Technology Enhanced Learning Analytics Dashboard in Higher Education

Rangana Jayashanka, E. Hettiarachchi and K.P.Hewagamage
University of Colombo School of Computing, Colombo 7, Sri Lanka
rja@ucsc.cmb.ac.lk
eno@ucsc.cmb.ac.lk
kph@ucsc.cmb.ac.lk

Abstract: During the COVID-19 pandemic period, all the Sri Lankan universities delivered lectures in fully online mode using Virtual Learning Environments. In fully online mode, students cannot track their performance level, their progress in the course, and their performances compared to the rest of the class. This paper presents research work conducted at the University of Colombo School of Computing (UCSC), Sri Lanka, to solve the above problems and facilitate students learning in fully online and blended learning environments using Learning Analytics. The research objective is to design and create a Technology Enhanced Learning Analytics (TELA) dashboard for improving students' motivation, engagement, and grades. The Design Science research strategy was followed to achieve the objectives of the research. Initially, a literature survey was conducted analyzing features and limitations in current Learning Analytic dashboards. Then, current Learning Analytic plugins for Moodle were studied to identify their drawbacks. Two surveys with 136 undergraduate students and interviews with 12 lecturers were conducted to determine required features of the TELA system. The system was designed as a Moodle Plugin. Finally, an evaluation of the system was done with third-year undergraduate students of the UCSC. The results showed that the TELA dashboard can improve students' motivation, engagement, and grades. As a result of the system, students could track their current progress and performance compared to the peers, which helps to improve their motivation to engage more in the course. Also, the increased engagement in the course enhances the student's self-confidence since the student can see continuous improvement of his/her progress and performance which in turn improves the student's grades.

Keywords: Learning Analytics, Information Visualization, Higher Education, Online Learning, Moodle Plugin

1. Introduction

Sri Lankan education system can be divided into three major categories: pre-education, school education, and higher education (Liyanage, 2014; Aturupane and Little, 2020). School education in Sri Lanka is a teacher-centered education system where teachers use the textbooks given by the government to deliver knowledge to students (Aturupane and Little, 2020). School students are passive learners where they memorize the knowledge which is spoon-fed by the teachers (Hettiarachchi, 2019). Usage of computing technologies to improve knowledge and skills is minimal in Sri Lankan schools. There are three exams conducted by the Sri Lankan government: Grade five scholarship exam, G.C.E Ordinary Level (O/L) exam, and G.C.E Advanced Level (A/L) exam. G.C.E (A/L) is the most competitive exam in Sri Lanka since this is the university entrance exam in the country (Liyanage, 2014; Alawattegama, 2020; Hettiarachchi, 2019; Aturupane and Little, 2020).

As opposed to school education, Sri Lankan universities promote student-centered education where students become active learners who need to search for knowledge by themselves (Weerasooriya, 2013; Hettiarachchi, 2019). University lecturers are more likely facilitators, and at the same time, universities encourage peer learning (Hettiarachchi, 2019). Sri Lankan universities use novel concepts in e-learning and multimedia technologies to facilitate the learning process (Lim et al., 2019). All the Sri Lankan universities use either Learning Management Systems (LMS) or Virtual Learning Environments (VLE) to facilitate teaching, learning, and assessment.

As a result, most students find it challenging to adjust to the student-centered educational setting practiced at the universities. We have identified four major problems in Sri Lankan higher education based on the literature (Weerasooriya, 2013; Weerasinghe and Fernando, 2017; Rameez, Fowsar, and Lumna, 2020; Tharmaseelan, 2007), semi-structured interviews with lecturers (N=12), and surveys with undergraduate students (N=136).

1. Even though VLEs are equipped with features to provide a rich and interactive educational experience to students, lecturers merely use it as a platform to only upload the materials (either ppt or pdf). Thus, the usage of interactive content is minimal.

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2. Even though VLEs collect a massive amount of students' learning data, using those data to identify the hidden patterns and deep insights to enhance the learning environment is minimal.
3. There is no real-time feedback given to students about their performance and progress in a course.
4. There is no way to improve the motivation and self-confidence of students to increase their learning engagement.

During the COVID-19 pandemic period (2020 -2021), Sri Lankan universities delivered courses on a fully online mode (Rameez, Fowsar, and Lumna, 2020). In the fully online mode, the interaction between the students and the lecturer is minimal, and the lecturer cannot recognize whether the students are following the course. Simultaneously, the students cannot track whether they are in the expected performance level, their progress in the course, and their performances compared to the rest of the class (Rameez, Fowsar, and Lumna, 2020). Thus, students are isolated in the digital environment in a fully online mode, which causes less motivation to interact with the learning activities.

There is a need for a technology-enhanced solution to the problems mentioned above. We can facilitate the university students by designing and implementing an information-rich Learning Analytic dashboard to overcome the issues mentioned above. Using a Learning Analytic dashboard, we can enhance higher education in both blended and fully online modes. As a result, students will be able to track their progress easily, identify missed learning resources and activities, identify the underperforming subtopics in a course, compare their progress with their peers, and create their personalized learning environment using a Learning Analytic dashboard system.

This paper presents a Learning Analytic research work conducted at the University of Colombo School of Computing (UCSC), Sri Lanka. UCSC offers Bachelor of Science in Computer Science and Bachelor of Science in Information Systems degrees. This research investigates the application of Learning Analytics for improving students' motivation, interaction, and grades by designing, implementing, and evaluating a Technology-Enhanced Learning Analytic Dashboard system (hereafter referred to as the TELA System). The TELA system was designed and created to facilitate the undergraduate students of the UCSC in both fully online and blended learning environments.

This paper consists of five sections. Section two covers the background of the research, which describes Learning Analytics and the application of Learning Analytics in higher education. The research questions and the methodology are discussed in Section three. Section four presents the results based on the research questions. Finally, the discussion and conclusion of the main findings are presented in section five.

2. Background

Digital tools and technologies used in education such as LMS, VLE, Virtual Labs, and MOOCs lead to generating a large amount of educational data. Learning Analytics can be defined as Analytics that are applied to learning data. The introduction of LMS and VLE, which afford the amassment and visual representation of large amounts of student information, has enabled the active development of the Learning Analytics field in the last five years (Shum and Ferguson, 2012). Consequently, learning analytics has evolved significantly in education, psychology, computing, and data science domains since the early 2010s (Ifenthaler and Yau, 2020; Prieto et al., 2019).

Different definitions for Learning Analytics can be found in the existing literature; however, the most suitable and most cited definition in literature is proposed by the 1st Learning Analytics and Knowledge Conference held in 2011. *"Learning Analytics is the measurement, collection, analysis, and reporting of data about learners and their contexts, for purpose of understanding and optimizing learning and the environments in which it occurs"* (Ferguson, 2012).

There are four types of learning analytics: descriptive, Diagnostic, Predictive, and Prescriptive, to offer various insights into learning and teaching. Table 1 describes the four types of Learning Analytics with examples.

Table 1: Four types of Learning Analytics

Learning Analytic Type	Description	Examples
Descriptive Analytics	Show what has happened using charts (pie charts, line charts, and bar charts) and text format.	• Number of dropout students from a degree. • Number of enrolled students for a course.
Diagnostic Analytics	Explain why a particular thing happened by analyzing data.	• Why did a student fail an exam? • Why a student dropped out of the course?
Predictive Analytics	Predict what will happen next based on the analysis from past events.	• Which students will not pass the exam? • Which course will have a lower number of registrations?
Prescriptive Analytics	Help the students to achieve their learning goals.	• Suggest Learning Plans. • Suggest additional learning resources.

The benefits of Learning Analytics are associated with four levels of stakeholders: micro-level (students), meso-level (lecturers), macro-level (higher educational institutions), and mega-level (government) (Ifenthaler and Widanapathirana, 2014). Table 2 provides the benefits of Learning Analytics for different stakeholders.

