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# Teachers' Performance Evaluation using a Learning Analytic Toolkit

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## ABSTRACT

The growth in the use of technology in the learning process has given institutions and individual teachers unprecedented opportunities to monitor and analyse how students interact with online content through "digital traces" they leave. The collection, measurement, analysis and reporting of such digital trace referred to as learning analytics (Siemens and Gaševic´, 2012). Learning Analytic Toolkits offer personalized learning process which enables students have efficient and effective learning experiences. Since the purpose of examinations is to ascertain the level of learning that have taken place between a teacher and the students, the researchers have developed a Learning Analytic Toolkit that can be used by the teachers, parent and management of the institutions to analyze and evaluate the students and teacher's performances in all or any particular subject. The researchers have adopted the Object-Oriented Modular Analysis and Design Method together with graphical method in the evaluation of the teachers and students' performances. The results obtained from the graphs provide at-a-glance valuable information to the stakeholders (school management, teachers and parent/student) to evaluate the performances of the students and teachers per subject.. The research is recommended to the management of secondary schools in decision making on the performances of their teachers and students.

**Keywords**: learning, learning process, learning analytic toolkits and performance evaluation

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## 1. BACKGROUND TO THE STUDY

The ways in which students experienced learning have significantly changed over the past two decades. 21st century education is now a 'mass' education system and uptake of technology in teaching and learning by teachers and students has dramatically increased (James, Krause, & Jennings, 2010) (Norton, Sonnemann, & McGannon, 2013). Teachers intuitively at regular times keep track of Student' learning through quizzes, class work, assignments, structured test, attendance, attention to details, examinations etc. but these tracks are easily forgotten, neglected or never opportune to attain the recognition of other stakeholders in the school on time; when in fact they can pose a great insight if promptly recorded and analysed to underscore the attainment of a learner, the learning process and the assessment strategy.

Growth in the use of technology in teaching has given institutions and individual teachers' unprecedented opportunities to monitor and analyse how students interact with online content through 'digital traces' they leave. The collection, measurement, analysis and reporting of such digital traces is referred to as learning analytics (Gaševic´ & Siemens, 2012). Existing work in learning analytics has shown much promise for understanding and optimizing learning processes, outcomes, and environments (Baker & Siemens, 2014). To date, much of this work has been dedicated to the development of predictive models of academic success (Gaševic´, Dawson, Rogers, & Gasevic, 2016). These can enable early identification of students who are at risk of failing and/or withdrawing from an academic degree program or course. Such predictive models have been integrated into systems such as Course Signals to provide feedback to both students and instructors (Arnold & Pistilli, 2012). In addition to establishing broad predictive models of student academic performance and retention, considerable research effort has been devoted to further our understanding of the learning process. For example, investigating student patterns of behaviour through social network analysis (Bakharia & Dawson, 2011), discourse and textual analysis of online discussion (Kovanovic´, et al., 2016), and detecting learning strategies (Winne, 2014).

Growth in the use of learning analytics has invited attention to how analytics data are presented, notably through learning analytics dashboards. Learning analytics dashboards and other presentation tools assist users in making data-informed decisions, and this has become a critical area of learning analytics research and development (Verbert, et al., 2014). Dashboards can provide insight into varied aspects of learning, allowing visualisation and interpretation of concepts such as structures formed in social networks (Bakharia & Dawson, 2011) activities in social media (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013), and the effectiveness of learning designs implemented in courses (Ali, Hatala, Gaševic´, & Jovanovic´, 2012).

Some studies have evaluated the effectiveness, usability, usefulness, and efficiency of different dashboards (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). Unsurprisingly, well-designed dashboards are very important for achieving desirable outcomes in higher education. For example, the Course Signals dashboard was found to increase student retention (Arnold & Pistilli, 2012). Likewise, (Corrin & de Barba, 2014) showed that students have difficulties in interpreting statistical results presented in commonly available learning analytics dashboards. Nevertheless, few studies have offered empirically validated principles for the design of learning analytics dashboards.\This paper explicitly addressed this issue by focusing on the needs of instructors to receive actionable feedback on the effectiveness of their learning designs and assessment strategies.

The sense at the start of a new class, subject/course or even weeks into the term or semester that the teacher could predict which students will fail the subject/course or which students will succeed? Not to create a self-fulfilling prophecy or "profiling" the students but based on some valuable mental data, collected from terms or semesters of experience, that can help in predicting who will succeed and who will not due to certain variables. In short, having hunches based on an accumulation of experience. The question is, what are those variables? What are those data? And how well will they help in predicting student performance and retention? More importantly, how will those data help the teachers in helping the students succeed in the subject/course? This is the promise of Learning Analytical Toolkit. Learning Analytics uses intelligent data, learner-produced data, and analysis models to discover information and social connections, and to predict and advise on learning (Siemens, 2016). This tool can be integrated into a learning management system such that teachers would have access to Learning Analytics tools provided via dashboards.

