keeping themselves engaged with dull materials, and knowing their status in the course. Now that students' testimonies have been examined, next is the attempt to check which SRL element behavior influences students' performance. Section 5.2.2 attempts to test the association of SRL behaviors with the students' GPA to discover if all, or some elements affect the students' GPA, if any.

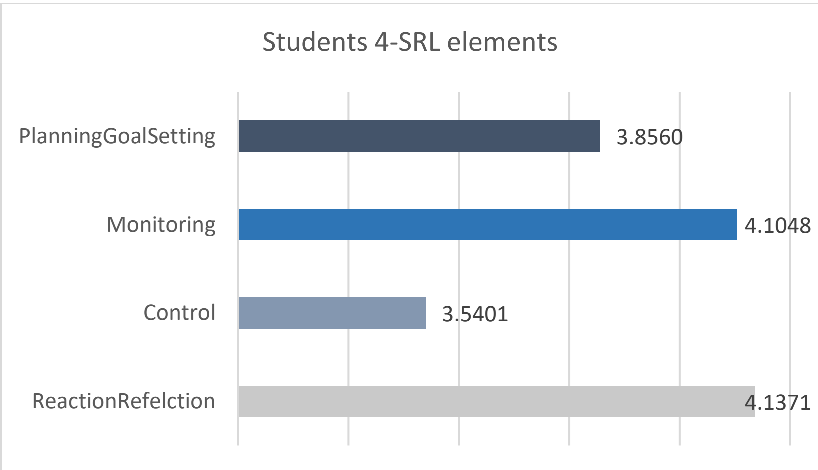


Figure 5-7: Students 4-SRL elements

5.2.2 Students' Self-regulated Learning Behavior and GPA

The interest to associate students' SRL behavior to students' performance is explored in this section. To analyse the questionnaire answers to examine the relationship between the SRL behavior elements and the GPA, only the students who have consented to share their GPA are analysed. The students who consented to the study were 419 students. N = 419, therefore, 419 data were collected. GPA data was merged with the survey data and accordingly, only the records of the students who consented were examined. SPSS stepwise regression was used to test which SRL elements affect the students' performance GPA. For this, SPSS stepwise multiple regression was conducted using Term GPA as a dependent variable and the 16 SRL elements as independent variables. The stepwise multiple regression was also used to determine which independent variable (16 SRL sub-elements) contribute the most to predicting the students' GPA. The results displayed below. The stepwise regression applied an alpha = 0.05 level of significant.

SPSS regression is used now to determine which SRL element of the total 16 had an effect on the students' GPA. Out of the 16 SRL sub-elements, 4 elements contributed the most to affect the GPA. Table **5-18** displays the resulted 4 SRL elements: loss of attention, keep track of deadlines, planning a study plan and managing to work even with dull materials. The other 12 sub-elements do not have a direct effect on the students' GPA.

Model	Variables Entered
1	Q6_2 I lose attention easily online ↓
2	Q5_1 - I keep track of Moodle deadlines ↑
3	Q4_2- I plan out a study plan for Moodle activities ↓
4	Q6_3 I manage to work even if Moodle materials are dull ↑
a. Dependent Variable: Term GPA (2018-Fall)	
Method: Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).	

Table 5-18: Regression–Students' SRL input associated w GPA

Furthermore, SPSS regression displayed 4 models that affected students' GPA, check Table **5-19**. A prediction Model constructed by the Regression is displayed below. Out of the 4 models, model 4 has the highest R^2 value of 0.64, with predictors in order of importance: (Constant), loss of attention easily online, keeping track of Moodle deadlines, planning out a study for Moodle activities, and managing to work even if Moodle materials are dull.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.147[a]	.022	.019	.86277
2	.206[b]	.042	.038	.85457
3	.229[c]	.052	.046	.85116
4	.253[d]	.064	.055	.84695
a. Predictors: (Constant), Q6_2 I lose attention easily online				
b. Predictors: (Constant), Q6_2 I lose attention easily online, Q5_1 - I keep track of Moodle deadlines				
c. Predictors: (Constant), Q6_2 I lose attention easily online, Q5_1 - I keep track of Moodle deadlines, Q4_2- I plan out a study plan for Moodle activities				
d. Predictors: (Constant), Q6_2 I lose attention easily online, Q5_1 - I keep track of Moodle deadlines, Q4_2- I plan out a study plan for Moodle activities, Q6_3 I manage to work even if Moodle materials are dull				

Table 5-19: Regression Model –Students SRL associated with GPA

Model 4($b = 3.808$, $p < .05$, $b_1 = -.124$, $b_2 = .161$, $b_3 = -.112$, $b_4 = .098$) with and R^2 of .064. Model 4 stated in Table **5-20** has the highest R^2 values, for this, it is chosen to predict Final course grades.

4	(Constant)	3.808	.268		14.226	.000
	Q6_2 I lose attention easily online	-.124	.036	-.168	-3.405	.001
	Q5_1 - I keep track of Moodle deadlines	.161	.051	.155	3.142	.002
	Q4_2- I plan out a study plan for Moodle activities	-.112	.046	-.122	-2.427	.016
	Q6_3 I manage to work even if Moodle materials are dull	.098	.043	.113	2.265	.024

Table 5-20: Regression Model -Predict GPA w SRL

So, the stepwise multiple regression analysis was conducted to evaluate whether all the self-regulated learning sub-elements were necessary to predict students' GPA. The linear combination of the loss of attention online, the tracking of deadlines, the planning of a study plan, and the managing to work with dull materials, all were significantly related to the students GPA, $F(4,14) = 7.076$, $P<0.05$). The coefficient of determination R^2 is .064, indicating that approximately 6.4% of the variance in the 4 SRL elements can be accounted for by the linear combination of the 4 SRL elements (the loss of attention online(negative), the tracking of deadlines(positive), the planning of a study plan(negative), and the managing to work with dull materials(positive)). The regression equation for predicting the students' GPA, check Table **5-20**, is:

Predicted student's GPA is equal to = $3.808 - .124\, x_1 + .161\, x_2 - .112\, x_3 + .098\, x_4$
Predicted GPA = 3.808 - .124 (Survey Answer Q6-2) + .161 (Survey Answer 5-1) - .112 (Survey Answer Q4-2) + .098 (Survey Answer Q6-3)

Predicted GPA = 3.808 - .124 (loss of attention easily online) + .161 (keeping track of Moodle deadlines) -.112 (planning out a study plan) + .098 (managing to work with dull materials)

Questions

- Q3-2: I lose attention easily online ↓
- Q2-1: I keep track of Moodle deadlines ↑
- Q1-2: I plan out a study plan for Moodle activities ↓
- Q3-3: I manage to work even if Moodle materials are dull ↑

Predicted GPA = 3.808– (.124) * Q3-2 + (.161) * Q2-1 - (.112) * Q1-2 + (.098) * Q3-3

So, a sample input survey answers where: (Strongly Disagree 1, Disagree 2, Neither 3, Agree 4, Strongly Agree 5)

- Q3-2: I lose attention easily online- 4
- Q2-1: I keep track of Moodle deadlines-5
- Q1-2: I plan out a study plan for Moodle activities-4
- Q3-3: I manage to work even if Moodle materials are dull-4

Predicted GPA = 3.808 – (.124) * 4 + (.161) * 5 - (.112) * 4 +(.098) * 4
= 3.808- 0.49 + 0.80 - 0.44+ 0.39
= 4.06

Another Sample with an attentive high SRL skills student

- Q3-2: I lose attention easily online- 1
- Q2-1: I keep track of Moodle deadlines-5
- Q1-2: I plan out a study plan for Moodle activities-3
- Q3-3: I manage to work even if Moodle materials are dull-5

Predicted GPA = 3.808 – (.124) * 1 + (.161) * 5 + (.112) * 3 – (.098) * 5
= 3.808– 0.124 + 0.80 - 0.33 + 0.49
= 4.64

Another Sample with low SRL skills student

- Q3-2: I lose attention easily online- 5
- Q2-1: I keep track of Moodle deadlines-1
- Q1-2: I plan out a study plan for Moodle activities-3
- Q3-3: I manage to work even if Moodle materials are dull-2

Predicted GPA = 3.808 – (.124) * 5 + (.161) * 1 - (.112) * 3 +(.098) * 2
= 3.808– 0.62 + 0.161 - 0.336 +.196
= 3.2

For better performance: The less student loses attention, the more student keeps track in Moodle, and the more student manages tasks even if materials are dull, all behaviors that can improve the performance.

An unexpected result was about the SRL planning and goal setting behavior: Planning a study plan. Analysing the Students' input indicated that the more students plan for a study plan for Moodle activities, the poorer the performance becomes. There are lots of factors that may lead to such outcome. Planning requires students' construction of the target and selection of efficient strategies for achieving it (Eilam & Aharon, 2003). Plan's execution requires monitoring of progress and modification of plan if needed to. Planning is associated with timing, so time could be an obstacle. Time constrain could be one of the factors as students tend to fall behind schedule due to their full load, or academic tasks or even personal tasks. Struggling to achieve a plan because of the time constrain may explain the low performance of students who spend more effort on planning. Other factors could be a poor plan, or not enough information to seek if a plan needs to change, poor utilization of resources. Lecturers' testimonies in the interviews indicated their awareness of students' struggle during the academic term, as some are working off campus, and some has family responsibilities and such. So, the more students plan with the struggle of time constrains and the inability to change a plan if it is not working, all may explain the low performance association with planning. So, upon the analysis, according to the constructed predicted model, students can be advised if they try to keep track of Moodle deadlines, and avoid losing attention easily online, and try managing even if Moodle materials are dull and try not to make too much planning for a study plan for Moodle activities, then they can have a chance to enhance their GPA.

5.2.3 Students' Attitudes Towards Dashboards

To test students' attitudes, the 711 survey entries are examined here. Students were utilizing to the completion progress dashboard throughout the Fall 2018 term in the researched participant courses. They were intrigued about it and they kept checking with their lecturers about the associated progress homepage alert chart, check Table **5-21**. The students had all the contact they need as support from IT or to contact the researcher personally in case they had any questions or queries about the dashboard. The tool was easy to use by the students, it needed more work from the lecturer's side, who needed to setup the tool at start of the term and continued to build on it during the term as it required adding tracking to any new assignment or resource.

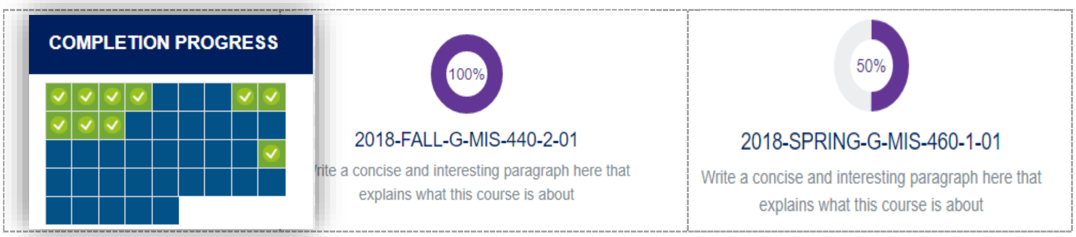


Table 5-21: Charts -Completion Progress Dashboard- Alert Chart

The three questions that sought the perceptions and attitudes of the students about the dashboard were:

- Q 5-1: I understand the purpose of Moodle dashboards.
- Q 5- 2: I believe Moodle dashboards are useful.
- Q 5- 3: I believe Moodle dashboards helped me understand where I stand in Moodle activities.

711 students answered the questions with a mean of 3.95 for understanding the purpose of the dashboard, 4.04 for believing in the usefulness of the dashboard, and 4.01 for believing that the dashboard helped to understand one's status.

The Mean displayed in Figure **5-8**, 75 % students understood the purpose of the dashboard and 76% believed that dashboards are useful, and 73.3 % are interested to use them in the future. Overall, 73.7 % were interested to use dashboards in Moodle, see Figure **5-8** and Figure **5-9**.

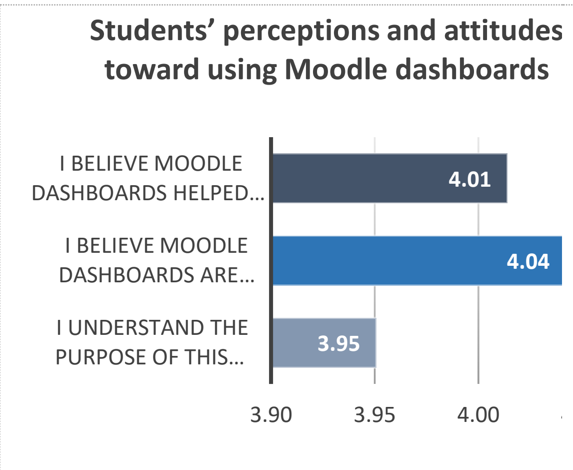


Figure 5-8: Mean of Students' attitude - Dashboard- May 2019

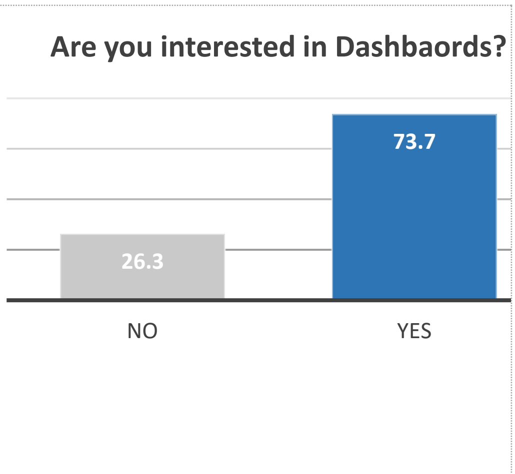


Figure 5-9: Students' interest to use Dashboard- May 2019

So, according to the questionnaire analysis, the majority of the students were interested in dashboards, they understood its purpose, its usefulness and its benefits.