Table 2: Benefits of Learning Analytics for different stakeholders

Stakeholder	Benefits
Student	• Check current performance level. • Track the progress towards learning goals. • Facilitate creating a personalized learning environment. • Improve motivation. • Improve engagement. • Improve self-confidence. • Improve grades.
Lecturer	• Increase the quality of teaching. • Evaluate teaching practices. • Identify students at risk of failure. • Modify the course content to meet cohorts' needs. • Identify Learning Designs that need to revise. • Increase students' interactions with the course.
Higher Education Institutes	• Improve the quality of the curriculum. • Optimize resource allocation. • Minimize the dropout rates. • Support to take financial decisions. • Meet institutional standards. • Improve student recruitment policies.
Government	• Support for quality assurance process. • Apply cross-institutional comparisons. • Support for policymaking. • Improve productivity.

2.1 Learning Analytic Dashboards

The design, implementation, and evaluation of Learning Analytics Dashboards (LADs) is a significant area of exploration in Learning Analytics research (Ahnn et al., 2019). Schwendimann and colleagues define (LAD) as *"a single display that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualization"* (Schwendimann et al., 2017).

LADs motivate students to set realistic goals and monitor their learning progress (Bodily and Verbert, 2017; Russell, Smith and Larsen, 2020). The below section provides an overview of the dashboards implemented to support students, lecturers, and student advisers. We analyzed the aim of the dashboard, data used to generate the feedback, and limitations of the dashboards.

Graf et al. (2011) implemented Academic Analytics Tool (AAT) to provide feedback to course designers about the students' interaction and learning process. ATT analyzed course materials, quizzes, and forum postings for the course revision process. However, usability testing of the ATT system was not conducted.

Arnold and Pistilli (2012) implemented a Dashboard called Course Signals to track student progress and provide feedback for both students and faculty staff. The data comprised LMS interaction, student performance, demographic data, and academic history. Course Signals predict the risk of failure of a student and visualize using a traffic light with three risk levels (high risk – red color, average risk – yellow color, and low risk – green color). The instructor needs to run the application to update the Course Signals. Also, the Course Signals only predict the risk level; it does not provide any insight into the reasons behind the student being at risk of failure.

Kuzilek et al. (2015) conducted research to predict at-risk students using demographic data and VLE interaction data. They created a dashboard to present a course overview and summary of individual students. However, the prediction results are sent to the course team via mail. Also, an efficacy evaluation of the dashboard was not conducted.

Charleer et al. (2018) implemented LISSA (Learning dashboard for Insights and Support during Study Advice) to assist study advisers in helping their first-year students to plan a more attainable program. Historical data and student grades were analyzed to create the visualizations. However, the LISSA dashboard visualizes only the academic performance of the student with comparing their peers. Therefore, this dashboard is helpful to students only with proper guidance from their study adviser. Moreover, the LISSA dashboard did not provide actionable insights to students.

Since our aim is to provide insights to students based on their participation and engagement in the VLEs, several Learning Analytic plugins already available for Moodle were also analyzed. We selected five Learning Analytic plugins and installed them in the Undergraduate Virtual Learning Environment (UGVLE) of UCSC to check the available features, advantages, and drawbacks of those systems. Table 3 provides details of Learning Analytic plugins with their purpose, benefits, and weaknesses.

Although some studies have found positive links between the use of LADs and academic success (Van Horne et al., 2018), little is known about the impact of LADs on at-risk students' academic achievement (Russell, Smith and Larsen, 2020). Despite some encouraging results, significant drawbacks in current LAD research also have been highlighted (Matcha et al., 2020). For example, according to several research studies, learners find it difficult to interpret data visualized on dashboards and utilize dashboard feedback to guide their learning strategies (Matcha et al., 2020). Students require quality feedback and timely assistance to improve learning outcomes (Hilliger et al. 2020). One challenge Learning Analytics faces is selecting the correct visualization technique to provide the students with learning analytics feedback (Leitner and Ebner, 2019). In addition, motivational research reported that negative feedback on performance could create discouragement, anxiety, and decreased motivation (Pekrun, 2006).

Table 3: Details of Learning Analytic plugins available for Moodle

Learning Analytic Plugin	Purpose of the Plugin	Benefits	Weakness
Progress Bar (Raadt, 2016)	Time Management Tool for Students.	• Shows progress in activities/resources of a course. • Colour coded to see completed/viewed quickly.	• Progress is not presented as a percentage. • Need to move the mouse over the graph to identify the resource/activity names. • Hard to use if there are lots of activities /resources in the VLE.
Analytic Graphs (Schmitt, 2018)	Provides five graphs to facilitate the identification of student profiles. • Grades Chart • Content Access Chart • Active users Chart • Assignment Submission	• Can identify the students with problems. • Shows active uses on a particular day. • Shows which users accessed many different resources.	• Hard to understand the charts (small size, no headings).

Learning Analytic Plugin	Purpose of the Plugin	Benefits	Weakness
	Chart • Hits Distribution Chart		
Heatmap (Raadt, 2020)	• Help teachers to improve their courses.	• Overlays a heatmap onto a course to highlight activities with more or less engagement.	• Visualize only the number of views and the number of distinct students who accessed the resources.
Forum Graph (Chan, 2016)	• Analyze interactions in a single Forum activity.	• Tooltip showing full user name, no. of discussions, and no. of replies when rollover node. • Shows top three users who posted the most number of postings.	• Cannot understand the flow of the discussion (Not presented in a Tree structure). • Students cannot access the chart. • Not work on the large Forum with lots of posts.
Graph Stats (Bugnet and Dvorovenko, 2016)	• Visualize daily visits to site or course.	• Shows the number of students who accessed the course each day.	• Do not give any deep insight about the course access.

According to Schwendimann, most LADs are designed for lecturers, with fewer dashboards built for students, and research on the effects of LADs is still in its early stages (Schwendimann et al., 2017). The most essential yet under-explored area of LAD research is large-scale studies emphasizing dashboards evaluations for adoption and impact on learning (Schwendimann et al., 2017). According to Matcha and colleagues, current LADs are rarely grounded in learning theory and have significant limitations regarding how LADs are evaluated and reported (Matcha et al., 2020).

The aim of the TELA dashboard is different from the research works mentioned above. Therefore, we decided to overcome the limitations and drawbacks of the currently available dashboards and provide simple information-rich visualizations to students from the TELA dashboard.

2.2 Self-Regulated Learning and LAD Feedback

The first step towards implementing successful LADs is to determine how learning sciences can incorporate into the design and pedagogical use of LADs (Jivet et al., 2017). LADs that have a pedagogical focus mostly use Self-Regulated Learning theory (Jivet et al., 2017). Self-Regulated Learning (SRL) is the ability to plan, monitor, and actively control one's learning process (Zimmerman, 2002). According to SRL theory, motivation is critical to academic success (Fleur, Bos, and Bredeweg, 2020). LADs can motivate students and assist them in reflecting on their SRL process (Muldner et al., 2015). One of the most important aspects of any SRL process is feedback. Feedback generated by the LADs can be used to empower students as self-regulated learners. The SRL cycle consists of three phases: goal setting, monitoring, and reflection (Zimmerman, 2002). However, most of the past research works only consider the reflection phase, and the other two phases are hardly addressed (Jivet et al., 2017). The TELA dashboard is designed and implemented to assist the students in all the phases of the SRL process by providing appropriate feedback.

3. Research Methodology

3.1 Research Questions

The objective of the present research is to introduce the TELA system to improve the motivation, interaction, and grades of the students. For reaching the above objective, research questions can be stated as follows;

RQ1: What are the information that needs to be visualized in the TELA system to support students to improve their motivation, interaction, and grades?