Learning analytics offers personalized learning, which would enable students to have more efficient learning experiences and certainty for predicting and improving student success and recognition in part because it enables educators and schools to make data-driven decisions about student achievement and retention. Data decision-making involves making use of data, such as the sort provided in Learning Management Systems (LMS), to notify educator's predictions. (Claris, 2015). Learning Analytical Toolkit looks beyond the data used in learning analytics that includes attendance monitoring, class participations, grades and more. It includes the regularity of LMS tool use, obtaining discussion board posts, and the number of times taking quizzes. (Claris, 2015). This thesis delves into the possibility of educators building a model of successful learner behaviours that can be used to support learners to engage in these behaviours. Alternatively, they can also identify at-risk learners as ones who diverge from this model.

## 2. STATEMENT OF PROBLEM

The purpose of examination is not for students to fail but to ascertain that learning has actually taken place. This gave rise to the need to predict learner's educational attainment in examination preparation which is the analysis of learning itself. Once learning is properly analysed then there can be early intervention plans to ensure unflinching success in examinations. The analytic toolkits used are:

**Blackboard Analytics for Learn**

Blackboard Analytics for Learn is a web-based LAT used to help students improve their learning experience. It's easily customized to an institutional need and integrates with Microsoft OneDrive, school information systems and Dropbox. Blackboard Learn can be deployed in three ways: cloud, self-hosting (on-premise) and managed hosting. It has the learning analytics feature with automatic notifications if failing class, visualization tool and call to action relating to course activity, ability to export data to SPSS or Excel, Customize and send targeted notifications to specific users or school- or district-wide with access to Gradebook in either list view or student view where students can see grading progress of each assignment/assessment. The major drawback of Blackboard Analytics for Learn is the cost implication; based on the estimate from different sources (Scavicchio, 2016); it is an unachievable toolkit for use in Nigerian institution.

**Modular Object-Oriented Dynamic Learning Environment (MOODLE)**
Moodle is a free software e-learning platform, also known as Virtual Learning Environment. It serves to help educators create online courses with a focus on interaction and collaborative construction of content (Claris, 2015). Moodle also allows several plugins such as Events Monitoring, Overview Statistics, Site-Wide Reports, Engagement Analytics, Logs, Forum Graph, Analytics (Piwik & Google) The above Learning analytics tools offer insights into the progress of learners and ensure that objectives are being met. Viewing trends of participation, submissions and other data can assist educators improve the eLearning experience, vastly helping retention rates and student successes (Moodle, 2015). The major drawback is that they are toolkit integrated into learning management system and cannot stand alone without MOODLE since, MOODLE usage in Nigerian institution is an emerging trend they all prove ineffective for the majority of Nigerian institution without one and teachers without access to MOODLE cannot use this beautiful analytical

**Brightspace Student Success System**
Brightspace Student Success System is an early intervention tool. With predictive analytics and visual diagnostics, you can spot potential problems sooner and give students the help they need before it's too late. It uses analytical insights to make predictions about student success and risk levels in your courses. The predictive analysis used by the Student Success System is adaptable to the instructional approach of each course, allowing you to monitor student engagement and achievement expectations for your courses. With the Student Success System, you can use the predictive models to monitor and design targeted interventions for at-risk students in active courses to improve student success, retention, completion, and graduation rates. Administrators add target courses to the system to generate predictions of student success, using historical courses for comparison, where historical courses are prior offerings of the target courses that are representative of the courses in terms of teaching and learning expectations. Administrators create and configure predictive models for target courses in the administrative Student Success System interface.

Instructors use the Student Success System to monitor predictions of student success levels for active and enabled courses on a weekly basis in five possible domains: course access, content access, social learning, grades, and preparedness. The weekly predictions produce a Success Index for every student in the course, letting you visualize and compare potential success rates for your students. With this level of workflow management, it has the feel of a customer relationship management system rather than a simple VLE reporting system. The indicators of engagement, with all the potential data sources behind them, are boiled down to simple red/yellow/green traffic lights for grade and effort. But these then trigger a range of automated and human interventions and communications which are tracked by the system. You can have all the metrics you like for measuring engagement but effective management of interventions is what could really start making an impact on student outcomes across an institution (Claris, 2015). The drawback of this tool is just as others which is a reliability on Learning Management System and a huge cost implication.