5.3 Lecturers Questionnaire Analysis

5.3.1 Lecturers' Course Design Choices and SRL Behavior

Another Questionnaire aimed to the participant lecturers. The first part of the questionnaire covered the most used instructional design elements used by the lecturers. According to the survey questions, the most used activity by the lecturers with a 15.69% utilization, was for uploading PowerPoint and other files. Followed by 14.71% for both Assignments and announcements, check Figure **5-10**.

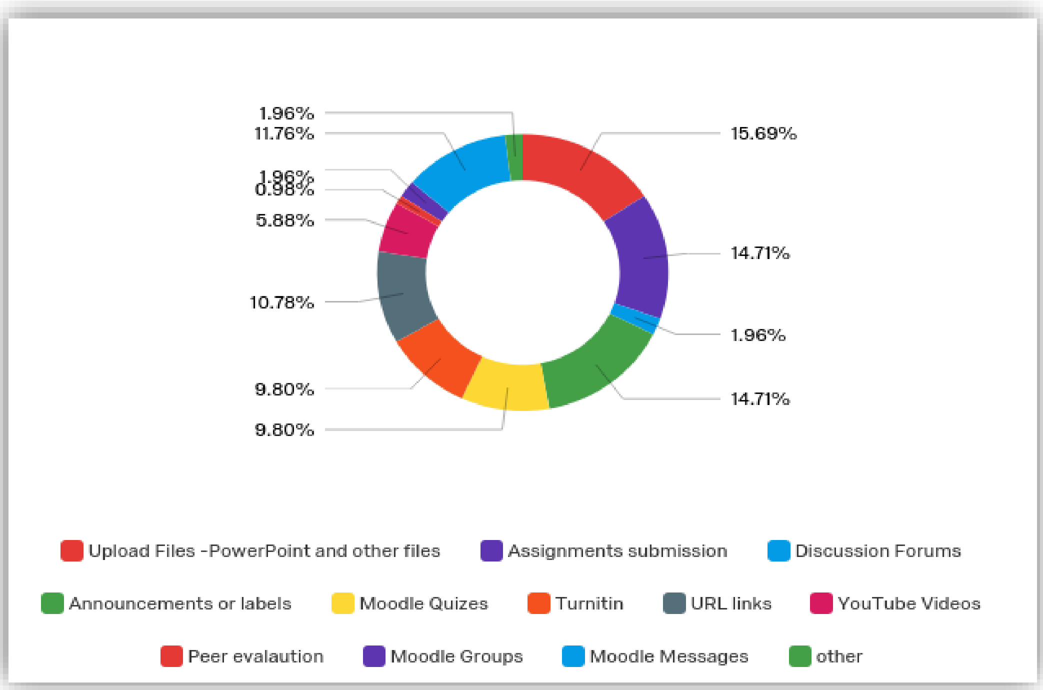


Figure 5-10: Lecturers' Moodle Design choices, May 2019

The lecturers’ interview testimonies indicated using mostly file uploads to prepare the course content at start of the academic term and specifically uploading the syllabus. Lecturers use announcements constantly. Some use labels to communicate the latest news or share comments on the course page, and few others use the news forum to communicate the class news. Along with seeking what Moodle resources the lecturers usually use, additional questions focused on seeking the lecturers’ SRL behavior toward the analytics and their perceptions and attitudes toward them.

This section reports the questionnaire analysis aimed to discover the lecturers' behavior towards Moodle usage, the analytical graphs, and the completion progress dashboard. The 5-LIKERT 16 internally reliable (Cronbach's alpha .868) questions were used in the survey to address lecturers' SRL behavior. SPSS was also used to produce the descriptive statistics. Similar to the students' questionnaires, the Attitude-mean average is used to summarize the attitude of each question. The questions applied the same Pintrich conceptual Self-Regulated Learning framework with the four phases of planning and goal settings, monitoring, control, and reaction and reflection. Similarly, the distribution of the 16 questions was distilled based on the use of SPSS Factor analysis, the questions were grouped into 4 categories as shown next.

Planning

- Q1-1: I have my Moodle course content ready at start of the academic term.
- Q1-2: I plan to make course design changes for my future courses based on my usage of Moodle analytics.

Monitoring

- Q2-1: I update my Moodle content periodically.
- Q2-2: I always check Moodle messages.

Control

- Q3-1: I edit and change Moodle course design based on students' performance.
- Q3-2: I edit and change Moodle course design based on peer observation and advise.
- Q3-3: I have edited and changed my Moodle course design based on using the Moodle dashboard and analytical graphs.

Reaction and Reflection

- Q4-1: My current Moodle course design element is effective.
- Q4-2: Moodle Completion Progress dashboard is useful.
- Q4-3: Moodle dashboard helped me guide the students.
- Q4-4: Moodle dashboard helped me identify students at risk.
- Q4-5: Moodle Analytical graphs are useful.
- Q4-6: Moodle Analytical graphs helped me guide the students.
- Q4-7: Moodle Analytical graphs helped me identify students at risk.
- Q4-8: Moodle analytics helped me to design the Moodle course effectively.
- Q4-9: Moodle analytics helped me to monitor students' engagement and performance.

Table **5-22** displays the descriptive data of the 5-LIKERT answers for the SRL planning and goal settings behavior. The lecturers strongly agreed on preparing Moodle content at start of the term with a mean of 4.38. They agreed to planning their course design upon the new analytic tools with a mean of 3.81.

Planning and Goal Settings	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Moodle content ready at start of the term	0	6.25	6.25	31.25	56.25	4.38	0.89	S Agree
Plan to make course design changes upon Analytics	0	6.25	25	50	18.75	3.81	0.83	Agree

Table 5-22: Lecturers SRL-Planning and Goal Settings

Table **5-23** displays the descriptive data of the 5-LIKERT answers for the SRL monitoring behavior. The lecturers strongly agreed on updating Moodle content periodically with a mean of 4.63. They agreed on using Moodle messages with a mean of 3.94. From lecturers' interviews testimonies, not all lecturers used Moodle messages. For communication through Moodle, they mainly depended on the discussion news forum. They used other communication mediums as the UBT email, personal emails and some used the WhatsApp application.

Monitoring	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Update Moodle content periodically	0	0	6.25	25	69	4.63	0.62	S Agree
always check Moodle messages	6.25	12.5	6.25	31	44	3.94	1.29	Agree

Table 5-23: Lecturers -SRL Monitoring

Table **5-24** displays the descriptive data of the 5-LIKERT answers for the SRL control behavior. The lecturers agreed on controlling when to change their Moodle content, it was either based on students' performance (mean of 3.44) or from peer observation (mean of 3.56). They differed though on conducting change upon the insight gain from Moodle dashboard and the analytics with a mean of 3.19.

Control	S Disagree	Disagree	Neither	Agree	S Agree	mean	sd	Attitude
	%	%	%	%	%			
Change content based on students' performance	6.25	18.75	18.75	37.5	18.75	3.44	1.21	Agree
Change course design upon peer observation	6.25	12.5	12.5	56.25	12.5	3.56	1.09	Agree
change upon Moodle dashboard and analytics	6.25	12.5	12.5	56.25	12.5	3.19	0.98	Neither

Table 5-24: Lecturers -SRL Control

Table **5-25** displays the descriptive data of the 5-LIKERT answers for the SRL reaction and reflection behavior. Out of the 9 elements, all lecturers strongly agreed upon the usefulness of the Moodle analytics graphs with a mean of 4.25. They also commonly agreed upon all the other reactions and reflections.

Reaction and Reflection	S Disagree %	Disagree %	Neither %	Agree %	S Agree %	mean	sd	Attitude
My current Moodle design is effective	0	0	12.5	68.75	18.75	4.06	0.57	Agree
Moodle dashboard is useful	0	0	6.25	50	43.75	4.38	0.62	Agree
Moodle dashboard helped me guide the students	0	0	18.75	56.25	25	4.06	0.68	Agree
Moodle dashboard helped me identify students at risk	0	6.25	25	50	18.75	3.81	0.83	Agree
Moodle analytical graphs are useful	0	6.25	0	56.25	37.5	4.25	0.77	S Agree
Moodle analytical graphs helped me guide the students	0	6.25	25	37.5	31.25	3.94	0.93	Agree
Moodle analytics helped me identify students at risk	0	6.25	18.75	50	25	3.94	0.85	Agree
Moodle analytics helped me design Moodle course effectively	0	12.5	31.25	50	6.25	3.50	0.82	Agree
Moodle Analytics helped me monitor students' engagement and performance	0	6.25	6.25	81.25	6.25	3.88	0.62	Agree

Table 5-25: Lecturers- SRL Reaction and Reflection

Lecturers' testimonies showed their confident in all the 16 self-regulated behavior elements. The testimonies showed highest agreement on preparing Moodle course content from start of the term (planning and goal settings SRL behavior), updating Moodle content periodically (monitoring SRL behavior) and admitting to the usefulness of the Moodle analytical graphs (reaction and reflection SRL behavior). Table **5-26** displays the 4 SRL elements statistics with highest mean for the monitoring skills- with a mean of 4.28 and the planning and goal settings skills with a mean of 4.09. The statistics data displayed lower SRL skills in the Control behaviors with a mean of 3.39.

Lecturers' SRL Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Planning and Goal Setting	16	2.00	5.00	4.0938	.75760
Monitoring	16	3.00	5.00	4.2813	.68237
Control	16	2.00	4.67	3.3958	.80938
Reaction and Reflection	16	2.89	4.89	3.9792	.54918
Valid N (listwise)	16				

Table 5-26: Lecturers' SRL behavior Descriptive Statistics

Figure **5-11** displays strong SRL lectures' behaviors: Monitoring, planning and goal settings and reaction and reflection. Followed with a slightly lower SRL behavior for the control behavior. Lecturers can work on increasing their SRL control behavior by keeping themselves engaged in the learning analytic tools and dashboards and conducting changes to course content based on the insight provided by the analytics.

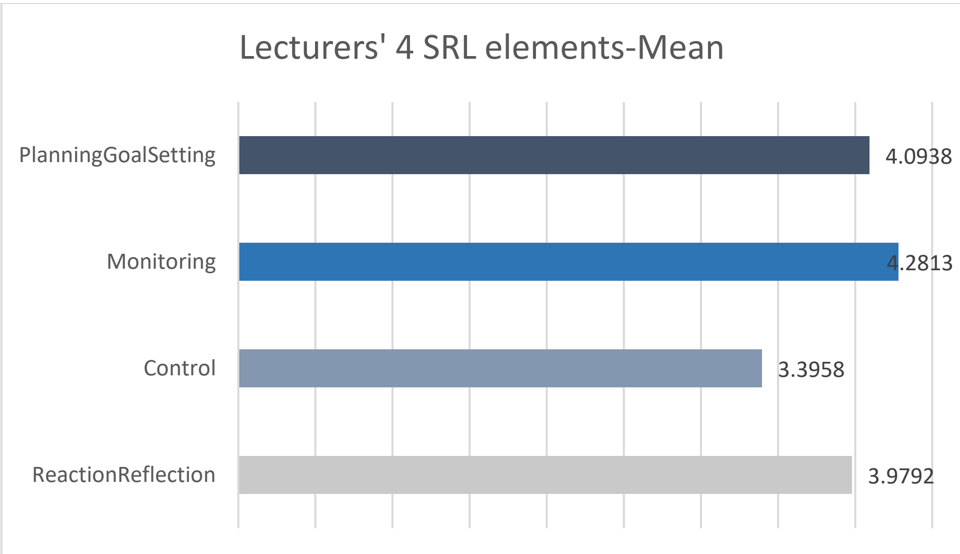


Figure 5-11: Lecturers' 4 SRL elements-Mean, May 2019

5.3.2 Lectures' Attitude Towards Dashboard and Analytical Graphs

The Lecturer's survey ends with questions seeking lecturers' opinions and attitudes toward both the analytical graphs and the completion progress dashboard.

The perception and attitude of lecturers toward using the completion progress dashboard and toward using the Moodle analytics graphs is displayed in Figure **5-12**. 94% of lecturers believed that Moodle dashboard is useful. 81% believed that the dashboard helped guide the students. 69% believed that dashboards identify students who are at risk. 94% believed that Moodle Analytical graphs are useful. 69% believed that Moodle analytical graphs guided them to help the students. 75% believed that Moodle analytics helped them identify students at risk.