RQ2: How to design and create the TELA system to support students to improve their motivation, interaction, and grades?

RQ3: Can the TELA system support students to improve their motivation, interaction, and grades?

3.2 Methodology

This research is based on the Design Science Research Process, a problem-solving approach by developing a new IT product called artifact (Saltuk and Kosan, 2014). The Design Science Research Process is used in an iterative process involving five steps (Saltuk and Kosan, 2014; Oates, 2006) described in Table 4.

Table 4: Steps in the Design Science research strategy

Step	Description
Awareness	Recognition and articulation of a problem.
Suggestion	Offers a very tentative idea of how the problem might be addressed.
Development	Implement the tentative design.
Evaluation	Examines the developed artifact and conducts an assessment of its worth and deviations from expectations.
Conclusion	Knowledge gained is documented. Unexpected or abnormal results that cannot yet be explained could be the subject of further research.

The research work conducted according to the Design Science research strategy steps is explained below. Figure 1 illustrates the flowchart of the research process.

In the Awareness Step, we studied the existing Learning Analytic tools currently being used to support the students in improving their learning. In this step, we investigated the literature to understand the drawbacks in the existing systems and how the proposed TELA system can address them. Our findings in this step are already presented in the Background section.

Under the Suggestion step, the need to design and develop the TELA system to increase the students' motivation, engagement, and grades was studied. It was needed to identify the detailed requirements for the TELA system to achieve the intended outcomes. There are numerous ways to collect data about prospective users in surveys, focus groups, and interviews (Goodwin, 2009; Lazar, Feng, and Hochheiser, 2010). For this research, surveys and interviews have been employed to identify requirements associated with users. Surveys were conducted to obtain the requirements expected by the users. Interviews helped determine the actual context where the proposed system is applied and the requirements expected from the system.

We conducted two separate surveys with third-year and fourth-year undergraduate students of the UCSC to identify the features that students expected from the TELA system. We selected both third-year and fourth-year students since they had more than two years of experience with university education and the UGVLE. Then, we conducted semi-structured interviews with 12 lecturers of the UCSC (two professors and ten senior lecturers) to identify the critical features since they are experts in teaching and learning. The findings with surveys and interviews are presented in the Results section under Research Question 1.

Under the Development step, the design and development of the system are carried out with design diagrams and prototypes. Table 5 gives the details of the proposed TELA system with four dimensions in Learning Analytics offered by Chatti et al. (2012).

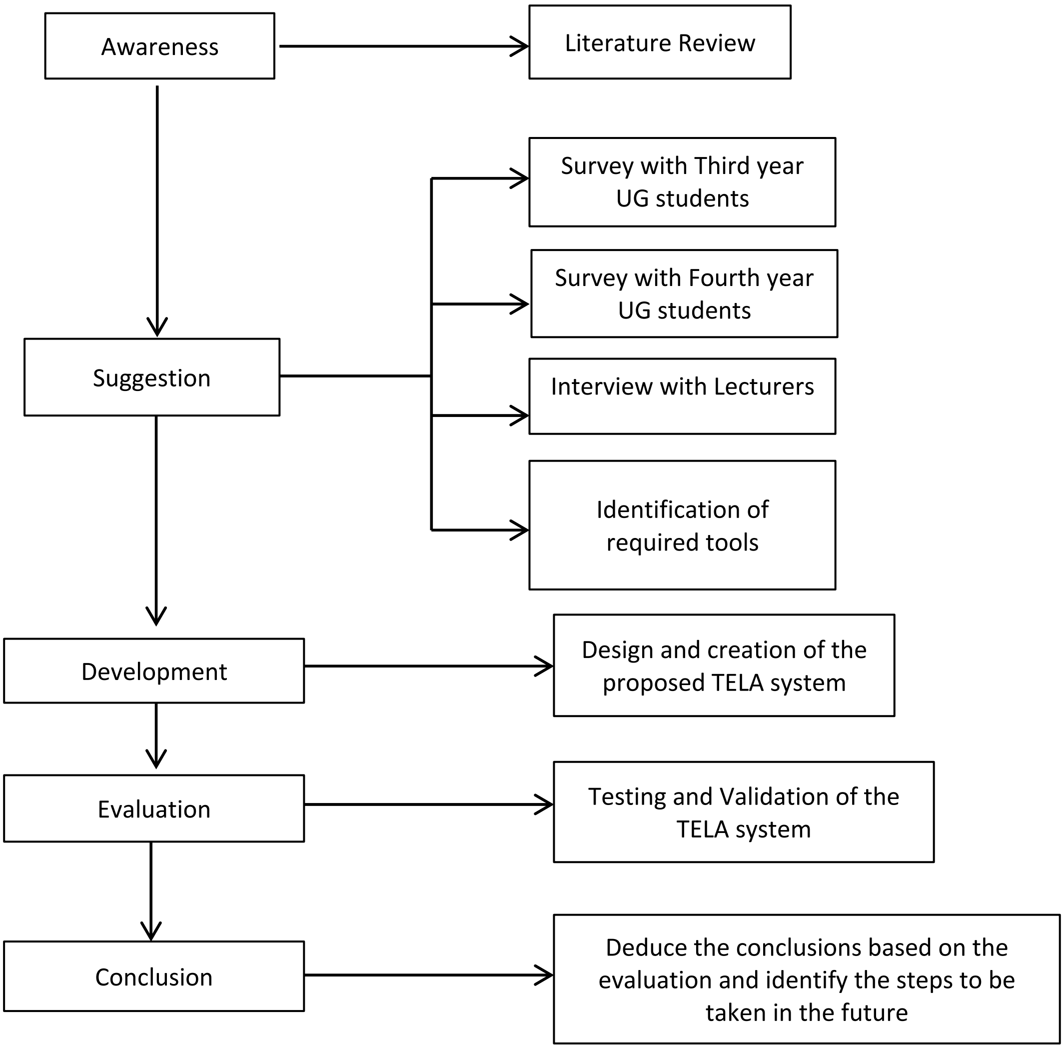


Figure 1: Flowchart of the research process

Table 5: TELA system with the Learning Analytic dimensions

Dimension	Description
What kind of data?	Learner's data collected in the Moodle database.
Who are the stakeholders?	Undergraduate students of the UCSC.
Why does the system use Learning Analytics?	To improve the motivation, engagement, and grades of the students.
How does the system perform the analysis?	Descriptive and Diagnostic analytics using statistics, data mining, and information visualization.

We considered the usability heuristics proposed by Nielsen (1995) for web applications and heuristics for evaluating e-learning programs presented by the University of Georgia (Benson et al., 2002) as design guidelines. Generally, for students, the interface of the TELA system should be flexible, efficient, user-friendly, and designed in a way that students can easily understand the visualizations. Reliability, consistency, and user-friendliness are addressed as the technical requirements associated with the TELA system. For reliability, the TELA system should able to handle large amounts of data. Also, the TELA system should provide consistency within the different visualization modules. The user interfaces are developed in a user-friendly manner as users should be able to understand the visualizations in a short period quickly. The system architecture diagram and the User Interfaces of the TELA system are presented in the Results section under Research Question 2.

Under the Evaluation step, we evaluated the TELA system by conducting Experimental Research in real learning environment. The experimental research aimed to evaluate whether introducing the TELA system can improve students' motivation, interaction, and grades. SCS 3209 – Human-Computer Interaction course at

UCSC was selected for the experiment. The data obtained through the experimental research are analyzed using mixed-method evaluation techniques (Frechtling and Sharp, 1997; Fuente- Valentín, Pardo, and Kloos, 2013). Evaluation results are presented in the Results section under Research Question 3.