**Completing the loop**
The Loop Tool is an open-source online application compatible with Blackboard and Moodle that allows teachers to access data from learning management systems in an easy and meaningful way. The Loop Tool can be downloaded and installed on a server by an institution. The framework consists of five dimensions namely Temporal analytics, Tool-specific analytics, Cohort dynamics, Comparative analytics and Contingency.

The drawback of the usage of this tool is the implementation (installation and integration) although there is a step-by-step guide on how to install the Loop Tool it can only be install on a Linux server with many intricate complications of requirement and thus needs Linux Operating System professional for implementation. The fact that solution cannot be simply loaded to a website or a WAMP like other open source solution e.g. MOODLE makes it ineffective and less attainable in Nigeria.
Also, Claris (2015), designed a learning analytic toolkit with MATLAB and MS Excel. Its numerous features include being a standalone tool for easy implementation with Learning Management System, Risk Quadrant, Intervention (Email and SMS Notification) etc.
The drawbacks are its lack of seamless integration with LMS, development in MATLAB limits is availability with respect to not being a web-based tool for easy accessibility for all stake holders in the academic setting

## 3. OBJECTIVES OF THE STUDY

The general objective of this study is to design and implement a light weight Learning Analytics Toolkit that can be used to forecast and evaluate students performance in a learning process. This learning analytical toolkit will

- Utilise data from LMSs (e.g. Moodle, Blackboard) or physical gradebook in the absence of LMS.
- Have a learning design component of the tool that enables teachers to "acknowledge" or describe their pedagogical intent.
- Link the acknowledgement to a technology-based tool
- Use the technology-based tool as a doorway to learning analytics
- Allow basic access/use data to be returned to teacher
- Also allow sophisticated activity/assessment-based on data to be returned to teacher

## 4. Methodology

The researchers adopted the Objected-Oriented Analysis and Design Method, using the Unified Modeling Language as a defacto in the analysis of the system. The analysis and design are illustrated as follows:

### 4.1 Interface Design

This page grants users access to the system.

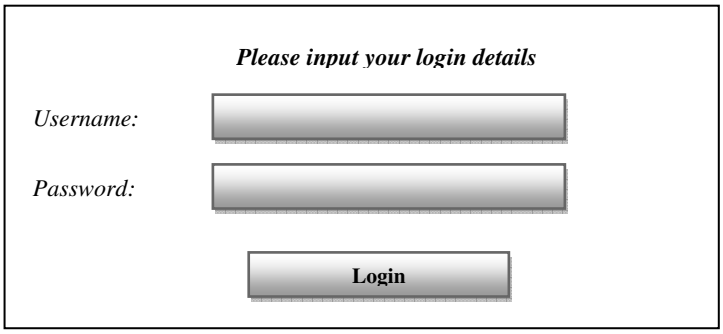



***Figure 1: Login Page of the system***

### 4.2 Design architecture

Teacher input the records either from a gradebook or an LMS then the records are analysed and the teacher receives the result. Other stakeholders like parent/student and management sees the analysed data and makes new queries.