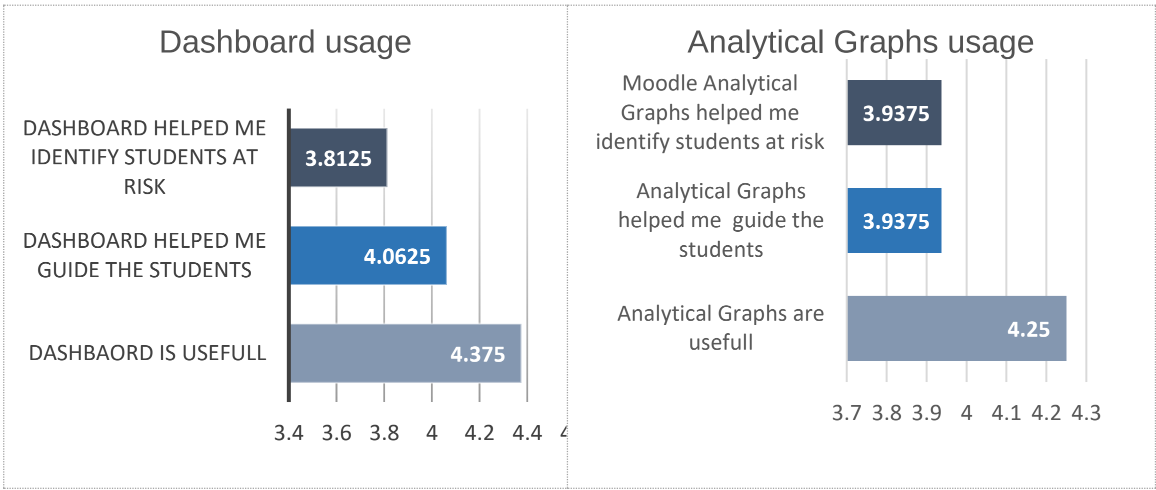


Figure 5-12: Dashboard and analytics usage, May 2019

A final question sought the interest to use Moodle analytical graphs and the course completion progress dashboard, and the respond was mainly huge interest to use them again with a 93.8% as indicated in Figure **5-13**.

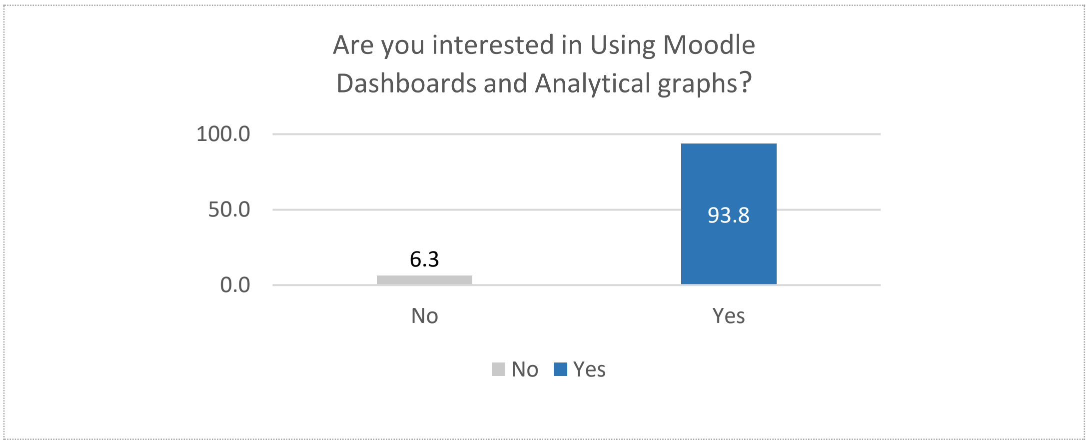


Figure 5-13: Lecturers perceptions -Analytics, May 2019

5.4 Semi-structured Interview Analysis

Because of the parallel mixed method approach adopted in this study and discussed at start of the analysis section 5, some interview testimonies have been used already in the previous analysis discussions. In this Semi-structure interview analysis section, the Braun and Clark (2006)'s thematic analysis approach, conducted on the 12 interview transcripts, is discussed and analysed. The Interviews' objective was to learn about lecturers' behavior toward Moodle analytics and their approach in designing their courses. This same objective was shared also by the quantitative methods: mining the analytical reports and questionnaires. The aim of the interviews was to check UBT Lecturers' instructional design habits and what design elements generated high students' engagements. It also aimed to understand lecturers' attitudes towards the new analytical tools that were added in the Fall of 2018 and lecturers using them during the research study period. Using Self-Regulated Learning theory, the 4 SRL behavior elements were used to build the interview questions: Planning and goal settings, monitoring and control and reaction and reflection. The 12 interviews were voice recorded with the permission of the lecturers. Once all the interviews were conducted, all were transcribed using Microsoft Word. The 12 lecturers' interview transcripts were coded for themes defined by the six-phase approach to thematic analysis by Braun and Clark (2006): Phase 1: Getting familiar with the data, Phase 2: Generating initial codes, Phase 3: Searching for themes, Phase 4: Reviewing potential themes, Phase 5: Defining and naming themes, and finally Phase 6: Producing the report. Part of searching for themes, ATLAS software was used to analyse the 12 interview scripts. Another tool used was the word cruncher to ease the process of finding common words among the 12 transcripts and word cloud. A sample word cloud for the combined 12 transcripts displayed in Figure **5-14**.

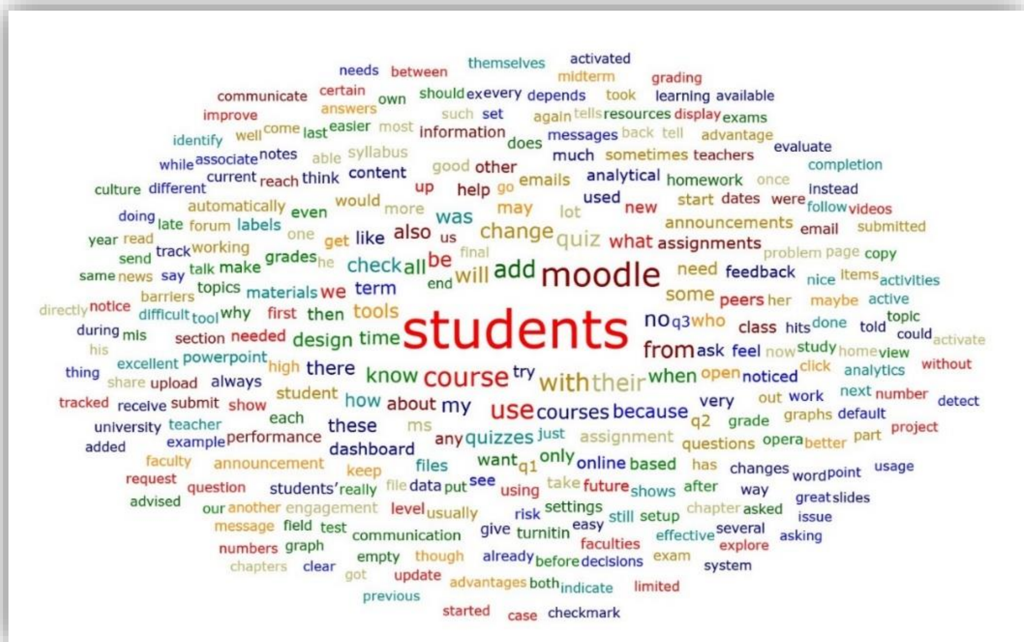
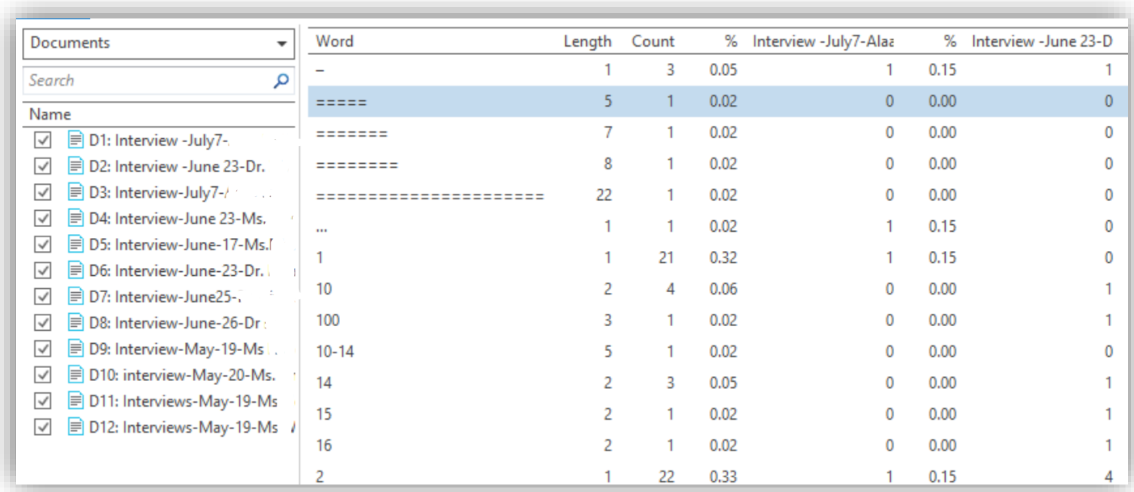


Figure 5-14: ATLAS Word Cloud -Interviews scripts, May 2019

There were common words that were helpful in coding the transcripts as: students, Moodle, syllabus, Quiz, add, feel, communicate, and more. The ATLAS Word Cruncher tool applied on the 12 transcripts extracted to an Excel file with over 148+ terms with 10 occurrences and more, check Figure **5-15**. A lot of words were ignored and not considered for the coding such as linking words as: “The”, “and”. Also, common topic words such as “student” and “lecturer” were also ignored. Other words were examined further.



Word	Length	Count	%	Interview -July7-Alaa	%	Interview -June 23-D
–	1	3	0.05	1	0.15	1
=====	5	1	0.02	0	0.00	0
=======	7	1	0.02	0	0.00	0
========	8	1	0.02	0	0.00	0
======================	22	1	0.02	0	0.00	0
...	1	1	0.02	1	0.15	0
1	1	21	0.32	1	0.15	0
10	2	4	0.06	0	0.00	1
100	3	1	0.02	0	0.00	1
10-14	5	1	0.02	0	0.00	0
14	2	3	0.05	0	0.00	1
15	2	1	0.02	0	0.00	1
16	2	1	0.02	0	0.00	1
2	1	22	0.33	1	0.15	4

Figure 5-15: ATLAS Word Cruncher, May 2019

Both Word ATLAS and Word cruncher helped in defining the analysis codes. The thematic analysis resulted in around 14 codes. The codes: Announcements, Email, PowerPoint, Syllabus, Turnitin, Assignment, and Quiz were categorized into the category: “Instructional Course Design”. The other codes: Ask, help, Feedback, risk, feel, change and time were categorized into the “Reaction and Attitude” category. Check coding process in Figure **5-16**

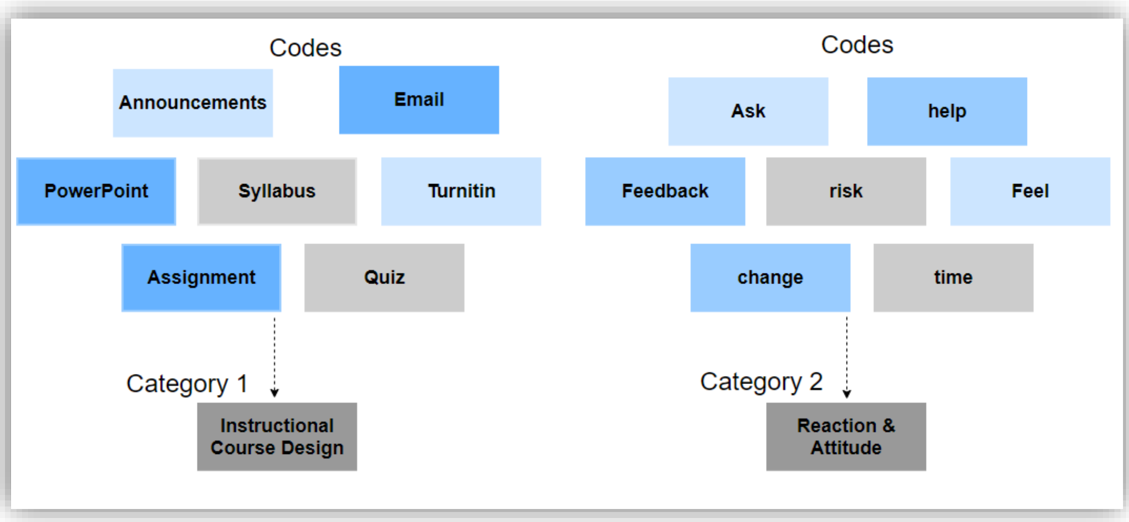


Figure 5-16: Coding into Themes

Once the interview scripts went through the six phases of thematic analysis; the two themes arose from the analysis of the 12 interview transcripts are: Instructional course design, and reaction and attitude. To ensure validity of the resulted themes, this data was shared with few of the interviewee lecturers and they agreed that it matches their interviews and key points. Anonymous sample of interviews and the resulted themes was also shared and discussed with few more lecturers in campus who have shared their feedback to finalize the resulted terms.