In the Conclusion step, we deduced the conclusions based on the evaluation results and identified the steps to be taken in the future. These results are discussed under the Conclusion section.

4. Results

4.1 RQ1: What are the information that needs to be visualized in the TELA system to support students to improve their motivation, interaction, and grades?

We conducted two separate surveys with third-year and fourth-year undergraduate students of the UCSC to identify the features students expect from the TELA system. In the beginning, we taught them about the Learning Analytic concept using a fifteen-minute presentation since Learning Analytics is a new topic for students. Then, we gave ten features (different information visualizations) and asked the student to rank them using a five-point Likert scale.

4.1.1 Survey Results of Third-Year Students

Eighty-two third-year students participated in the survey. Among them, 40 are male students, and 42 are female students. Table 6 summarizes the results of the survey conducted with third-year students.

Table 6: Results of the survey conducted with third-year students

Expected TELA system features	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Graphical visualization of time spent for online learning activities	36.6%	54.9%	8.5%		
Provide feedback about your performance after completion of Quizzes	57.3%	36.6%	6.1%		
Inform about sub-topics that you need to improve your performances	53.7%	40.2%	6.1%		
Graphical visualization of activities completed inside a course	46.3%	46.3%	7.3%		
Early detection of risk of failures	51.2%	36.6%	11%	1.2%	
Graphical visualization of your performance and progress over different periods	51.2%	37.8%	11%		
Evaluation of former and current grades and predictions for future grades	40.2%	48.8%	8.5%	2.4%	
Performance comparison with your peers	28%	45.1%	18.3%	4.9%	3.7%
Suggest learning partners (nearby, same knowledge, same learning pattern) for grouping and collaboration of learning activities	25.6%	46.3%	23.2%	3.7%	1.2%
Support to improve your grades by planning your learning activities and manage time efficiently	39%	46.3%	14.6%		

4.1.2 Survey Results of Fourth-Year Students

Fifty-four fourth-year undergraduate students participated in the survey. Among them, 27 are male students, and 27 are female students. Table 7 summarizes the results of the survey conducted with fourth-year students.

Table 7: Results of the survey conducted with fourth-year students

Expected TELA system features	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
Graphical visualization of time spent for online learning activities	46.3%	42.6%	11.1%		
Provide feedback about your performance after completion of Quizzes	74.1%	20.4%	5.6%		
Inform about sub-topics that you need to improve your performances	63%	27.8%	9.3%		
Graphical visualization of activities completed inside a course	51.9%	40.7%	7.4%		
Early detection of risk of failures	61.1%	24.1%	13%	1.9%	
Graphical visualization of your performance and progress over different periods	59.3%	37%	1.9%		1.9%
Evaluation of former and current grades and predictions for future grades	46.3%	37%	9.3%	3.7%	3.7%
Performance comparison with your peers	29.6%	31.5%	29.6%	7.4%	1.9%
Suggest learning partners (nearby, same knowledge, same learning pattern) for grouping and collaboration of learning activities	24.1%	38.9%	25.9%	5.6%	5.6%
Support to improve your grades by planning your learning activities and manage time efficiently	51.9%	42.6%	5.6%		

4.1.3 Interview results with lecturers

After analyzing the survey results, we conducted semi-structured interviews with 12 lecturers (two professors and ten senior lecturers) of the UCSC to identify the essential features of the TELA system. All the lecturers agreed that the TELA system would support students to improve their learning engagement and grades since the system provides real-time Learning Analytic feedback. From the interviews, we have identified four critical aspects that need to consider when designing and creating the TELA system, as listed below.

1. The lecturer should upload the lecture materials as interactive content. If the lecturer uploads the lecture notes in pdf or PowerPoint format, students will download them and read them offline. Therefore, we cannot capture the learning happening outside the VLE.
2. The lecturer should provide a Quiz after completing each sub-topic. Then, the TELA system needs to analyze the Quiz data and visualize it to the students. Thus, students can easily monitor their performance level, progress and compare their current status with their peers.
3. Students’ interaction with the Forum discussions is minimal in Sri Lanka. Considering this aspect, lecturers asked to build a feature for Forum Analytics where students can quickly identify the discussion topics with a higher number of comments.
4. The TELA system interfaces should keep simple, where students can easily understand the visualizations.

4.1.4 Features selected for the TELA system according to the surveys and the interviews

By analyzing the results of surveys and interviews, we identified the information that needs to be visualized in the TELA system to improve students' motivation, interaction, and grades. Accordingly, it was decided to divide the TELA system into three main modules: Access Analytics, Quiz Analytics, and Forum Analytics. Table 8 describes the different visualizations in each module with the related phase of the SRL cycle.

Table 8: Visualizations in TELA modules

Module	Visualization	Description	Chart Type
Access Analytics	Progress bar	Graphical visualization of the activity completed by the student in the course. [SRL – Monitoring]	Linear Graph
	Resource Access Count	Access count of each resource by the student. Class average access count also presents in the same chart. [SRL – Monitoring, Goal setting]	Bar Chart
	Daily Action count	The number of actions executed by the student each day in the course. [SRL – Monitoring]	Line Chart
	Daily Online time	The active online time of the student each day in the course. [SRL – Monitoring]	Line Chart
	Daily Action count – in all courses	Number of actions executed in each day in all the enrolled courses by the student. [SRL – Monitoring]	Line Chart
	Daily Online time – in all the courses	The active online time of each day in all the enrolled courses by the student. [SRL – Monitoring]	Line Chart
	Time spent for interactive learning Materials	Total time spent reading each interactive learning material by the student. [SRL – Monitoring]	Bar chart
Quiz Analytics	Quiz Marks vs Class Average Marks	Comparison between the marks obtained by the student and the average mark of the class for each quiz. [SRL – Reflection]	Bar chart
	Quiz Marks vs Class Highest Marks	Comparison between the marks obtained by the student and the highest mark of the class for each quiz. [SRL – Reflection]	Bar chart
	Current Status	Calculate the average mark of the student for all the quizzes and graphically visualize the status. [SRL – Goal setting]	Gauge chart
	Quiz Time	Time spent to complete each quiz by the student. [SRL – Monitoring]	Line chart
	Question Time	Time spent for each question in a quiz by the student. [SRL – Monitoring]	Bar Chart
Forum Analytics	Forum Graph	Graphically visualize the connection between parent posts and child posts in a discussion forum. [SRL – Monitoring]	Tree Graph

4.2 RQ2: How to design and create the TELA system to support students to improve their motivation, interaction, and grades?

Undergraduate Virtual Learning Environment (UGVLE) is the VLE used by UCSC to facilitate the teaching, learning, and assessment activities of undergraduate students. UGVLE is a Moodle-based VLE system, and we decided to implement the TELA system as a Moodle plugin since we can easily install it to the UGVLE. The TELA system has been designed as an interactive system that combines hardware, software, data, procedures, and people into the system architecture. In this section, the system architecture of the proposed TELA system is explained. The architecture of the TELA system is illustrated in Figure 2.

Student needs to log into the course and need to access the uploaded lecture notes, complete the quizzes, go through the interactive learning content, and participate in the forum discussions. From the VLE course page, students need to connect to the TELA system (Figure 3). There are three modules in the TELA system; Access Analytics, Quiz Analytics, and Forum Analytics. Each module executed the queries and retrieved the information from Moodle database. That information is passed to the view component of the TELA system, which generates information visualizations for the student. All the modules are programmed in the PHP programming language. In addition, HTML, CSS, and JavaScript are used for front-end development. The features of each module in the TELA system are explained below.