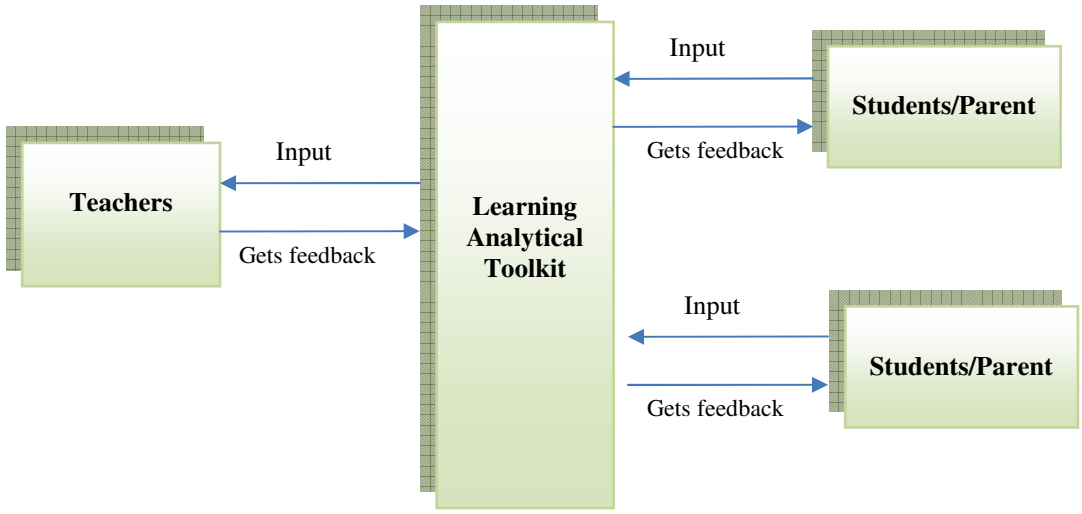



**Figure 2: Conceptual Framework of the system**

### 4.3 Interaction Diagram of the system

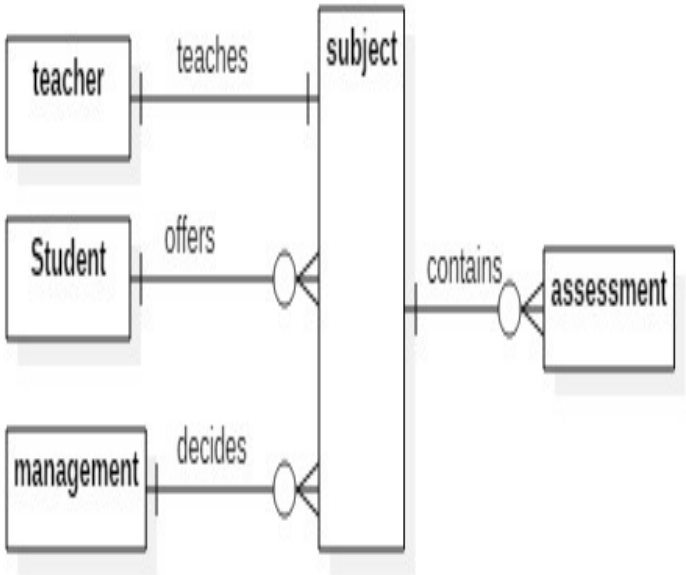



**Figure 3: Interaction Diagram of the system**

### 4.4 Class Diagram of the system

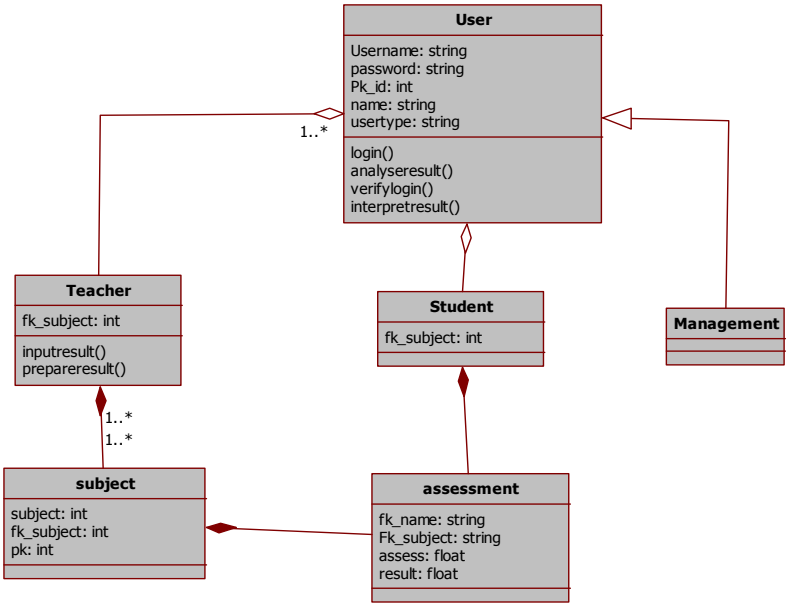



Figure 4: Class Diagram of the system

## 4.5 Use case Diagram of the system

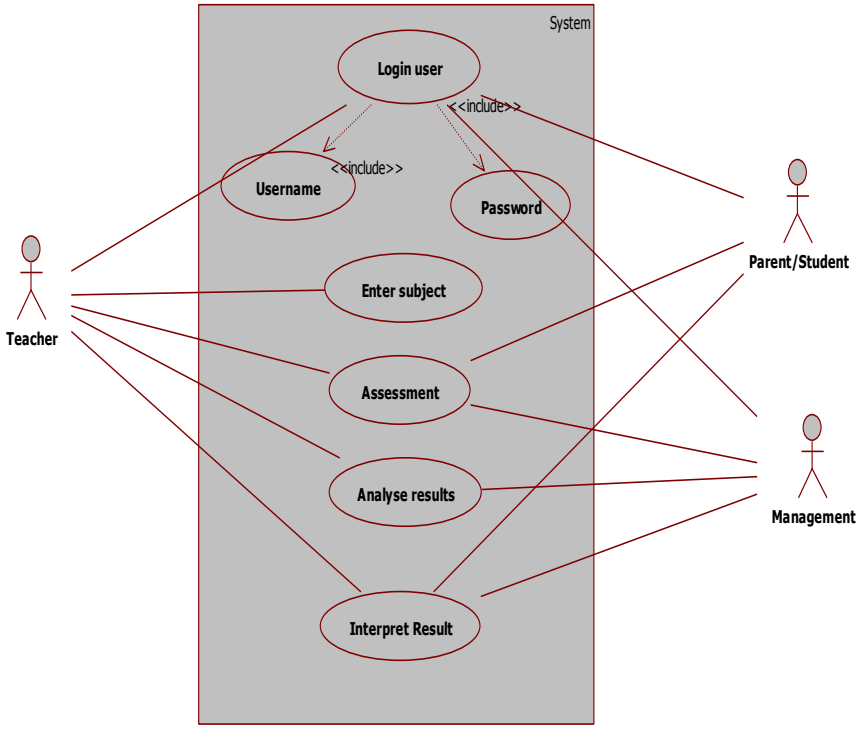



Figure 5: Use Case Diagram

## 4.6 Database Design

A simple design needs at least three tables the user table that handles access (login) to the LAT, the subject table that handles the teacher-subject allocation and the main table which is the assessment table. Due to the fact that a learning management system may not available it is expedient to record data in a simplified graded format. In a secondary school running 3 terms per year of 11-14weeks per term data (results of assessmentor group of assessments) can be gathered every week with two continuous assessments and an examination. Each roll represents a student while each column a unit of assessment this which must be graded (e.g. marks obtainable is 10) the unit of assessment vary from subject to subject or course to course depending on what the teacher believes is a prerequisite for the mastery of the subject/course. An example of a good template is illustrated in Table 1.

**Table 1: Proposed Assessment Template**

| Item | Code | Description | Maximum obtainable score |
|---|---|---|---|
| Week1 | WK1 | Background knowledge | 10 |
| Week2 | WK2 | Topic 1 Assessment | 10 |
| Week3 | WK3 | Theme Activity | 10 |
| Week4 | WK4 | Topic 2 Assessment | 10 |
| CA1 | FST | First Structured test | 20 |
| Week6 | WK6 | Topic 3 Assessment | 10 |
| Week7 | WK7 | Attendance /Accuracy of notes | 10 |
| Week8 | WK8 | Topic 4 Assessment | 10 |
| Week9 | WK9 | Theme Activity | 10 |
| CA2 | SST | Second Structured Test | 20 |
| Exam | Exam | Examination | 60 |