5.4.1 Instructional Course Design

All the lecturers agreed on usually having a start-up plan when designing their instructional Moodle course design. They usually start by organizing the Moodle course page upon either topics or upon week dates. Most lecturers relied heavily on the Backup-Restore Moodle tool. This allowed them to restore previous course materials and accordingly, they just needed to adjust and update the content. All lecturers talked about the importance of adding the syllabus early on. Followed by the PowerPoint slides, PDF and Projects and assignments. The majority though added the content gradually while hiding some items and displaying them on a weekly basis. The lecturers shared the same interest in organizing the course files and made use of certain resources such as PowerPoint and Word files. They used Moodle quizzes, assignments and mainly used Moodle labels for announcements and news forums. There were some issues that lecturers faced concerning the Moodle resources as students did not access the files:

> *Lecturer 3*: "Lots of excellent students do not click on files that I have tracked. They have one student photocopy the files and share it with her peers, so they do not click on the files themselves."

Having high GPA students helping their peers through other medium communications such as WhatsApp to help them access materials, may disturb the analytical trail of students on LMS. This is a very interesting and unique finding that seems to be a very common practice in the Saudi context. This behavior is popular in students in the Saudi context and mainly in medical schools (Alkhalaf, et al., 2018). They share resources and help-files online with their peers, also mostly using WhatsApp. Some lecturers advised students to download Moodle materials themselves, and not to rely on borrowed materials from current or past students. Lecturers indicated that the Moodle materials are always updated and changed per term, so they emphasized the need to download these materials to their students.

When Discussing Moodle resources with the lecturers, all agreed on how they always tended to upload PowerPoint slides, but this changed suddenly in

2018, when the UBT administration required lecturers to stop uploading the slides to encourage students to learn from the books. All lecturers complied with this request, but the students were not thrilled. The lecturers believed that it will slowly come back. Also, the use of discussion forums is usually used to communicate course news and updates. Each Moodle course has a news forum at start of the course homepage, where some lecturers use to post news for the students. Some argued that not all the posts triggered email notifications. Other lecturers used Moodle labels to announce any news.

Other resources that came up in the interviews were the Moodle and Turnitin Assignments. Both were used, but assignments were becoming less popular as most of the lecturers used Pearson MyLab, an additional integrated e-learning block in Moodle. Another reason for the less utilization of assignments was the usage of quizzes as an alternative for assignments because of the automatic grading. This is a popular Moodle resource that is used among the lecturers. The history of using quizzes was discussed and the importance of peer advice that motivated most lecturers to use this tool. There was a major Moodle upgrade in 2016, importing test banks to Moodle feature was improved. Most lecturers used Moodle quizzes for mainly assignments. The lecturers relied on having the automated graded feature to facilitate their workload. Learning about quizzes and other tools indicated the importance of peer feedback and how they learn from each other.

> *Lecturer 7:* “I want to explore quizzes more in upcoming terms. I feel the students do not concentrate on the knowledge. They take homework answers from their peers. But, if I use the numerical quiz as a homework, it may help the students.”

Also, communicating with the students is done often through Moodle news forums, personal emails, or the WhatsApp application. The lecturers rarely use Moodle message. But they were enthusiastic about the new analytical tools and they have used them throughout the fall term and discussed their benefits, follows.

5.4.2 Reaction and Attitude

Most lecturers utilized the Moodle analytics graphs and the completion progress dashboard. They indicated that students were interested and had huge curiosity about the new dashboard. Lecturers liked that they could observe students' engagement.

> *Lecturer 8:* "I know if a student is late or did not submit. So, if students insist on this submission, I will know. These saves time. It also encourages students to compete in engaging in Moodle".

Lecturers indicated that this is a nice tool to have for the students as they do not need to keep checking with the lecture if the assignment was received. They can know just that from viewing the green check mark on the dashboard. The lecturers indicated that the students were excited about this dashboard. Some lecturers added the Moodle blocks of the analytical graphs and the dashboard once again in their proceeding Spring term. Tracked data associated with each student, being displayed in dashboard can easily points the students at-risk to the lecturers. Lecturers can certainly attempt to help the students at-risk. Lockyer et. al (2013) stated that interventions can involve sending reminders to students, emailing them, plan group discussion and more. UBT Lecturers when asked about their actions when they observed that students needed help, the majority responded that they would share the dashboard results with the students and show them an anonymized chart without revealing students' names and attract their attention to the instant performance and engagement data.

> *Lecturer 5*: "I did this once in class and showed my lecturer dashboard to the students, I hid the students' names and shared with them how instantly, in real time, I would know their participation in the quiz or the course page."

When asked if there were any changes they would do for future courses based on the analytics of this academic term, the majority of lecturers responded that they are pleased with the analytics and dashboards as they provide essential insight for re-designing their next term courses. They usually do that all the time, but, with the analytics, it gave them more motivation to do the changes needed. Lockyer et. al (2013) discussed how analytics helped with course re-design. The authors discussed how traditionally lecturers depended on their past experience to design a new course. They usually rely on their previous notes, or students survey. With the analytics, lecturers can re-visit the learning analytics collected during a course, which can support their planning of conducting the course in the proceeding term. Some UBT lecturers even did some changes during the academic term itself.

> *Lecturer 9*: "Using the Analytical graph of the course content, I noticed that there was not a lot of hits on the Syllabus and lots of students did not even open the syllabus, I was shocked because I have 33 students and there were only 6 hits toward the 3rd week of classes. I went back to the course page and added a marquee attention statement to READ the Syllabus. The syllabus contains the requirements for the final project and the Midterm case study, and

I had to create some attention for this content to attract the student to read the syllabus".

In terms of improving course design, Sclater, et al. (2016) advised when designing a unit of learning for the second time, it is important for lecturers to have learning analytics data that show which learning activity has been used the most, which ones that have resulted in high achievement and which ones were the most difficult. UBT lecturer participant can work on re-designing their next unit of learning and update their Moodle content by using the analytical data behind their current courses.

Chapter 6 Discussions of Findings

The various data analysis findings about UBT's use of learning analytics are discussed further in this section. The case study focused on studying learning analytics at UBT with respect to students' and lecturers' usage in the Moodle LMS system. This section discusses first the learning analytics findings. This includes discussing all the data mining analysis conducted on the various learning analytics reports. Once the discussion of data mining analysis is done, the focus is shifted to the students' behavior and attitudes findings, followed by the lecturers' behavior and attitude findings. All the research questions are addressed and discussed as well. To start discussing the analysis and help to answer the research questions, see Table **6-1** which maps the research questions to the data sources and the analysis techniques (Blevins, 2013).

RQ #	RQ	Data Source	Method and Analysis	Examine
RQ 1	To what extent, if any, does students' performance relate to their learning analytics			
RQ 1.1	To what extent, if any, does students' course Final Grade relate to their Moodle Learning Analytics Metric: *Total-Activity*	User Statistics Report *(Fall)* GPA *(Fall)* Final Course Grade *(Fall)*	*Method*: Data mining *Analysis*: Correlation and Trend analysis	Students' performance in relation to their learning analytic movements in Moodle
RQ 1.2	To what extent, if any, does students' GPA relate to their logged events in the Moodle Log report?	Log files *(Fall)* GPA *(Fall)*	*Method*: Data mining *Analysis*: Correlation and Trend analysis	Students' performance in relation to their learning analytic movements in Moodle
RQ 2	To what extent, if any, learning analytics affect students' engagement and course design choices			
RQ 2.1	What LMS course design elements generate the highest students' engagement?	Activity Reports *(Fall)* Log files *(Fall)* Interview scripts *(Fall)*	*Method*: Data mining Interviews *Analysis*: Trend Analysis Thematic analysis	Students engagement and lecturer's course design options
RQ 2.2	What patterns of student engagement, recognized	Activity Reports *(4-yr)* Log files *(4-yr)*	*Method*: Data mining	Students' engagement

	from LMS course design elements, can be seen in historic Moodle data from the past 4 years?	Interview scripts *(Fall)*	*Analysis*: Trend Analysis Thematic analysis	patterns and Lecturers course design pattern
RQ 3	What are students' and lecturers' behavior and attitudes toward learning analytics and Dashboards?			
RQ 3.1	To what extent, if any, does students' GPA relate to their self-regulated learning behavior?	Survey *(Fall)* GPA *(Fall)*	*Method*: Questionnaire *Analysis:* Correlation and Regression	Students SRL behavior
RQ 3.2	What are Students' perceptions and attitudes toward using Moodle dashboards?	Survey *(Fall)*	*Method*: Questionnaire *Analysis:* *Descriptive*	Students' perception and attitudes toward Moodle dashboard
RQ 3.3	What are lecturers' perceptions and attitudes toward Moodle LA and dashboards?	Survey *(Fall)* Interview scripts *(Fall)*	*Method*: Questionnaire Interviews *Analysis:* *Descriptive* Thematic analysis	Lecturers' perception and attitudes toward Moodle dashboard

Table 6-1: Research Questions Summary Table

6.1 Learning Analytics Findings

Data mining analysis was conducted to discover the knowledge behind the learning analytics. Analysing LMS data allows lecturers to discover meaningful patterns (Gašević, et al., 2016) and rich data collected can provide insight about students' activities and inform educators with recommendations on how to enrich the learning process (Kotsiantis, et al., 2013). The data mining analysis conducted in section 5.1 resulted in tracking and recording 419 students' learning analytics associated data and collecting up to 917,251 records of course learning analytics. Three different types of reports were mined and analysed: "User Statistics", "Log Reports" and "Activity Reports" for the purpose of examining students' engagement and performance in relation to learning analytics, and lecturers' Moodle course design choices, which were the objectives of **RQ1** with its sub-questions **1.1** and **1.2** and **RQ2**, with its sub-questions **2.1** and **2.2**:

> **RQ 1:** To what extent, if any, does students' performance relate to their learning analytics.
> **RQ 2**: To what extent, if any, learning analytics affect students' engagement and course design choices.

6.1.1 Learning Analytics and Students Performance

The learning analytics that were used to examine students' performance were the Moodle LA metric *Total-Activity*, collected from the "User Statistics" report and the Moodle Log reports that recorded all users' actions in the courses. Performance was measured by the students' final course grade and the students' GPA. To answer **RQ1**, two sub-research questions are discussed in this section. The first sub-research question **RQ 1.1**:

> **RQ 1.1**: To what extent, if any, does students' course final grade relate to their learning analytics Metric: *Total-Activity*?

To answer RQ 1.1, data mining analysis of "User Statistics" was conducted. The analytics of "**User Statistics**" focused on collecting students' movements in each course and tracking their clicks. This was measured by the number of views and posts the student does in each course. So, a student logging to Moodle, and accessing their course page, and downloading a Syllabus, these would count as views. If the student uploaded an assignment, or added a discussion entry in the forum, these would count as posts. So, the data collected here was about the students' total views and posts. This was called the *Total-Activity* metric. All 419 students' *Total-Activity* metrics were collected for each course they are enrolled in. From the data mining process discussed in section 5.1.1, additional process was done to obtain and input and merge the students' GPA and final course grades. By this, the mined file "**User Statistics**" was ready to be analysed to examine any sort of association between the students *Total-Activity* metric and the student's performance. So, examining the relationship attempted to discover the association for example, between a student with a total activity of 400 and a grade of 70 or another students' total activities of 1300 and a Grade of 95. This examination answered the research sub question **RQ 1.1**. The resultant mined Excel file of the 419 records containing students' *Total-Activity* metric and their associated courses final grades along with the GPA, were analysed using SPSS correlation. With a significant correlation at the 0.01 level (2-tailed), the Final grades turned out to have a significant positive correlation of 0.265 to the student' *Total-Activity* metric. A similar correlation examination was also conducted using GPA, and it was also proven to have a significant positive correlation with a value of 0.293 associated with the *Total-Activity* metric

A follow up data mining process to interpret the resultant data and discover further knowledge was conducted to predict students' performance based on their analytics in the course (Curve estimate regression was used to test the relationship further between students' final grade and their *Total-Activity* metrics. As a result, a set of regression models were listed, and the quadratic model turns out to be the best for this case, earning a higher R^2 value of .083. The resultant model equation that can help in predicting students' final grade in a course from observing their movements in the course (*Total-Activity* metric) is:

$$\text{Final Grade} = 72.513 + 0.054 * (\textit{Total-Activity}) - 0.00004025 * (\textit{Total-Activity})^2$$

Similarly, another regression examination was conducted to construct a model for the GPA association with *Total-Activity* metric. The resultant quadratic equation is:

$$\text{GPA} = 3.381 + 0.004 * (\textit{Total-Activity}) - 0.000002663 * (\textit{Total-Activity})^2$$

So, the learning analytics metric, to an extent, affects the students' final grade in the associated course and also their GPA. The Final grade has a positive association of 0.265 to the *Total-activity* metric, whereas the GPA has a positive association of 0.293. An association of 26% and 29% is not strong. But, in the UBT case, with the traditional course settings, and the use of Moodle as a supportive platform for further learning and assessments, it seems applicable to have this not so strong positive association. This though calls for further research into other factors that may affect students' performance. So, **in summary, RQ 1.1** indicated that the students' Final grade has a positive correlation of 0.265 to the *Total-activity* metric. This correlation, though, does not prove causation as discussed in the analysis, section 5.1.1.