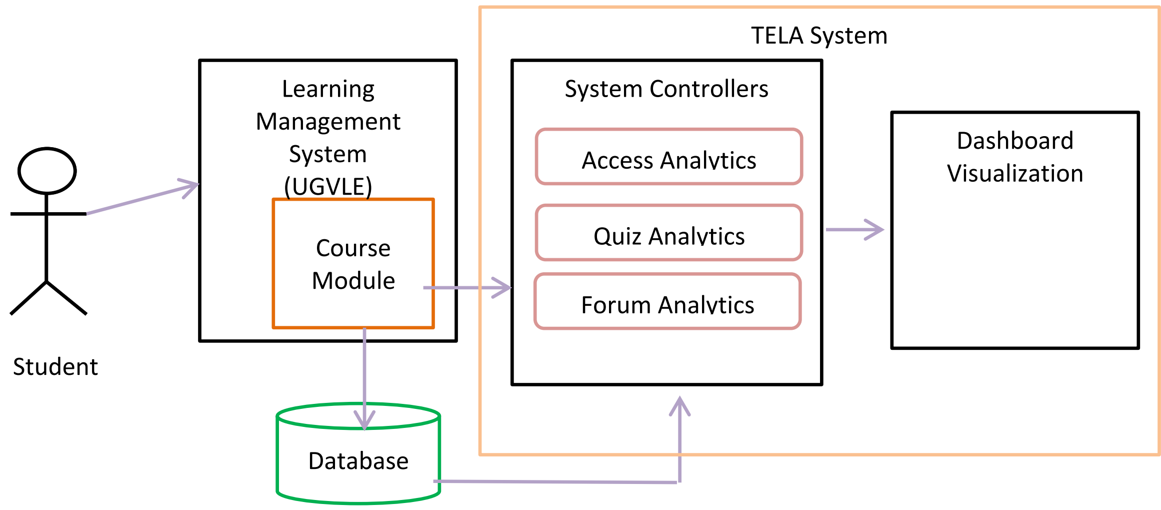


Figure 2: System Architecture of the TELA system with main components

4.2.1 Access Analytics Module

Access analytic module visualizes the student's interaction information with the activities and the learning materials in the course. In addition, a comparison between the student's interaction and the class average interaction is also presented in some visualization to increase student's motivation and engagement. All charts (information visualizations) included in the Access Analytics Module are explained below.

- Progress Bar

Progress Bar graphically visualizes all the activities and the resources in the course according to the order (Figure 4). Accessed resources and completed activities are colored in green. Activities which are having deadlines in the future are colored in blue. The activities student did not complete before the deadline, and the resources student did not access yet are colored in red. The student's progress of the course is given on the top of the graph as a percentage. This Progress Bar aims to improve the motivation of the student to complete the task and enhance the student's interaction. At the same time, this will enhance the student's self-confidence (ex: if the progress is above 80% and most of the items are in green color).

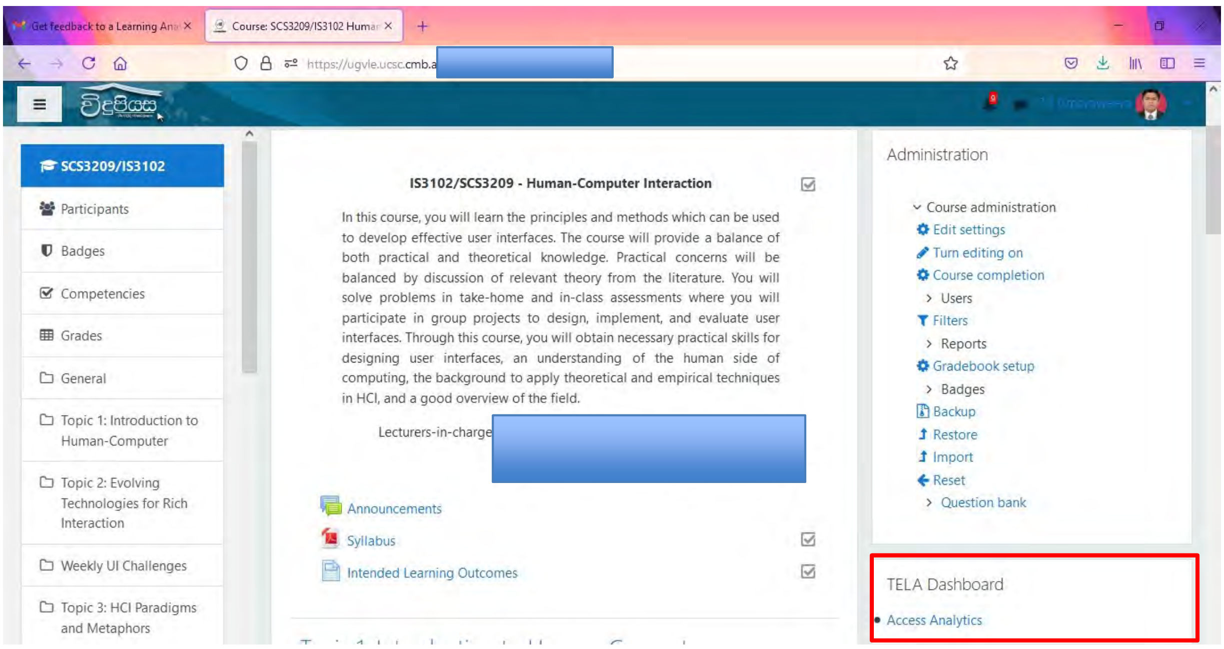


Figure 3: TELA system installed in UGVLE

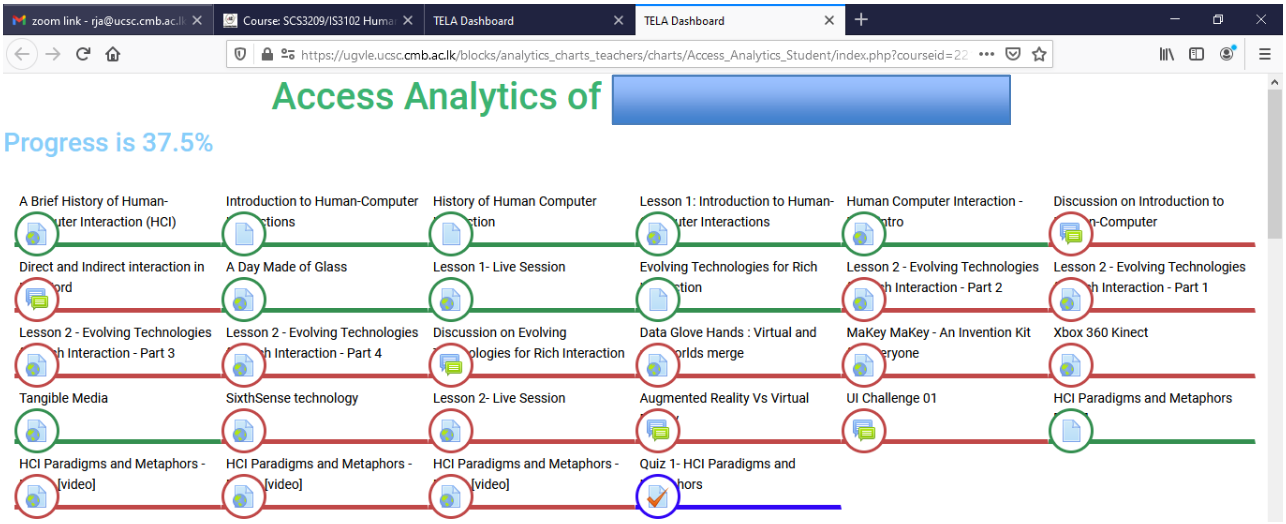


Figure 4: Progress Bar

- Resource Access Count

Resource Access Count graph (Figure 5) visualizes how many times the student has accessed each resource. The same chart illustrates the average class access of each resource. This visualization aims to improve the student's motivation and engagement since the student can compare his/her current progress with the rest of the class. If the student's access counts are less than the class average access count, the student needs to interact more with the resources. Here students can set goals (ex: I will read Presentation 2 three times this week, I will post two posts in the Forum) and work to achieve the goals. This visualization is especially effective in increasing engagement in interactive content like forum discussions where the student has to be active only.