## 5. DATA ANALYSIS

The above data will be analysed with the following constants per subject per class (these will be additional column to the above table) Student Name, Subject, Class highest, class lowest, class average

**Table 2: Database Table Design**

| Item | Code | Description | Maximum obtainable score |
|---|---|---|---|
| name | Name | Student name | |
| subject | sub | Subject | |
| Week1 | WK1 | Background knowledge | 10 |
| Week2 | WK2 | Topic 1 Assessment | 10 |
| Week3 | WK3 | Theme Activity | 10 |
| Week4 | WK4 | Topic 2 Assessment | 10 |
| CA1 | FST | First Structured test | 20 |
| Week6 | WK6 | Topic 3 Assessment | 10 |
| Week7 | WK7 | Attendance /Accuracy of notes | 10 |
| Week8 | WK8 | Topic 4 Assessment | 10 |
| Week9 | WK9 | Theme Activity | 10 |
| CA2 | SST | Second Structured Test | 20 |
| Exam | EXA | Examination | 60 |
| ST1 | ST1 | Sum (WK1:WK4) + 3*FST | 100 |
| ST2 | ST2 | Sum (WK6:WK9) + 3*SST | 100 |
| Total | TTT | Sum (WK1: SST)/3 +Exam | 100 |
| Remark | RMK | Teacher Remark | |

## 6. DATA VISUALIZATION

- A student is shown a graph of his(er) scores against the class highest and lowest in a selected subject over various assessment
- A student is shown a graph of his(er) score against the class highest and lowest in a selected assessment over various subjects
- A student is shown a graph of his(er) score against the class highest and lowest in overall assessment in all subjects
- A teacher is shown a graph of individual student's score against the class highest, average and lowest in the subject for any assessment
- A teacher is shown a graph of average score against the class highest and lowest in the subject over various assessment
- A management staff (eg form-teacher) has access to all the above

## 7. DATA PRESENTATION

The input page implements a table format with ajax call for individual assessment while the output page implements a JavaScript interactive graphical presentation of data such that it gives more details at each node on mouse over and individual series can be hidden or unhidden by mouse clicks