Examining the second type of learning analytics (**Log Reports**)' association with the students' performance answered the second research sub-questions **RQ 1.2:**

> **RQ 1.2:** To what extent, if any, does students' GPA relate to their logged events in Moodle log report?

Mining the Moodle courses Log reports gave additional insight into associating the students' performance to their analytics. The report "**Log Report**" collects every single action done in the course from start to end. It collects all information about the student, instructor, guest, administrator, and any other assigned user and collects every single movement and action conducted. Examples of actions are viewing a resource, attempting a quiz, submitting a quiz, and deleting a submitting. The set of actions are called events. Data mining analysis for the Fall 2018 log file was conducted in sec 5.1.3. One of the discoveries attempted to associate the students' GPA with their type of actions (events) conducted in Moodle. The mining process helped to highlight this. Examining students' GPA and what type of events they usually conduct helped to give further insight into the association of students' performance to their analytics. Each student had a particular pattern when accessing resources and activities in Moodle. Highlighting the type of events and the extent of using these events associated with high GPA students (A Students) can provide guidance to other students with lower GPA on how to improve their performance. Trend analysis was used to highlight 'A' students' usage of the Moodle resources. The data mining analysis conducted for the log file associated with the students' GPA showed that the topmost frequently used resources by the 'A' students were viewing Discussion forums, viewing profiles, reviewing quiz attempts, submitting a submission, and uploading a file. The other students have already used some of these events, but 'A' students stood out with the high percentage of utilization of these events. The log file analysis indicated that 74% of Discussion forum viewings were done by the 'A' students, so, the remaining 26% viewing was done by the mid-to-low GPA students. The Discussion forums viewing high utilization indicate that 'A' students tend to communicate and check class news constantly. According to the lecturers' interview analysis, the discussion forums used in the UBT learning environment are mainly used for course news and communication, not commonly used for course online activities nor assessments. So, ‘A’ students tended to be keen to follow up continuously during the term with any announcements and class news. The analysis also indicated that 72% of user profile viewing was conducted by the ‘A’ students. The user profile viewing event is triggered by the interest to check one’s profile and checking the lecturer’s and peers’ contact. So, continuous viewing of the profile indicated attempts at communicating and viewing contact. A similar percentage of 72% of reviewing quiz attempts was also conducted by the ‘A’ students. Reviewing a quiz attempt means viewing the answers of a conducted quiz. If this was done during the term several times, because of the high percentage, this indicated that the ‘A’ students kept reviewing quiz content, for possibly the purpose of studying and learning to increase knowledge or for preparing for a midterm or a final exam or even a project. The log analysis also indicted 70% of submission viewing and file uploading was conducted by the ‘A’ students. This indicated that the ‘A’ students participate constantly in submitting work either in Moodle Dropbox, or any type of Moodle assignment. So, **in summary**, **RQ 1.2** highlighted the Moodle events mostly utilized by higher GPA students: viewing Discussion forums, viewing profiles, reviewing quiz attempts, submitting a submission, and uploading a file.

To conclude, the analysis of the association of the students’ performance to their Moodle analytics by data mining “**Students Statistics**” and “**Log Reports**” **RQ1** and its sub-questions **RQ 1.1**, **RQ 1.2 were answered**. Students in a traditional face-to-face learning environment that highly utilize Moodle online learning resources can enhance their performance by increasing their level of activities in Moodle, by increasing the number of views and posts in Moodle. The students' statistics report analysis indicated that such increase in Moodle movement gave a 26% chance to enhance the students' course final grade and a 29% chance to enhance the students' GPA. Also, to enhance the students' GPA, the logged events analysis provided a certain pattern the students can follow to enhance their performance. Following up continuously with the class news and announcements, intending to communicate continuously with class peers and lecturer during the term, reviewing quiz attempts several times during the term to possibly prepare for further exams, and submitting required files during the term and uploading multiple times, are all factors that may help to improve students' GPA.

6.1.2 Learning Analytics and Engagement and Course Design

Now that students' performance has been examined, students' engagement with Moodle course elements and lecturers' course design choices were addressed in answering **RQ 2** and its sub questions **2.1**, **2.2**:

> **RQ2**: To what extent, if any, learning analytics affect students' engagement and course design options.

Both "**Log Report**" and "**Activity Report**" data mining analysis are used to answer RQ2 and its two sub questions RQ 2.1, RQ 2.2. Both reports record similar elements of the course design as explained in the methodology section 4.1.3. "Log Report" automatically collects all sorts of actions (events) conducted by all users in the Moodle course and it is one-click to download the whole file, ready to be processed. While the "Activity Report", a short-grouped activity report that has to undergo several steps of data transformation to acquire a formatted file ready for processing.

To answer the research sub questions RQ 2.1, both Fall 2018 “Log Reports” and “Activity Reports” combining a total of **616,757** records of analytics were mined and the analyses were discussed in sections 5.1.2 and 5.1.3.

RQ 2.1: What LMS course design elements generate the highest students’ engagement?

Starting with the mined Fall 2018 “Log Report” containing **614,824** records of data, the data mining resulted in displaying the topmost logged events. These events were triggered by specific LMS course design elements. The top events that were associated with the students and got the highest students’ engagement were viewing a quiz attempt, viewing status of a submission, viewing a Turnitin assignment, viewing submission of a form, review quiz attempt and its summary, and uploading a file. The associated course design elements for these top events are Moodle Quizzes, Turnitin Assignments, Discussion forums, and Moodle Assignments. So, according to the Log report analysis, the highest students’ engagement was mainly related to assessment tools such as: Quizzes, Turnitin and assignments.

Similarly, the mining of the Fall 2018 “Activity Report” containing **1933** records of data was conducted. It resulted also in displaying topmost Moodle activities conducted in UBT courses along with the number of hits for each. These were the assessment tools: Quizzes with 35% usage and assignments with 17 % usage. Lecturers in the interviews expressed the importance of conducting

Moodle quizzes for the students as it saved time, and automatically calculated the grades. Discovering these topmost activities of Moodle course design content helps lecturers to incorporate what course design element that increase students' engagement.

So, **in summary**, **RQ 2.1** indicated that the topmost course design elements that generated the highest students' engagement were mainly the assessment tools such as: Quizzes, Turnitin and assignments.

While the Fall 2018 data mining results attempted to highlight the LMS elements with the highest students' engagement and answered RQ 2.1, a **4-year historic data** analysis attempted to convey the same objective but highlighting an engagement pattern over a 4-year period. This was the objective of **RQ 2.2**:

> **RQ 2.2**: What patterns of student engagement, recognized from LMS course design elements, can be seen in historic Moodle data from the past 4 years?

The same types of the two analytical reports "**Log Report**" and "**Activity Report**" were also used, but for the 4-year data (2015 → 2018) with a total of **300,494** records of analytics to mine. The mining highlighted the top events utilized in the UBT learning environment. The pattern of students' engagement exhibited different engagements from year to year. Some events experienced a continuous increase in each new year. Some events had a sudden drop or change. The following is the pattern found for the top logged events associated with students' engagement. For example, the year 2015 covered only 5% of quiz engagement compared to the sudden 30% jump in engagement in the proceeding 3 years (2016, 2017, 2018). This 3-year period engagement boost was because of the Moodle software upgrade in 2016 that improved the import-Moodle test bank feature as discussed during the lecturers' interviews.

Another instructional design pattern change was about the viewing-Turnitin-assignment event. It increased continuously during the first 3 years and engagement was dropped suddenly in 2018. When discussing Turnitin with lecturers and why the sudden decline in using it, a few indicated the lack of support and the limited workshop conducted about Turnitin in that timeframe. The file-upload event had a similar increased pattern but, since 2015, it started with 19% usage, then it gradually increased until it reached 35% in 2017 and then a sudden drop once again in 2018 to 16%. Discussing this issue with the lecturers, the use of Pearson MyLab decreased the need for Moodle assignments, so, less submissions and uploading was done in 2018. This was the same pattern with the submitting-a-submission event. All due to the use of MyLab instead of Moodle assignments. There was a different pattern with the discussion-viewed event. It had a steady increase during the years and then a sudden decrease started in 2018. According to the testimonies, this was due to changes in administration in that year with less attention provided to Moodle workshops.

Similarly, the mining of the "Activity Report" for the 4-year data (**2886** records data) shared close results to the mined "Log Reports". Quizzes had steady increase from 2015, starting with 7% usage and gradually increasing, reaching 34% in 2018. Assignments were utilized the highest in 2017 with 34% of all the years, and then suddenly a drop to 14% in 2018. Discussion forums were utilized in the same percentage during the years, except for a sudden increase in 2016.

Observing the Activity analytics and the event logs, especially among different years at UBT gives attention to the institution’s policy and administrative changes and software decisions conducted. For example, the integration of additional blocks to Moodle such as Pearson MyLab, interrupted the utilization of Moodle’s own tools. But Pearson MyLab provided learning materials and assessments that benefited the students and helped them learn. MyLab has also its own analytics that can be observed by the lecturers. To abandon creative add-ons and tools just to allow the full utilization of Moodle resources may not be convenient as this would require lecturers to build their own materials, exams, and assessments, which needs time. UBT can try to utilize both (the add-ons resources and the existing ones) and may incorporate both analytics in the Moodle platform, with an open-source software, this possibility is applicable. Policies to integrate the analytics can help to provide full information on students’ footprint activities. So, **in summary, RQ 2.2** highlighted the 4-year pattern of students’ engagement. This discovered mainly topmost events utilized: Assessment tools such as quizzes, Turnitin, assignments and Discussions. Also, top resources utilized: Quizzes, PowerPoint, Syllabuses, and assignments. All discovered data shared similar variations over the 4 years due to some institutional and policies changes. For instructional course design best practice and for increasing students’ engagement, lecturers can add more assessment tools and assessment resources to their Moodle instructional course design. Lecturers can also adopt more quizzes, Turnitin assignments. Lecturers can also utilize discussion forums as assessment tools. Providing the top engaged Moodle course elements in the course design and attracting students to use these resources can help to enhance students' engagement and performance. So, to conclude the analysis of the association of the analytics to students' engagement and course design by data mining both "**Log Report**" and "**Activity Report**", along with the lecturers' testimonies, **RQ2** and its two sub-questions **were answered.** The analysis highlighted the Moodle course instructional design elements and patterns that generated high students' engagement which they were mainly the assessment tools.

6.2 Behavior and Attitudes Findings

The lecturers and students who participated in this study, completed a questionnaire at the end of Fall 2018. The questionnaires aimed to examine students' and lecturers' behavior and attitudes toward learning analytics and the dashboards. The lecturers were also interviewed to get further insight into their behavior and attitudes. **RQ 3** with its sub questions: **3.1, 3.2** and **3.3** examined students and lecturers' behavior:

> **RQ 3**: What are students' and lecturers' behavior and attitudes toward learning analytics and dashboards?

6.2.1 Students' SRL Behavior and Attitudes Towards LA and Dashboards

The questionnaires questions examining behavior and attitudes were built upon Pintrich's Self-Regulated Learning (SRL) theory as discussed in the data collection section 3.2. The questionnaire analysis reported in section 5.2

provided an insight into students' learning behavior and examined further its relation to their grades and queried their attitudes towards the **completion progress dashboard.**

Elements of SRL: planning and setting one's goals, monitoring, control and reaction and reflection (Pintrich, 2004), were queries sought through surveying the students. Examining the students' learning behavior and having an insight into their self-regulated learning behavior may point them out as active participants in their learning process (Zimmerman, 1990). The SRL behavior elements that UBT students stood out with were the reaction and reflection and monitoring behaviors. The lowest SRL behavior skill was for the control behavior element. This low control SRL behavior skill can be improved by raising the students' interest and enthusiasm to manage their own learning. Taking control of own's learning helps one to understand areas of weakness and strength that can help students adjust and perform better. Managing time seems to be the main issue affecting students' behavior (Eilam & Aharon, 2003). The university can help to improve students' control skills by providing workshops for time management and encouraging lecturers to provide the needed support. Introducing the students to educational dashboards, as UBT has done, can help to increase the SRL behavior elements including the control behavior. Educating students how to manage tasks and understand how to utilize time will help them gain control of their own learning and manage their tasks and stay focused and engaged in the learning environment.

Further examination on the SRL behavior and its association with the students' performance was examined and the questionnaire analysis (section 5.2) helped to answer the research sub-question RQ 3.1:

> **RQ 3.1**: To what extent, if any, does Self-Regulated Learning behavior affect students' GPA?