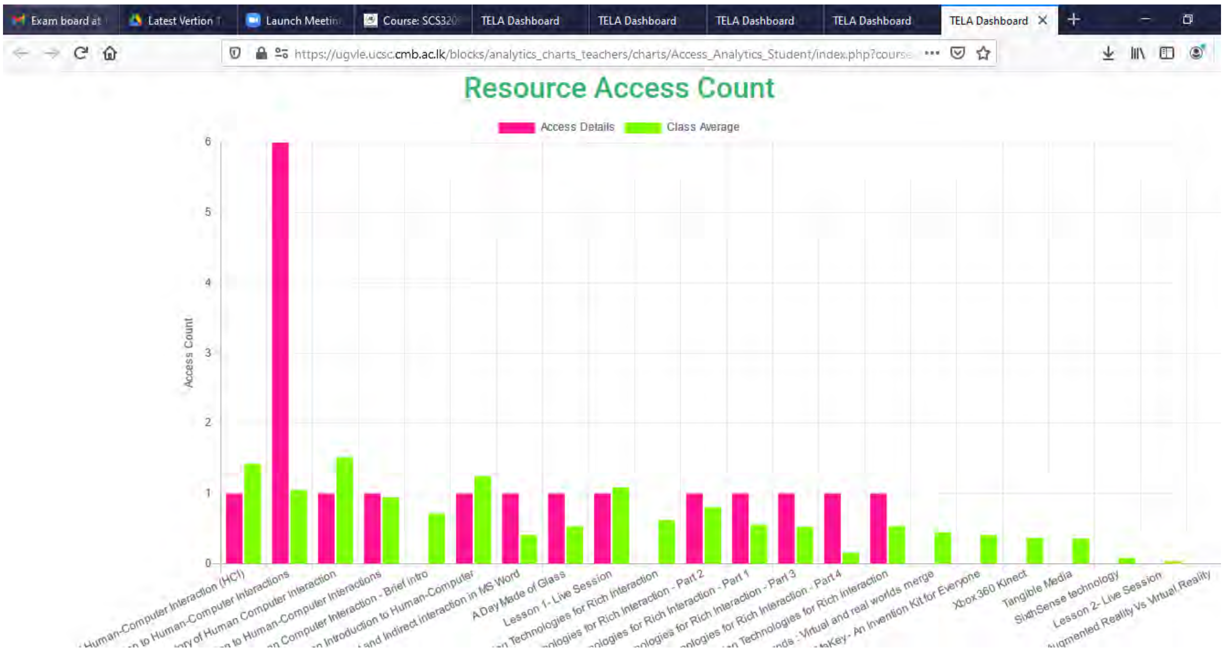


Figure 5: Resource Access Count

- Daily Action Count

Student can find out the number of actions he/she executed each day using the Daily Action Count graph (Figure 6). Student can quickly identify whether he/she accessed the course in the recent past and can engage more in the course if the interaction is low.

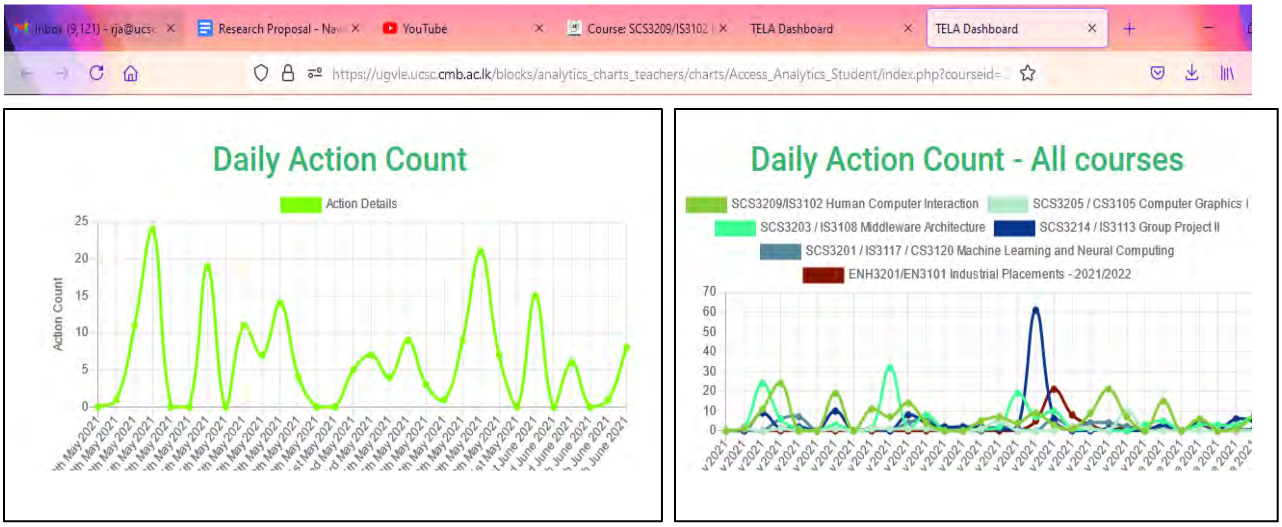


Figure 6: Daily Action Count

Figure 7: Daily Action Count – All Courses

- Daily Action Count all courses

A student can compare his/her engagement in a particular course with the other courses enrolled in a semester. Using this graph (Figure 7), a student can quickly identify the courses that he/she needs to increase the interaction. Using this visualization, a student can create his/her plan to balance the interaction between the courses.

- Daily Online Time

This graph visualizes both logged-in times in the course and the actual online time in the same chart (Figure 8). The exact online time is calculated by summating actions whose time difference is less than 15 minutes. Student can identify how he/she used the time effectively by using this graph. For example, if the logged-in time is higher than the actual online time, that means the student keeps idle during that period, or he/she may do other activities. Using this graph, a student can stop other activities and use the time effectively by fully engaging in the learning activities.

- Time Spent for SCORM material

This graph illustrates the time spent on each lecture note uploaded as interactive learning material, including SCORM (Figure 9). Thus, students can easily find out the lecture notes that are having less engagement. Using this visualization, the student can increase the interaction. At the same time, if the time spent on interactive learning materials is high, it causes to increase the student's self-confidence.

Using all the visualizations in the Access Analytics module, we hope to increase students' motivation and engagement with the course. When the engagement with the course increases, it causes to improves the self-confidence of the student. All these are positively affected to increase the grades of the student.