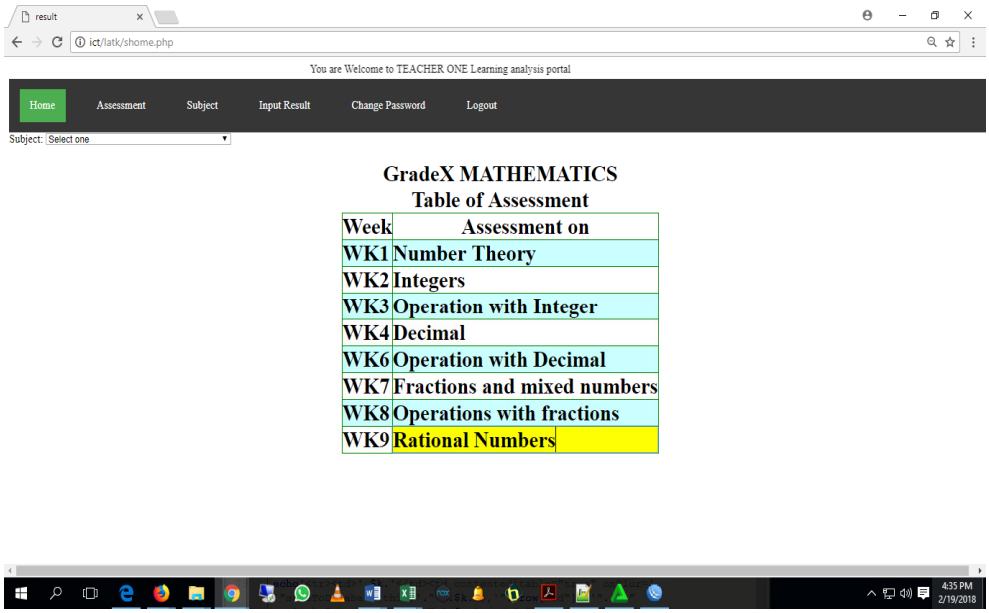
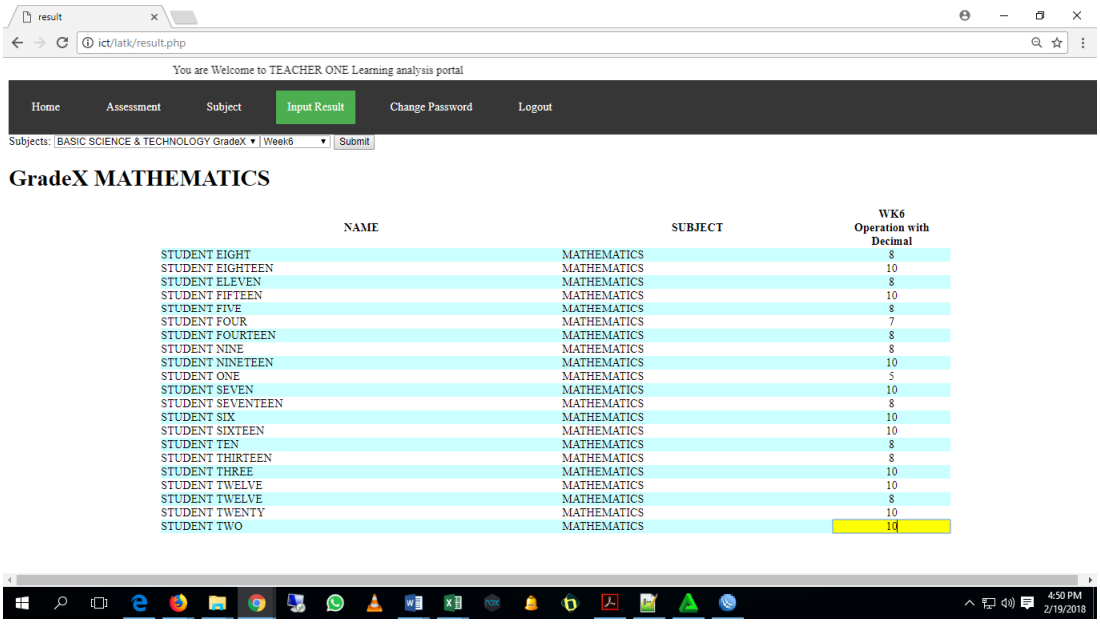