Questionnaire Questions 1- 16 were collected, and SPSS Regression analysis was conducted to test the association of the GPA with 16 different SRL elements. To answer research sub-question **RQ 3.1**, a stepwise regression analysis was conducted in section 5.2.3 and resulted with 4 out of the 16 SRL elements affecting the students' GPA either positively or negatively. The resultant model had the highest R^2 of 0.64 among the different models displayed. The four elements affecting the students' GPA were: Loosing attention easily online (**Control ↓**), keeping track of Moodle deadlines (**Monitoring ↑**), planning out a study plan for Moodle activities (**Planning and Goal settings ↓**), and managing to work even if Moodle materials are dull (**Control ↑).**

There are certain characteristics that identify Self-regulated learners, as indicated by Mega, et al., (2013). Self-regulated learners tend to constantly plan, organize, monitor, and evaluate their learning during this process. They set standards and goals for their learning (Mega, et al., 2013). Out of the 4 associated SRL elements results in the analysis, 3 elements identified strong SRL skills of the UBT students. Two elements demonstrated control and the third demonstrated monitoring; Control (Managing to work even if Moodle materials are dull and managing not to lose attention online) and monitoring

(Keeping track of Moodle deadlines). The fourth SRL element of establishing planning and strategy did not have a positive effect on the students' grades. So, creating a study plan for Moodle did not work positively here. The other 12 SRL elements did not have any effect (neither positive, nor negative) on the students' grades, such as setting goals to utilize Moodle, or estimating the time needed to do a task in Moodle, or knowing the grades update or even asking for help when needed and more. So, in this case, if students adopt behaviors related to control such as increasing efforts, changing or negotiating tasks, and behaviors related to monitoring such as self-observing and monitoring time and monitoring needs (Pintrich, 2004), these efforts can help to raise one's GPA. You (2016) shared similar results that examined SRL and academic achievements. You (2016) found that time management skills dominated mostly as a major predictor of achievement. In this research study though, several SRL elements contributed to predict the performance of the students. This showed when regression modeling was used to analyze the 5-LIKERT SRL questionnaire, and predicted the students' performance using the model:

GPA = 3.808 -. 124 (loss of attention) + .161 (Tracking deadlines) - .112 (planning a study plan) +. 098 (working with dull materials)

So, **in summary**, **RQ 3.1** indicated that four SRL elements affected student GPA: Loosing attention easily online (**Control ↓**), keeping track of Moodle deadlines (**Monitoring ↑**), making a study plan for Moodle activities (**Planning and Goal setting ↓**), and managing to work even if Moodle materials are dull (**Control ↑).** With an unexpected result, discussed in the analysis section 5.2.2, where too much planning affected the students' grades negatively, that indicated the need to learn more about the challenges behind this result and the need to use planning in an effective way.

A second analysis sought the students' attitudes towards the use of the Moodle completion progress dashboard. To answer the second research sub-question **RQ 3.2**:

> **RQ 3.2**: What are Students' attitudes towards using Moodle dashboards?

SPSS descriptive statistics were used to analyze 3 attitude questions. 75% of students understood the purpose of the dashboard, 76% believed that the dashboard was useful, and 73.3% were interested in using them. The results matched what the lecturers indicated in their interviews. Students were interested in the dashboard. They were even curious and competitive when using it.

> L*ecturer 8*: "Yes, the students are interested. One student showed up querying about her 20% usage in the dashboard compared to her peer with a 70% completion rate. I comforted her and I explained again to her that this is a measurement for how much she is using Moodle and viewing the needed resources. Then, she replied that yes, she did not use Moodle much."

According to Lecturer 8, the student came back after a while pleased that her completion rate was raised to 99%. The lecturer was happy, but she reminded her that this does not reflect the final grade, she needed to prepare well for the exam. The overall satisfaction with the dashboard was indicated by 73.7 % students' satisfaction rate.

For UBT students to experiment with the **completion progress dashboard**, this raised the awareness for students to be more reflective. Reflecting back to one's work is a skill that needs more attention and needs to be adopted more in the Saudi learning context (Nasseif, 2019). Nasseif (2019) indicated the importance of enriching the reflection and self-evaluation students' skills to be adopted in the Saudi educational institutions. Students' feedback in Nasseif (2019) indicated the need for course assessment tools that allow students to self-reflect and self-evaluate. So, having an easy-to-use tool such as the completion progress dashboard, that is both interactive and visually appealing, can certainly help to promote self-reflection and self-evaluation skills of students. Lecturers' testimonies in this research study from the interviews embraced the enthusiasm the students had with exploring this new dashboard tool. Other SRL research suggested that prompting students to reflect upon their own learning is useful for improving SRL skills.

So, **in summary, RQ 3.2** indicated that 75% of students understood the purpose of the dashboard, 76% believed that the dashboard was useful, and 73.3% were interested in using them.

For this research study, the fact that the visual display caught the attention of the students with the different color checkmarks, prompting them to use the dashboard and reflect and react towards using the dashboard, support the claim of Bannert and Reimann (2012) that one can improve students' SRL behavior by prompting them and encouraging them to be active participants in the course activities.

6.2.2 Lecturers’ Behavior and Attitudes Towards LA and Dashboards

Similar to exploring students’ attitudes and behavior, part of this research explores the lecturers’ behavior in Moodle concerning how they build their course design, what Moodle tools and resources they adopt. Both interviews and questionnaires were conducted to cover behavior and attitudes actions. Both the questionnaires and the interviews were built upon the Self-Regulated Learning (SRL) elements where lecturers as learners dealt with a new technology and got to learn and adjust their behavior when dealing with Moodle analytics and the dashboard. They got to plan and set goals for learning these new tools and they got to monitor and control their usage and react and reflect upon using these new tools. The Questionnaire analysis in section 5.3 and the interview analysis conducted in section 5.4, helped to provide an insight into lecturer’s adoption of learning analytics and dashboards and their behavior and attitudes and helped to answer RQ 3.3:

> **RQ 3.3**: What are lecturers’ perceptions and attitudes towards Moodle Learning Analytics and dashboards?

The questionnaires started by seeking lecturers’ input on their course instructional design choices and then followed by seeking their opinions towards the **completion progress dashboard** and the **analytical graphs** and if they have welcomed this experience and if they are willing to try these analytical tools once again. Such experience helps the lecturers make use of the new tools and benefit from them. The lectures used the insight as indicated by Bakharia, et al. (2016) to gain from the analytics contextual knowledge to make decisions in improving the delivery of the learning objectives, then adopt the learning design. The top resources used by UBT lecturers according to their testimonies were uploading files, assignments, and announcements.

UBT's lecturers stood out with the SRL monitoring skills, followed by the planning and goal setting skills. Lecturers as learners exceled in planning their Moodle course design and content and monitoring the progress of the students during the term and adjusting their course design based on input sought during the academic term. The top Planning and goal setting activity was preparing the Moodle course design at start of the term. The top Monitoring skills activity was the periodical update of the course design content during the term. The top reaction and reflection activity were the admitting of the usefulness of the Moodle analytical graphs. The lowest SRL behavior element was for control.

Descriptive statistics were also used to analyze the lecturers' attitudes toward the analytical graphs and the completion progress dashboard. 94% of lecturers believed in the usefulness of the dashboard and the analytical graphs. 81% of lecturers believed that the dashboard helped guide the students, where only 69% of lecturers believed that analytical graphs helped them guide the students. Also, 69% of lecturers believed that the dashboard identified students at risk, whereas 75% felt that analytical graphs did help them to identify at-risk students. Overall, 93.8% of lecturers are willing to use the analytical graphs and dashboard again. The lecturers' attitudes results revealed a higher positive attitude towards the analytics compared to students as lecturers had 93.8% willingness to use the analytics, compared to the 73%

students had. This is expected as the lecturers had more analytical tools to use and investigate and explore their benefits, whereas the students had a small dashboard, that if setup effectively by the lecturers, can help the students. But, if the tool was not setup and neglected and not monitored well by the lecturer, the student may lose interest in using these tools.

To understand further the lecturers' attitudes, interviews were conducted, and interview scripts were analyzed (section 6.4). The interview questions were built also upon SRL. Lecturers' testimonies in the interviews highlighted their planning and goal settings as each lecturer described their strategies when building their Moodle courses. They all understood the importance of uploading the syllabus and course outline and learning outcomes. The testimonies also highlighted their monitoring and control SRL skills when dealing with the analytics and dashboard. They mostly shared their strategies when setting up the Moodle blocks and monitoring the students' progress throughout the academic term and adjusting content or communicating any students' outcome related to the analytics. The lecturers' reaction and reflection of SRL elements were highlighted in their actions towards the analytics and dashboard during the term as well. The interview analysis indicated how the Moodle completion progress dashboard helped to identify inactive students from the start of the term, and how this helped lecturers to reach out to them or attempted to change current instructional design elements in the course. Some lecturers even revisited some of the design elements in their course and noticed the lower clicked resources and attempted to add changes to increase the attention to the resource. A sample of change was adding HTML marquees in the Moodle course content to attract students' attention to click the resource.

So, **in summary, RQ 3.3** indicated that lecturers were very pleased with both the analytical graphs and the dashboard and that they would use it again. To conclude the questionnaire and interview analysis that examined both students' and lecturers' behaviors and attitudes, RQ 3 and its sub-questions were answered. Students SRL behavior of monitoring and control affected positively their GPA, where an unexpected behavior related to Planning affected the GPA negatively. Reasoning discussed in the analysis such as lack of time and inadequate planning may have caused this negative association. In regards to students' attitudes, 73.3% indicated interest in using the dashboard again, compared to 93.8% of lecturers'. The lecturers' top SRL behavior was related to planning and goal settings and the monitoring of behavioral skills. Lowest skills though were for the control behaviors. This did not stop the lecturers from exploring and learning and using the new analytical tools and dashboard. They were pleased using the Moodle Analytical graphs block and the Moodle completion progress dashboard. Lecturers understood the purpose of the analytics and found promising benefits concerning recognizing students who are at risk and acknowledge how the analytics can help in reaching out to students and the value in adjusting their course design elements.

6.3 Summary of Findings

The UBT case study helped to highlight major learning analytics issues in the Saudi Arabian Higher education. The case study focused on analyzing the use of learning analytics and dashboards in the higher education context focusing on both students and lecturers experience. The case study started in the summer of 2018 by implementing the Moodle analytic graphs blocks and the completion progress dashboard and training the lecturers to use them. Then, it kept track of the analytics and students and lecturers' engagement during the academic term of Fall 2018 term. Different analytical data sources were collected from both the Fall 2018 term and a 4-year consecutive historic period. Data mining for these different analytical Moodle reports was conducted, followed by statistical and trend analysis using Excel and SPSS. Interviews and questionnaires were used to support investigating the learning analytics at UBT. Data collection and mining analysis started at end of fall 2018 and lasted until the start of Fall 2019. The learning analytics and dashboard experience at UBT was overall, a successful experience where both the lecturers and students were enthusiastic and pleased to participate. Lecturers' and students' attitudes and perceptions about the use of Moodle Analytics graphs (viewed only by lecturers) and the completion progress dashboard (viewed by both lecturers and students) were positive and earned high percentages for interest in the tools and for the benefits of understanding learning behavior.

The availability of the educational dashboards in the educational institutions help students to be more involved in monitoring their own actions and give them a chance to track their progress. It can be challenging if students do not understand the purpose of this visual colorful icons panel, and it can add confusion if the students were not oriented enough about it and were not followed up and supported in their usage during the term. The support of the lecturers helped to avoid such challenges, and with the institutional support in providing training and future workshops, such confusion and discomfort can be minimized.

Also, exploring Moodle behavior in terms of SRL elements was helpful. It was helpful to examine technology usage and translate its usage into SRL terms. This worked best for both students and lecturers. Students expanded their awareness about their own behavior and learning skills. Such awareness also came in handy for the lecturers who themselves were learning about new technology tools independently during the academic term.

A summary of the findings is listed next. As stated in the methodology section 3.1.2, the data mining findings are highlighted using the four data mining stages defined by Minelli, et al., (2013): Descriptive data - Facts and Statistics data about number of participants, reports and such; Diagnostic data - what is the discovered knowledge; Predictive data: what future prediction can be constructed; Prescriptive data - what recommendation is recommended as a next step. All findings listed help to provide recommendations to enhance students' performance, engagement and improve course instructional design.

6.3.1 Students' Performance and Total Clicks in Moodle

Key Finding: Higher number of clicks (*Total-Activity*) records significant positive association with the course final grades and the students' GPA.

- **Descriptive data:** Total students who consented to use their LA and grade data = 419 students, number of users' statistics visited= 419 users' statistics, highest *Total-Activity* = 1522*,* lowest *Total-Activity* = 13*,* highest *Course grade* =100 *,* lowest *course grade* = 0 *, highest GPA is 5, lowest is 1.5.*
- **Diagnostic data:** There is a significant positive correlation of 0.265 between students' analytical movements in the course (*Total-Activity*) and Final course grade. There is also a positive correlation of 0.29 between students' analytical movements in the course (*Total-Activity*) and the students' GPA.
- **Predictive data**: Predictive models that resulted from the study to predict final course grade and GPA using the *Total-Activity* metric is:

  Final Grade = $72.513 + 0.054 * (\textit{Total-Activity}) - 0.00004025 * (\textit{Total-Activity})^{2.}$
  GPA = $3.381 + 0.004 * (\textit{Total-Activity}) - 0.000002663 * (\textit{Total-Activity})^{2}$
- **Prescriptive data:** With a 26% positive association of the final course grade and a 23% positive association with the GPA, students can attempt to improve their performance by being more attentive to the online learning resources available in the LMS system. Increasing the number of hits (increasing the total activities metric) provides a chance for improving the student final course grade. But, the 26% and 29% effects are not that strong, this calls for further research to investigate other factors that might affect performance in the UBT traditional course setting with heavy utilization of Moodle.