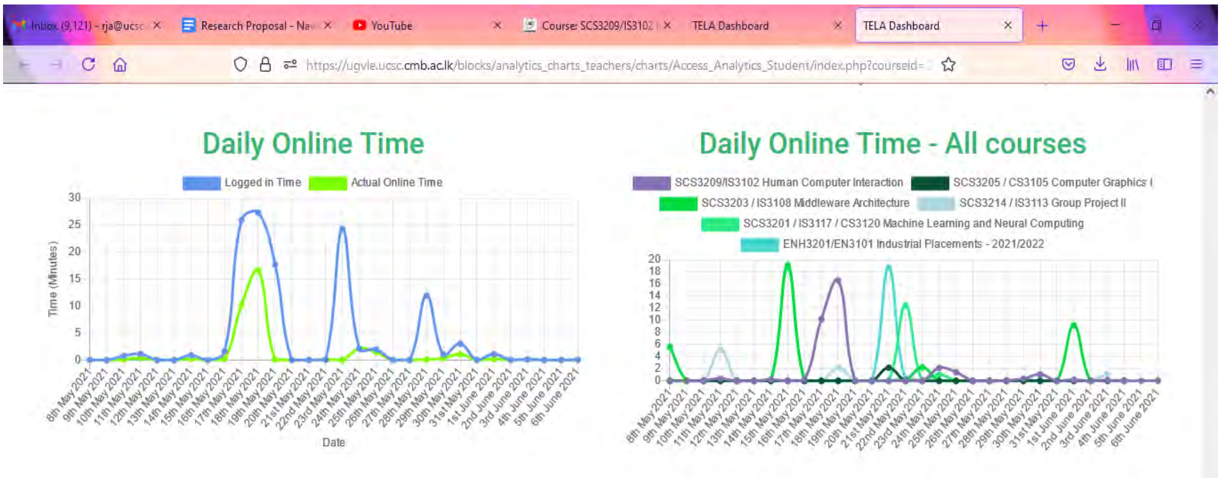


Figure 8: Daily Online Time

4.1.2 Quiz Analytics Module

We suggest that the lecturer should post a quiz after completing each sub-topic. Students need to complete the quiz before the deadline, and the TELA system analyzes quiz data and generates several graphs for the students. Using those graphs, students can evaluate his/her current performance level and identify the sub-topics that need to improve. Below we explain different charts in the Quiz module.

- Quiz Marks with Class Average

This graph visualizes the marks achieved by the student and the average mark of the class as a bar graph (Figure 10). Students can compare his/her marks with the class average marks and determine whether the performance is below the class average. Using this visualization, students can make goals and do the learning activities to increase the marks gradually. This visualization aimed to increase the motivation of the student to improve his/her marks. As a result, the student will engage more in the course to increase the marks in upcoming quizzes. Subsequently, this will improve the student's self-confidence since the student can see continuous progress in his/her marks.

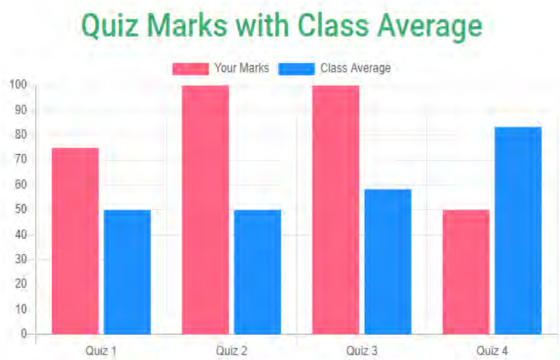


Figure 9: Time spend on SCORM Material

Figure 10: Quiz Marks with Class Average marks

- Your Current Status

This graph visualizes the student average mark of all the quizzes with the current performance level (Figure 11). We divided performance levels into five categories: Very Poor (Red: 0-20 marks), Poor (Orange: 20-40 marks), Average (Yellow: 40-60 marks), Good (Light Green: 60-80 marks), and Excellent (Green: 80-100 marks). This graph indicates the student's current performance level based on the average marks using the pointer. Using this visualization, we try to increase the student's motivation since this visualization shows the student's current performance level; he/she can set targets to improve the performance continuously. As a result, the student will create his/her learning environment and interact more with the lecture notes and interactive contents in the course—finally, this effect will improve the student's grades.

- Quiz Marks with Class Highest Marks

This graph visualizes the student's marks with the class's highest marks (Figure 12). Using this visualization student can compare his performance level with the class's best performance level. Student can create his/her own personalized learning environment to increase his performance level to the class best level. This visualization supports increasing the grades of the student. Simultaneously, a student can quickly identify the sub-topics underperforming in the initial stage since the quiz is based on the sub-topics. Then the student can put more effort into solving the unclear parts.

- Quiz Time

This graph visualizes the time taken by the student to complete each quiz with the average class time (Figure 13). Using this visualization, students can check his/her speed and practice to increase the speed. In addition, this chart will support when answering the exam paper, which will help improve the grades.

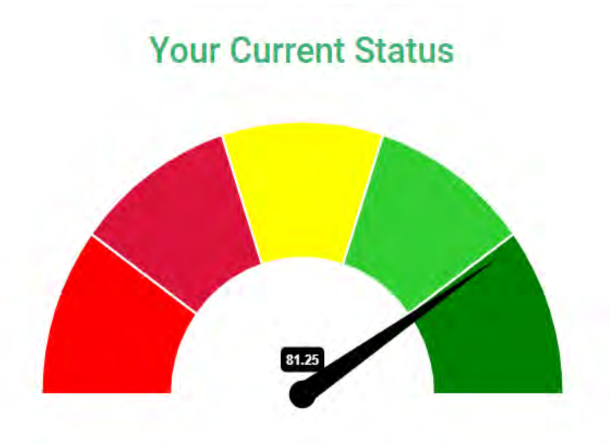
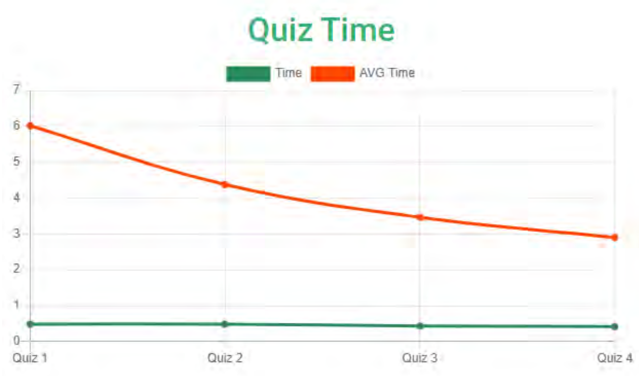


Figure 11: Student's current status

Figure 12: Quiz Marks with Class Highest marks

- Question Time

This graph visualizes the time taken for each question in a quiz according to the answered sequence (Figure 14). Using this graph, students can identify the more challenging questions (the questions that took more time to answer) and put more effort into studying those sections. This chart will support improving the answering speed of the student.



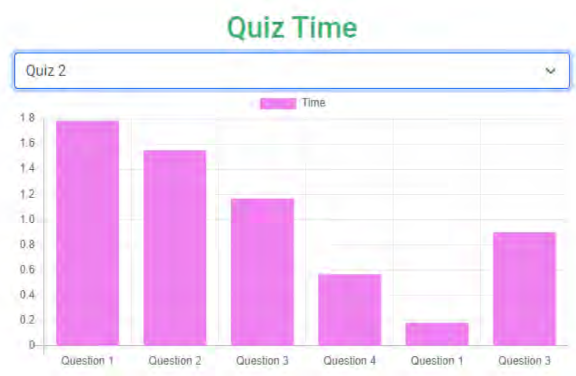


Figure 13: Quiz time

Figure 14: Question time

4.1.3 Forum Analytics Module

This module visualizes the forum interaction in a tree structure (Figure 15). Each node represents a post published by a student with a link to the parent node. Using this graph, students can quickly identify the topics which have more comments. Then, students can read the content. At the same time, this increases the student's motivation to participate in the forum discussion. When the mouse moves on to a node, it pops a small window containing the details (name of the student, discussion subject, and the message posted).

Figure 15: Forum Analytics Visualization

4.3 RQ3: Can the TELA system support the students to improve their motivation, interaction, and grades?

The validation of the TELA system was done by conducting Experimental Research. Qualitative and quantitative techniques were used to analyze the impact of introducing the TELA system. T-statistical analysis was used as the quantitative technique. A questionnaire was given at the end of the course for the qualitative analysis to obtain the students' perceptions about the TELA system. Also, we conducted interviews with the treatment group students to evaluate the information visualizations in the TELA system. The validation study aimed to evaluate whether the introduction of the TELA system has a positive impact on students' motivation, engagement, and grades.