**Figure 6: Teacher Inputs the Learning Analysis Components**




| NAME | SUBJECT | WK6 Operation with Decimal |
|---|---|---|
| STUDENT EIGHT | MATHEMATICS | 8 |
| STUDENT EIGHTEEN | MATHEMATICS | 10 |
| STUDENT ELEVEN | MATHEMATICS | 8 |
| STUDENT FIFTEEN | MATHEMATICS | 10 |
| STUDENT FIVE | MATHEMATICS | 8 |
| STUDENT FOUR | MATHEMATICS | 7 |
| STUDENT FOURTEEN | MATHEMATICS | 8 |
| STUDENT NINE | MATHEMATICS | 8 |
| STUDENT NINETEEN | MATHEMATICS | 10 |
| STUDENT ONE | MATHEMATICS | 5 |
| STUDENT SEVEN | MATHEMATICS | 10 |
| STUDENT SEVENTEEN | MATHEMATICS | 8 |
| STUDENT SIX | MATHEMATICS | 10 |
| STUDENT SIXTEEN | MATHEMATICS | 10 |
| STUDENT TEN | MATHEMATICS | 8 |
| STUDENT THIRTEEN | MATHEMATICS | 8 |
| STUDENT THREE | MATHEMATICS | 10 |
| STUDENT TWELVE | MATHEMATICS | 10 |
| STUDENT TWELVE | MATHEMATICS | 8 |
| STUDENT TWENTY | MATHEMATICS | 10 |
| STUDENT TWO | MATHEMATICS | 10 |