6.3.2 Students' Performance and Moodle Logged Events

Key Finding: High GPA students tend to have a particular pattern recorded in the Moodle log file. A set of Moodle events are highly utilized by the high GPA UBT students.

- **Descriptive data:** Total students who consented to use their LA and grades data = 419 students, number of Fall 2018 log files examined = 60 reports, with a total of 614,824 records of data and a total of 110 different type of logged events.
- **Diagnostic data**: The Moodle log events utilized by the '*A'* students are: *Discussion-forums-viewing*, *user-profile-viewing*, *reviewing-quiz-attempts*, *submission-viewing,* and *file-uploading*.
- **Predictive data:** To improve one's GPA, student can try to be keener to communicate with the lecturer and classmates, keener to prepare and review knowledge, and keener to submit the required tasks.
- **Prescriptive data:** Recommended actions for course lecturers to build the course instructional design to support more communication tools and install the completion progress dashboard to allow students monitoring their submissions. Low-to-mid GPA students can utilize more the assessment and communication resources to improve their performances.

6.3.3 Students' Self-Regulated Learning Behavior and GPA

Key Finding: UBT students stood out with 4 elements of self-regulated learning that promote their learning behavior and affect their GPA accordingly.

- **Descriptive data:** Total students who filled the survey and consented to use their LA and grade data = 419 students, SRL behavioral elements examined = 16 sub elements for (planning, monitoring, control, reaction, and reflection).
- **Diagnostic data:** The resultant four sub elements affecting the GPA are mainly Control and Monitoring elements. 3 elements affecting the GPA positively: Keeping track of Moodle deadlines, and avoiding loss

of attention online, and managing to work and study even if Moodle material is dull at any point. The last element effects the GPA negatively which is the additional planning to plan out a study plan specifically for Moodle activities, a unique finding.

- **Predictive data**: A predicted GPA model that resulted from the 5-LIKERT answered input of the SRL elements:

  GPA = 3.808 -. 124 (loss of attention easily) + .161 (Tracking deadlines) - .112 (creating a study plan) +. 098 (managing to work with dull materials)

- **Prescriptive data**: Recommendation for students to adopt behaviors related to control, such as increasing efforts, changing or negotiating tasks, and behaviors related to monitoring such as self-observing and monitoring time and monitor needs, all efforts that can help to higher students' GPA.

6.3.4 Lecturers' Course Design and Students' Engagement

Key Finding: What course instructional design elements increase students' engagement.

- **Descriptive data**: Number of activity reports analyzed: 60 Fall 2018 reports and 59 historic reports, the same for the log files: 60 Fall log files and 59 historic log reports, with a total of 915,318 records of data.
- **Diagnostic data:** Course design elements that obtained highest students' engagement according to the LA analytics, using Trend analysis are Moodle assessment tools such as Moodle quizzes, Turnitin Assignments, and Moodle assignments.
- The historic pattern of course design that resulted from analyzing the 4-year analytical data indicated the top engaged Moodle activities were Quiz engagement, Turnitin Assignments, Moodle assignments and Discussion forums. It also highlighted a sudden drop and sudden increase in the activity engagement due to some institutional changes in administrative and software changes such as the Moodle upgrade.
- **Prescriptive data**: Based on the students' engagement numbers, one can advise lecturers to incorporate more assessment tools in their

instructional design. They can also utilize other Moodle resources to add assessment elements to it such as using the discussion board and utilize it as an assessment in the course, containing course topics activities rather than just using it as a course news announcement.

Below are the main SRL behavioral key findings of lecturers' and students' behavior according to their testimonies in the questionnaire:

6.3.5 Students' Behavioral Highlights

Key findings: There were several major highlights that came out in regards of students' behavior. There was one standout behavior that came out of the students' survey. The odd result was the negative association of the SRL skill '*planning'* with the students' performance. The more the UBT student plans, the lower the GPA. The analysis discussed how time constraints and poor plan utilization may have contributed to this low performance outcome. Another of the students' behavior that stood out in the analysis came out from the interview analysis of lecturers' testimonies. UBT students tended to share Moodle resources with their peers through other communication mediums such as WhatsApp. The Saudi context students seem to lean towards helping each other and keeping their peers updated with the course materials. This notion may disturb the analytics of Moodle as some students are not utilizing the resources directly. Other behavioral findings included:

- Students highest SRL skills according to their testimonies was the reaction and reflection skill with a mean of 4.13 and monitoring with a mean of 4.10.

- Students' reaction skills include: Changing strategies when no progress, asking peers and lecturer for help and learning from mistakes when failing at a task.
- Students monitoring skills include tracking of their deadlines, knowing their grades, accessing updated course news, and keeping up with the weekly reading and assignments.
- The lowest students' SRL skills was for control with a mean of 3.57.
- According to the students' testimonies, they feel they lack more in control skills such as knowing when behind schedule, loosing attention online, and managing dull materials.
- Adding students' analytical dashboard can help to strengthen the students' SRL behavioral skills. The institution can also provide workshops to help students increase their control behavior skills.

6.3.6 Lecturers' Behavioral Highlights

- Lecturers' highest SRL skills according to their testimonies was monitoring with a mean of 4.28.
- Lecturers' monitoring skills mainly was updating Moodle content periodically.
- The lowest lecturers' SRL skills was control with a mean of 3.39.
- According to lecturers' testimonies, they feel they lack more in control skills such as in changing Moodle course design content upon changes in students' performance, or peer observation or upon the new insight from the completion progress dashboard and the analytics graphs.

- Similarly, adopting and implementing analytical dashboards can help lecturers enhance their control skills as they can witness the benefits of adjusting and changing upon real-time data.

Based on the Analysis conducted in this research study for the different data sources and based on the students' and lecturers' input through the questionnaire and the interviews, one can describe successful learners and successful course designers in relation to learning analytics. Successful learners according to the UBT case study can improve their performance if they increase their level of online activities and participation. Also, if they can adopt more monitoring and control SRL behaviors, they can improve their performance. They can also try to conduct all their assigned quizzes and submit all their assignments and be in constant communication throughout the term with the course news, and in contact with the course lectures and their peers, all in order also to improve their performance.

Successful course designers can improve their course instructional design if they monitor students' actions through the analytics and dashboards to make any needed changes or adjustments during the academic term. They can also improve the course design and increase students' engagement by adding more of the assessment tools such as Quizzes, Moodle assignments and Turnitin assignments. Now, that the study findings are finalized, generalizing this case study, limitations, recommendations, study contribution and future study are discussed next.

Chapter 7 Conclusion

7.1 Case Study Generalization

Extending this study and generalizing it, would be a recommended step as learning from this one case can help to understand many more cases (Yin, 2013). Though, careful consideration should be conducted before generalizing the UBT case study. Also, even though, Moodle data sources are used by a lot of educational institutions, one should be careful before building a generalized model for the log-data, for example, and attempt to predict academic success (Gašević, et al., 2016). This is because even though many institutions have an LMS, the ways learners use LMS differ. Are they totally dependent on LMS (online learning environment), flipped learning, or semi-depended as in a traditional environment? To generalize a case study is to interpret the same findings on a larger population. To generalize the UBT case study, the researched participants and courses need to have similar characteristics to this study as in being a higher education institution with a traditional face-to-face environment that facilitate LMS for online learning activities that are used in and off campus. The main characteristic is the high utilization of LMS activities in a traditional setting. Generalizing the study in a learning environment that does not use LMS will not be effective. At least, the minimum requirement is similar utilization of LMS. With a current study participant of 711 students and 60 courses sample, covering similar diverse characteristics such as gender, campus location, course types, students' level, one can attempt to generalize it to a bigger population. By this, the UBT case study can be generalized to any higher educational institution with a traditional setting and high utilization of LMS in Saudi Arabia.

7.2 Limitations

Discussing the research outcomes and findings have provided an insight on students' analytical movements in relation to their performance and behavior. Though, the data collected about students' clicks did not point directly to causation. For a traditional face-to-face learning environment, it was clear that clicks did not indicate learning. It is more about indicating engagement (Douglas, et al., 2016). Focusing on examining the correlation between students' clicks and their performance triggered a limitation as this did not provide a causation. With the weak association between the clicks and the performance, it is important, as discussed, to explore other variables that may contribute further to the students' performance. As stated in the findings' discussions, variables such as students' characteristics, gender, demographics, school type, student level, and such can provide further insight to the performance. The analysis findings did highlight the role of clicks in pointing out students' engagement and instructional design tips for the lecturers.

In regards of the research process itself, there was also some limitations and challenges. One of these limitations was about obtaining students' consent at the start of the research. It was done very carefully to follow Lancaster ethics policies. To have an established UBT learning analytics policy available could have allowed more students to be part of this study. This will facilitate data collection in future research and allow for more students' participation.

Also, the use of surveys to convey learners' input may not be one of the strongest methods. Winne (2017) explained that questionnaires data, being self-reported may suffer loss, distortion, and bias. The reliability of research was best ensured by applying multiple methods and not relying only on surveys.

Another limitation was a major struggle during the data collection period. Davies, R. et al. (2017) indicates that capturing activities and tracing them in LMS is a challenge. In this research, data extraction and mining the different Moodle reports were massive operations that took time and effort to manage. Ensuring valid, correct, and consistent data took huge efforts and consumed a lot of time. A recommended solution would be adopting automation tools that solve this complexity.

Another limitation was related to conducting the interviews. Because of the heavy schedule of the lecturers and because of my request to meet face-to-face, it was particularly challenging to complete the interviews. The interview period took around 5 months to complete. I was meeting lecturers in 2 different campuses (Dahban and Jeddah). The lecturers’ schedules were very tight, but they were very cooperative and shared their time enthusiastically and provided me with all the information I needed and more.

A final limitation was about the dashboard usage, concerning the Moodle completion progress dashboard’s green checkmark that displays a completion flag for an assignment, or a resource. The green checkmark works effectively for individual student. But, with group assignments, a green or red flag is only triggered by the group leader. The other team members do not have the displayed green check, which may be interpreted as a missing assignment or task. Dashboard complexity should be avoided, and students and lecturers training, and support is needed to fully utilize the visualized tool and maximize its benefits.

7.3 Recommendations

Discussing the limitations faced in this research case study provided an opportunity to suggest a set of recommendations either to UBT or any other educational institution employing learning analytics or attempting to adopt such tools.

The institution’s development team can help to automate the process of linking students records with their grades and analytics. Automation would ease this process up and save time to do more. UBT can construct a customized analytical dashboard to report the analytical results to lecturers and students.

With the use of digital tools in educational institutions, there is always a need to provide support and help. Shacklock (2016) emphasized the role the institution senior leaders to take immediate action to improve digital literacy, data capabilities and data management. UBT can implement training and development workshops per academic term. By this, professional development is conducted to enhance the performance of the lecturers and provide an enriching learning environment.

Further recommendations involve the practice of learning analytics. Wise & Jung (2019) recommended lecturers when identifying low levels of activity should change the course design to stimulate greater engagement. For example, make the quizzes part of a video, or re-visit the activity and re-write it better.

Vivolo (2014) talked about having two approaches reactive and proactive when analyzing the learning analytics data. Reactive actions involve making current changes to a course after checking the performance on an exam or an assignment. A proactive change requires setting up prevention measurement prior to an assignment or quiz in future terms.

Another recommendation is related to observing the number of students' hits. What would a high number of hits for a video resource for example, indicate? According to Vivolo (2014), aside from technical reasons, there are 2 options: either the content is so interesting that the students are dying to listen to it again and again. This may be true, but not to the extent of 13 times. The other option would be that students are struggling with the concept, and this is more likely the reason. In this case, recommendations include create a Q and A discussion for this specific concept. Create a review sheet, host additional office hours, reach out to the students with excessive number of hits.

7.4 Case Study Contribution

Discussing the major findings, limitations and recommendations of the research case study helped to outline the major contribution this case study to theory, practice, literature, and policy. Contributions are summarized in this section.

7.4.1 Contribution to Theory

Among the different variations of the theory continuum (Ridder, 2017), theory building, theory development and testing theory, this case study is more about testing theory. To have a rich single case study design and methodology helps to highlight the purpose in theory contribution. This case study can be considered an instrumental case as the focus is more on the researched issue and the case playing a supportive role (Ridder, 2017). Observing the research questions, the data collection examining both qualitative and quantitative data (surveys, interviews, data analytic analysis) helped to provide further insight on the phenomenon of both Self-regulated learning (SRL) and educational data mining (EDM) in the Saudi Arabian higher education context.