Therefore, the following propositions were defined in light of the aim mentioned above.

1. The TELA system supported students to improve their interaction with the learning materials.
2. The TELA system helped students to improve their grades.
3. The TELA system supported students to improve their motivation to engage more with learning activities.

SCS 3209 – Human-Computer Interaction course, a third-year course of the UCSC, was selected as the scenario for evaluation. We selected 100 students from the course and divided them into two groups as each group consisted of 50 students. Initially, we conducted a pre-test for both groups to check whether there is a significant difference between the two groups regarding prior knowledge. The average mark of group A was 63.42, while the average mark of group B was 63.22 for the pre-test. There was no statistically significant difference between the two groups since the p-value was 0.9012 for the t-statistical analysis. After the pre-test, one group was randomly selected as the treatment (pilot) group, and we introduced the TELA system to them. Both groups participated in the online lectures conducted, and they accessed the uploaded learning materials to the UGVLE. The only difference between the two groups was that students in the treatment group could access the TELA system via the UGVLE. In contrast, students in the control group couldn't access the TELA system.

The data analysis with respect to the propositions is presented below.

1. The TELA system supported students to improve their interaction with the learning materials.

To analyze this, t-statistical distribution was carried out among the treatment group and the control group. This was done based on the students' average resources access count. The aim was to check whether the use of the TELA system positively impacted students' interaction with the learning materials.

As the null hypothesis, H0: "The average resource access count of the treatment group was equal to the average resource access count of the control group," was taken.

Table 9 presents the results of the t-statistical analysis. The null hypothesis (H0) can be rejected since the p-value is less than 0.05. By considering the t-statistical analysis, it can be stated that students' interaction with the learning materials has been improved through the usage of the TELA system.

Table 9: Results of the t-statistical analysis about the students' interaction.

	Treatment Group	**Control Group**
Average resource access count	4.15	2.89
Observations	50	50
P (T<=t) two tails	0.0383	

2. The TELA system helped students to improve their grades.

To analyze this, another t-statistical analysis was conducted among the treatment group and the control group. This was done based on the average marks obtained for the post-test. The aim was to check whether the use of the TELA system had a positive impact on the students' marks.

As the null hypothesis, H0: "The average of the post-test marks of the treatment group was equal to the average of the control group" was taken.

The results of the t-statistical analysis are presented in Table 10. The null hypothesis (H0) can be rejected since the p-value is less than 0.05. In addition to that, the average mark of the treatment group is higher than the control group. Therefore, it can be stated that the students' marks (grades) have been improved through the usage of the TELA system by considering both the t-statistical hypothesis test and the mean values.

Table 10: Results of the t-statistical analysis about the students' marks.

	Treatment Group	**Control Group**
Average marks	67.3	63.48
Observations	50	50
P (T<=t) two tails	0.0238	

3. The TELA system supported students to improve their motivation to engage more with learning activities.

We interviewed the students in the treatment group to obtain their feedback with respect to the introduced TELA system. The interview was conducted for about 45 – 75 minutes with each student and evaluated each information visualization in the TELA system. The results of the evaluation are given in Table 11.

Table 11: User Evaluation of the TELA system

Module	**Feature**	**Highly Useful**	**Useful**	**Neutral**	**Not Useful**
Access Analytics	Progress Bar	94%	6%		
	Resource Access Count	90%	10%		
	Daily Action Count	10%	40%	50%	
	Daily Action Count – All Courses	14%	66%	20%	
	Daily Online Time	38%	50%	12%	
	Time Spent for SCORM material	86%	10%	4%	
Quiz Analytics Module	Quiz Marks with Class Average	96%	4%		
	Quiz Marks with Class Highest Marks	96%	4%		
	Your Current Status	94%	6%		
	Quiz Time	54%	46%		
	Question Time	12%	40%	48%	
Forum Analytics	Forum Graph	78%	22%		

Module	Feature	Highly Useful	Useful	Neutral	Not Useful
Overall System Evaluation					
Question			**Yes**		**No**
It was helpful to improve learning using the TELA system.			95%		5%
The automatic personalized feedback provided was satisfactory.			96%		4%
The feedback helped to identify the under-performing topics in the course.			96%		4%
The TELA system is supported to improve motivation.			94%		6%
The TELA system helped to improve the learning engagement.			96%		4%
The TELA system supported improving the marks continuously.			93%		7%
The TELA system supported you in conducting learning activities during the COVID-19 pandemic period.			92%		8%

According to the evaluation results, the TELA system has meaningful Learning Analytic visualizations that support the student to improve motivation, engagement, and grades. At the same time, all students said that this system is beneficial in situations like the COVID-19 pandemic period, where all the lectures are conducted in a fully online mode. Students can easily capture their progress, underperforming sub-topics, and progress using the TELA dashboard even though students are isolated from the lecturers and peers in a fully online environment. Some students said they missed accessing some lecture notes since the uploaded resources in the UGVLE are high. Students said it is easy to identify the missed activities and learning materials using the TELA dashboard. Some students requested not to include additional visualizations in the dashboard since it is difficult to understand the information. Two students asked to have a dark background in the UI. We decided to give an option for the user to change the background theme according to their flavor in future implementations.

5. Conclusion

The Higher Education sector faces different problems from time to time. During the COVID-19 pandemic period, both lecturers and students face various issues. Lecturers cannot recognize whether the students follow the course or not, identify the at-risk students, and identify the most challenging topics in the course for the students. Simultaneously, the students cannot track whether they are in the expected performance level, their progress in the course, and their performances compared to the rest of the class. The student's motivation to engage with the learning activities is also less in a fully online mode since students are isolated in the digital environment, especially due to the COVID-19 pandemic. We designed and implemented a Learning Analytics dashboard called TELA to improve undergraduate students' motivation, engagement, and grades in fully online and blended learning environments. Initially, we conducted a literature survey to analyze the features and limitations in the currently available Learning Analytic Dashboards. Then we studied currently available Learning Analytic plugins for Moodle and identified their drawbacks.

We conducted two surveys with undergraduate students and interviewed the lecturers of the UCSC to identify the required features of the TELA system. Based on their feedback analysis, we designed and implemented the TELA system as a Moodle Plugin with three modules: Access Analytics, Quiz Analytics, and Forum Analytics. Finally, we conducted Experimental Research with third-year undergraduate students of the UCSC to evaluate the system. According to the results, the TELA system can improve students' motivation, engagement, and grades. Initially, the student can track his/her current progress and performance level compared to the peers, which helps to improve the motivation of the student to engage more with the lecture notes and learning activities. When the engagement with the course increases, it causes to enhance the self-confidence of the student since the student can see his/her progress in the course and continuous improvement of the performance. All these effects improve the grades of the student. The TELA system is effective in both fully-online learning environments like the COVID-19 pandemic period and blended learning environments.

Based on the results obtained through the study, it shows that the formative assessments have a higher impact on students learning process. Therefore, irrespective of a pandemic situation, curriculums can be enhanced by including formative assessments at the end of each sub-topic of the course. In this case, the students' performance captured using the TELA system can provide valuable insights for students to improve their performance with respect to identifying study areas where they need to focus more on as well as identify their stand with respect to peers. Furthermore, research discovered the importance of having forum discussions to promote peer-learning among the students. As a result of actively participating in forum discussions students will be able to enhance their knowledge on the given topic as well as clarify doubts while collaborating with peers. Therefore, Lecturers can enhance the curriculum by including forum discussions on different topics to promote the peer-learning and collaboration among the students.

As future work, we are planning to conduct another Experimental Research to test the impact of the TELA system in an online learning environment with a large sample of students. We are also improving our research by designing and developing a Learning Analytic dashboard for teachers to enhance their teaching practices, support to identify the students at risk of failure and improve Learning Designs.

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