**Figure 7: Teacher Inputs Value/Score on the Learning Analysis Components**

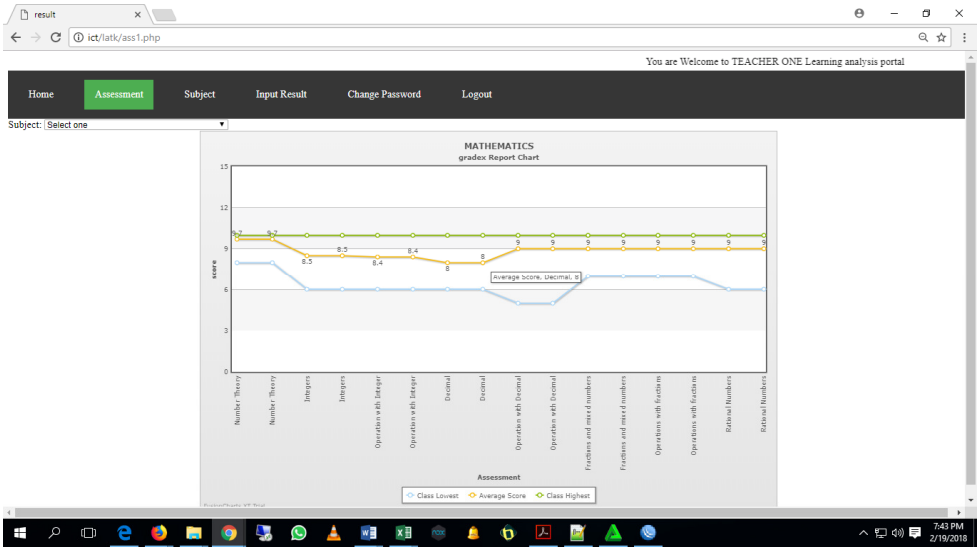



**Figure 8: A chart of class Average vis-a-vis highest and lowest for each component in a particular subject**

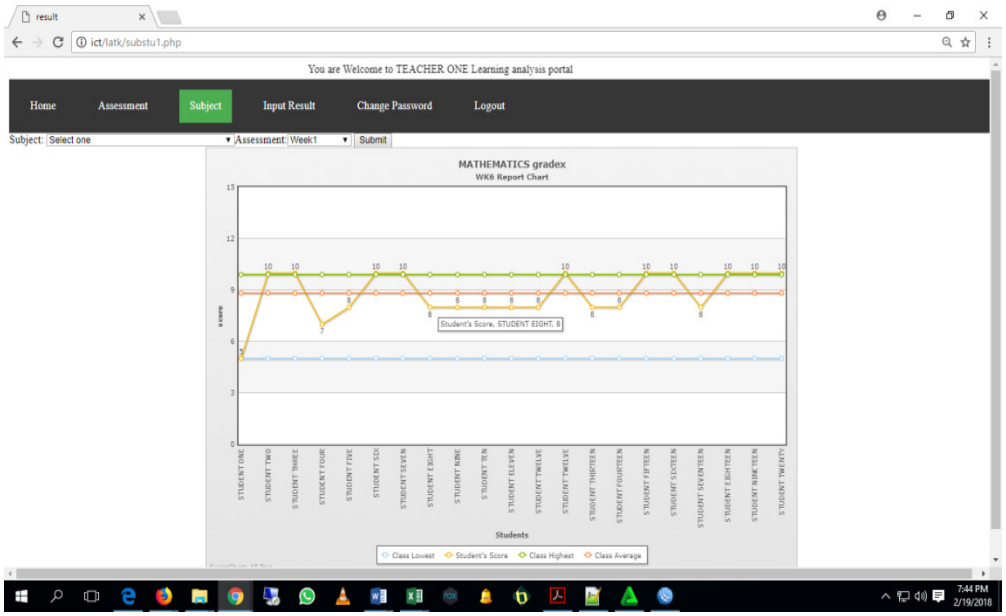



Figure 9: A chart of individual student's score against the class highest, lowest and average in a particular learning component

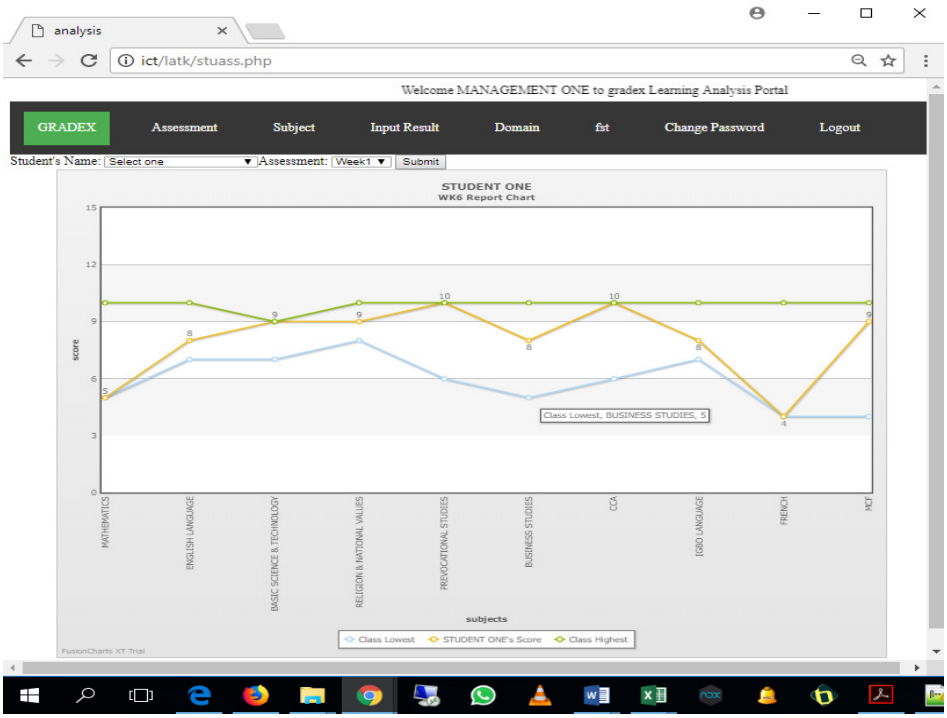



Figure 10: A chart of individual student's score in an assessment series for all subjects against the class highest and lowest

## 8. DISCUSSION OF FINDINGS

The issue of teachers intuitive/non-intuitive track of Student' learning through quizzes, class work, assignments, structured test, attendance, attention to details, examinations etc. been forgotten, neglected or never opportune to attain the recognition of other stakeholders in the school becomes a thing of the past.

The graphical representation allows at-a-glance interpretation of results which when available on time fosters early intervention plan to avert failure. When it is observed that as early as two to three weeks into the classes there has been a recurrence of failures the stakeholders (parent, students, teacher, management) creates and sustains early intervention plans to forestall such failures. When the results are imputed regularly for example, weekly:

- It will easily expose lazy teachers who fail to assess if the students are learning or not.
- It will expose lazy student who chooses not to be assessed or did not do the assessment
- No teacher will continually cook up scores on a weekly basis because it can be easily researched into.
- With the aid of supervision, the inputted data can be trusted vis-à-vis the generated information

## 9. CONCLUDING REMARKS

The investigation revealed that teachers' performance evaluation using a learning analytic toolkit can be developed to help the teachers and management in decision making about students performance. The researchers adopted the Object-Oriented Analysis and Design Method using the Unified Modeling Language in the analysis and design of the system.

## 10. CONTRIBUTIONS TO KNOWLEDGE

The lightweight LAT can be easily integrated to any School management System thus creating opportunity for the teacher to record regular student attainment at ease as simple as from their smartphone and thus giving the stakeholders real-time access to valuable information for decision making.

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