The SRL theory is an important theory used in a lot of educational research studies. It helps to highlight the learners' behavior and assist in identifying methods to improve learners' regulated learning. SRL was useful in this case study in identifying skills that influence students' performance. SRL was helpful also from start of the research when designing the methods to collect the data. Collecting students' and lecturers' testimonies was facilitated and organized with the use of SRL-based questionnaires. The way SRL elements are composed (4 elements of Pintrich (2004): planning, monitoring, control and reaction and reflection) aided into obtaining insightful data about the learners' behavior. The obtained input from the learners' help guiding learners to adjust their learning strategies to perform better and guiding lecturers in making decisions in course design and assessment tools, help to promote more self-regulated learning. Such benefits of exploring Learners' behavior attract more researchers to explore this in their educational studies.

A helpful recommendation for researchers is to have additional creative instruments, other than questionnaires, to obtain SRL learners' behavioral data. This is needed especially with the exposure to using new technologies. SRL can adopt and incorporate learning analytics as done in some research studies as Winne (2017) and Kim, et al. (2018) that are referenced in the Literature review.

An interesting SRL behavior that seems unique to the Saudi context stood out. The standout behavior came out from the students' survey that examined their SRL skills. The odd result was the negative association of the SRL skill '*planning'* with the students' performance. The more the UBT student plans, the lower the students' GPA becomes. Eilam and Aharon (2003) explained more about this phenomenon. The analysis discussed that time constraints may explain the lower performance of students who spend more effort on planning. Other factors could be a poor plan, or not enough information to seek if a plan needs to change, or poor utilization of resources. Lecturers' testimonies in the interviews indicated their awareness of students' struggles during the academic term with time management, as some of them were working off-campus, and some had family responsibilities.

As for applying Romero, et al. (2008) EDM process, it did assist in clarifying more the phenomenon of data mining, especially with the use of descriptive statistics and trend analysis as part of the data mining tools. Romero's data mining detailed process aided this research case study with the huge raw data extracted from Moodle. The four steps of the data mining process were useful: 1. collect data, 2. pre-process data, 3. apply data mining algorithm and 4. interpret/evaluate and deploy the results. Romero, et al. (2008) provided a guideline that is easy to follow and provided a list of many data mining techniques both free and commercial. In this research case, trying to utilize existing resources at the institution, without the use of specialized data mining software while following the same path of Romero, et al. (2008)'s data mining process was possible with the guidelines provided. For example, Romero (2007) explained how statistics and visualization can be used as a guideline. Since I could not use customized or specialized tool, I made use of the available resources in campus and used SPSS and Excel. This helped to summarize, filter, and categorize data, visualize the data using Pivot tables and analyze the data using correlations and regressions. Romero, et al., (2008)'s explanation of the process steps is useful, and the list of recommendations and data mining techniques provided are useful to any researcher initiating to mine educational data.

A recommendation that can be added to Romero's data mining process is to provide an ease-of-use reference for educators to use a general data mining technique and provide a sample usage on how, for example, Excel is utilized in data mining. This will benefit lecturers who have access to raw analytical data to try to make use of the 4-steps data mining process themselves to come up with knowledgeable action steps that will help in students' assessment, monitoring, feedback, reflection and more.

7.4.2 Contribution to Learning Analytics Practice

The application of learning analytics and dashboard in the case study helped to summarize some of the contribution. One is to distinguish between individual users and groups when tracking tasks in the Moodle completion progress dashboard to best utilize the dashboard and to avoid students' confusion. Another one is to advise lecturers to use reactive and proactive actions when dealing with learning analytics data such as making changes to current instructional design or setup prevention measurements in the upcoming terms. Also, advise lecturers to create extra measurements to reach out to students' excessive usage of a resource such as developing Q and A, review sheets or additional office hours.

7.4.3 Contribution to Learning Analytics GCC and MENA Literature

This research case study stands out by examining learning analytics in an under-researched area, the GCC and MENA region, specifically Saudi Arabia. This case study focused on a specific Moodle Learning analytic metrics, *Total-Activity* and provided further insight on collecting this metric and correlating it to student's performance and behavior. Moreover, linking grade to SRL was not done a lot, specifically in the GCC and MENA literature. Furthermore, the case study added examining SRL behavior of lecturers which is not done often compared to examining students. Also, contributing to literature was done by detailing instructional design best practice based on the analytics provided. In addition, researching 4- year historic data was also not covered a lot in the GCC and MENA literature, specifically for the purpose of instructional design. There was also the discussion of the negative association of the SRL planning behavior to students' grades, which make it a unique outcome.

Another interesting unique finding about students' behavior that stood out from the interview analysis of lecturers' testimonies is that UBT students tend to favor social network communications with their peers over communication in Moodle, for the purpose of helping each other and keeping peers updated with course materials, that is, they used mediums such as WhatsApp, rather than the LMS. For this, high GPA students tended to download Moodle resources themselves and shared them with their peers to help them. This notion may disturb the analytics of Moodle as some students are not utilizing the resources directly. This seems a very growing practice in the Saudi context. It was noticed with medical students who tended to share online resources and help-files with their peers through non-LMS mediums such as WhatsApp (Alkhalaf, et al., 2018). A lot of research literature explored the use of WhatsApp in various educational contexts and also specifically with medical students. The instant messenger design model for medical education is a popular way that it is addressed (Coleman & O'Connor, 2019). Similarly, this is noticed in the Saudi context medical students. Alkhalaf, et al., (2018) indicated that nearly 99% of participants reported using WhatsApp (over 53% use for academic activities). College students in other majors also tend to use WhatsApp in communications among peers and share academic data. The reason could be because, as indicated by Alkhalaf, et al. (2018), WhatsApp helped in facilitating instant and clear communication of knowledge in less time. While writing this contribution section, now in May 2020, the practice of sharing LMS materials with peers has increased heavily during the COVID-19 epidemic period where in the academic year of 2020 in Saudi Arabia and all around the world, online learning was adopted suddenly, and learning had to shift from face-to-face to online interaction. Abu Elnasr et. al (2020) discussed how students' personal usage of social media has promoted social media usage for sustaining formal teaching and learning as a response to COVID-19 in higher education. Abu Elnasr et. al (2020) indicated that students used social media for building an online community and supporting each other. Planning behavior and networking using WhatsApp instead of LMS were the two most interesting behaviors revealed about the Saudi context.

7.4.4 Contribution to Institutional Policies

Similarly, some of the contributions to institutional policies can include establishing learning analytics data protection and privacy policies. Similar to the recent established Lancaster's learning analytics policies, UBT can follow the same path to build one. This can involve getting students' consent at start of each academic year to collect academic data, library usage, LMS usage and such. Also, another contribution would be to develop and implement automation tools to link, transfer and organize data among the different information system in the institution. Finally, adopting new tools in the institution requires employing training and support procedures for both students and lecturers. UBT at time of publishing this research has adopted Blackboard, part of its e-learning development plan. UBT can continue with its technology development plans and learning analytics adoption with this recent LMS adoption.

7.5 Future Studies

With the thousands of learning transactions available in any educational institution, there are great opportunities to explore more and to mine more. For example, students' and courses' characteristics were not the focus in this research study. So, in the UBT case study itself, further research can focus on students' characteristics such as gender, level, course level and such. Further research can focus also on the time variant, and explore time spent in activities or on viewing course modules and analyze if it effects the students' performance.

In regards of theory, I believe this case study has started the discussion of associating Self-regulated learning behavior with analytics in a traditional learning setting because most SRL research are mainly conducted in an online setting. To expand this scope in future research will help to explore more about user's SRL behavior and link it directly to their analytics found in the log file. Winne (2017) did this by examining specific LMS actions in relation to the analytics such as clicking a hyperlink, highlighting a text, reviewing a note, and such. Another expansion would be to examine the relation of the *Total-Activity* metric on the students' SRL behavioral elements or associating the SRL behavior to the students' behavior in the LMS logged events. Another opportunity is to explore more about SRL and lecturers in higher education. This is not commonly done in research, compared to students and SRL. So, questions such as the effects of SRL behavior on lecturers' teaching, instructional design, or assessment skills, all can be explored in future research. A further look at SRL behavioral elements can be examined through the Moodle logged events. An examination can categorize the 100+ logged events according to the suitable SRL behavior element and conduct the analysis after this transformation is applied. This will be a unique approach to consider and it would be interesting to observe the results. Since Moodle platform is used by a lot of educational institutions, this examination process can be generalized and applied by any other university examining SRL behavior for both students and instructors.

With the availability of massive data in the log file, there are still a lot of other opportunities to explore about the log data elements. Such opportunities if explored, can help to build learning analytics and data mining research field. A final note is to have a further look on the educational institutions roles in dealing with learning analytics as indicted in this research the importance of providing the needed support and training. Institutions roles with LA is examined and encouraged in many recent papers such as Tsai, et al., (2020). Tsai, et al., (2020) indicated that LA has been an active research field for a decade now, yet evidence of impact remains nonvisible. Tsai, et al., (2020) aimed to present a picture of the institutional adoption of LA in European Higher education. This can be aimed also for future research in the GCC and MENA region

Chapter 8: Bibliography

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Chapter 9: Appendix One

Questions are Likert scale questions and open-ended questions.

Theory or framework in use	Participant	category	Question
SRL (Pintrich)	Student	Behavior - learning	**Pintrich conceptual framework, four phases:** **Phase 1: Planning and Goal settings** • Q1-1: I set goals to help me to utilize Moodle. • Q1-2: I plan out a study plan for Moodle activities. • Q1-3: I can estimate how much time a Moodle task needs. • Q1-4: I dedicate set of hours for Moodle activities and resources. • Q1-5: I set strategies to manage my studying that includes Moodle usage. **Phase 2: Monitoring** • Q2-1: I keep track of Moodle deadlines. • Q2-2: I know my grades when they are updated. • Q2-3: I periodically access Moodle to check any new news or updates. • Q2-4: I make sure I keep up with the weekly readings and assignments. **Phase 3: Control** • Q3-1: I know when I am behind of schedule. • Q3-2: I lose attention easily online. • Q3-3: I manage to work even if Moodle materials are dull. **Phase 4: Reaction and Reflection:** • Q4-1: I change strategies if I am not making progress. • Q4-2 I ask my peers when I need help. • Q4-3: I ask the instructor when I need help. • Q4-4: When I fail at something, I try to learn from my mistakes
SRL (Pintrich)	Student	Attitude toward Dashboard usage	**Cont. Phase 4: Reaction and Reflection:** • Q5-1: I understand the purpose of Moodle dashboards. • Q5-2: I believe Moodle dashboards are useful. • Q5-3: I believe Moodle Dashboards helped me understand where I stand.
SRL (Pintrich)	Lecturer	Moodle usage a Behavioral learning	• Q1: What are the Moodle resources you use mostly: PowerPoint lectures, smartboard lectures, quiz, etc. • Q2: What Moodle activities you use mostly: Discussions forums, announcement, quiz, etc. **Planning and Goal settings**

			• Q1-1: I have Moodle course contents ready at start of the term. • Q1-2: I Plan to make course design changes for my future courses based on my usage of Moodle Analytics. **Monitoring** • Q2-1: I update my Moodle content. • Q2-2: I always check Moodle messages. **Control** • Q3-1: I edit and change course design based on students' performance. • Q3-2: I edit and change Course design based on peer observation and advise. • Q3-3: I have edited and changed my Moodle course design based on using Moodle analytics and the analytical graphs.
SRL (Pintrich)	Lecturer	Attitude toward the Analytics and Dashboard usage	**Reaction and Reflection** • Q4-1: I believe that my current Moodle course design elements are effective. • Q4-2: I believe Moodle dashboards are useful. • Q4-3: I believe Moodle Dashboards helped me guide the students. • Q4-4: I believe Dashboards helped me to identify students at risk. • Q4-5: I believe that Moodle Analytical graphs are useful. • Q4-6: I believe Moodle Analytical graphs helped me guide the students. • Q4-7: I believe that Moodle Analytical graphs helped me to identify students at risk. • Q4-8: Moodle Analytics helped me to design the Moodle course effectively. • Q4-9: Moodle Analytics helped me to monitor students' engagement and performance.

Chapter 10: Appendix Two

SRL (Pintrich)	**Questions about lecturers' outcome and expectations from their experience of using LA and Dashboards.** **SRL- Planning and Goal settings** **Moodle learning activities and course design.** **Q1**: What is your approach in designing Moodle Learning activities? Follow-up Questions: **Q1.1** You choose the tools and resources based on what? **Q1.2** How do you usually evaluate the Moodle design elements? So, you can improve them for future courses? **Q1.3** Have you had feedback from students or your peers in regards of Moodle design elements? **Q1.4**: Do you believe in your own abilities to design course effectively? **SRL- Monitoring and Control** **Questions about Moodle log files (LA) and Dashboards** **Q2:** Describe how was your experience with Moodle log files and dashboards? Follow-up Questions: **Q2.1** Did you make any adjustment during the term in your course design based on the analytics? **Q2.2:** Were you able to monitor student engagement using LA/Dashboards? **Q2.3** Do you plan to make any adjustment in future course design based on the analytics? **Q2.4** What are the advantages and barriers of Moodle log files and dashboards? **SRL- Reaction and Reflection** **Questions about identifying students at risk.** **Q3:** Describe was your experience in identifying students at risk? Follow-up Questions: **Q3.1** Were you able to identify students at risk from LA and dashboards? **Q3.2** Have you reached the student and were able to help and advice? **Q3.3** Did the student performance improved based on the alert?