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## **Using Learning Analytics to Investigate Student Performance in Blended Learning Courses**

### **Abstract**

Many higher education institutions today offer online delivery as an alternative or addition to provide more flexibility to learners. However, students being confronted with such services come with different expectations to what that means to their learning paths and behaviours. Learning Analytics is a rather new and innovative way of making student behaviour and performances explicit through analysing large sets of learner data.

In this article, we take the case of online and blended learning from the University of Mauritius and hold the analysis of student interaction data against their performances and achievements. The study encompasses the entire population of first year students over two consecutive academic years of an undergraduate programme in Web and Multimedia Development. We classified the data into distinctive parts namely participation (or engagement), coursework marks, exam marks, and overall results to identify relationships that may influence student retention.

### **Keywords**

Online delivery, Learning Analytics, student engagement, performance, achievements

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# 1 Introduction

ICTs have revolutionised both traditional classroom teaching and the distance education concept. The advances in educational technology have helped to enhance students' learning experiences, through self-paced and self-regulated learning activities where they can exert better control over their learning (JUNG, 2001). There are certain perceived advantages behind the reasoning as to why it is better to opt for online learning. These include, but are not limited to factors such as widening access to new groups of students, ubiquitous access and increased flexibility, learner self-regulation, improved learning support respectively (cf. GOODYEAR, 2001; OLSON & ROBERT, 2002). However, at the same time, there are some concerns relating to the effectiveness of online instruction. Previous research has reported that learners found that online delivery sometimes fails to meet their actual needs in terms of instructional effectiveness, ease of locating information on the platform, learner support, or even the design layout of the online learning environment (HRC, 2009). These deficits can lead to information overload or information anxiety (BAWDEN & ROBINSON, 2009) and hence to frustration which may ultimately result in high dropout rates (RODRIGUEZ, 2012).

Learning Analytics is an emerging field of research in technology enhanced learning. It is based on the principle of using large educational datasets from online student activities and other data sources to identify behaviours, attitudes, learning paths, and trends that can highlight potential issues and areas for improvement in terms of the educational design, delivery, and administration of student learning (GRELLER & DRACHSLER, 2012). Learning Analytics refers to the collection and compilation of data, which is then analysed to assess the progress of learners, as well as judge their past and anticipated future performances. Assessing learners in this way might be in terms of different variables, such as their way of participating, their responses and their academic achievements (SIEMENS, 2013). In an online learning environment, learning data can be compiled by gathering information on learners' performances in assignment submissions, in online tests or

quizzes, through their engagement with learning resources or in discussion fora as well as their reflective comments and feedback posted (cf. ERADZE, 2016).

In this paper, we are aiming to use Learning Analytics datasets from the virtual learning environment of the University of Mauritius to measure the level of interaction of students in online course provisions. This research is of great importance in the local context of the Mauritius Higher Education sector, as public universities face severe cuts in their government grant-in-aid support. Thus, universities have aligned their strategic plans to place e-learning and online education at the heart of their delivery. There is, however, still some resistance from academics and some degree of scepticism in the student community with respect to the new educational models that are being proposed.

From our analysis, some conclusions will be drawn on how online elements of a course connect to student achievement or (potential) failure, and what that means for course design.

## **2 Previous work on the effectiveness of online learning**

Enrolment in online courses has considerably increased in the higher education sector. According to a survey by ALLEN & SEAMAN (2011), the rate of increase in online enrolment has slowed by about 10%, but has still outpaced the overall growth in higher education enrolment by approximately 1%. Despite this trend, the study showed that one third of professors still believe that face-to-face education (F2F) is superior to online education in providing students with quality instruction. This proportion has remained nearly constant since 2003 (ALLEN & SEAMAN, *ibid.*).

A survey of the literature reveals that the discussion around effectiveness of online learning has somewhat calmed down after much activity in the late 1990s and early 2000s. In one of the early studies on the effectiveness of online education, PICCO-

LI et al. (2001) found no significant difference in the performance of students between face-to-face and online delivery. In fact, during the study, a virtual learning environment (VLE) was used for daily instruction, but all course exams were conducted in person. However, students in the online sections of the course pointed out that they had higher self-efficacy than did their face-to-face peers, but also reported lower satisfaction in their course.

The effectiveness of online education has largely been investigated and reported for situations where no stark contrasts in the results have been obtained between face-to-face and online courses. In a teacher education course, traditional, online, and classroom-in-a-box were compared and no significant difference in student performance was found between these three delivery modes (SKYLAR, 2005). Student satisfaction was likewise shown to be roughly equal. However, in a Thai business statistics course, students in the online course were observed to perform significantly better than students in an equivalent F2F course (SUANPANG, 2006). LAMERES & PLUMB (2014) compared the performance of online and F2F students in a classroom and lab-based electronics course and found again no significant difference in their achievements.

From these and other comparative studies, we can take it that the evidence of whether online learning is better or worse than classroom tuition in terms of pedagogical outcomes is inconclusive and very context specific. For this reason, we decided to use the evidence from our own data and analytics to compare and evaluate student engagement and achievements. The motivation for this came from the desire and need to put arguments influencing course design and delivery mode into the local debate and making it context specific to Mauritius and our students.

### **3 Background work on Learning Analytics**

Online environments hold a lot of information about student interactions that can be held against their learning outcomes and achieved grades as assessed by their lecturers. Additionally, universities possess other student data like their schooling

background, grades or personal data including their gender. The exploitation of this “big data” in education through educational data mining and Learning Analytics has gathered pace in recent years with many universities around the world using the information they hold on students to investigate, reflect on, and improve their services. National education authorities like SURF in the Netherlands (cf. ENGELFRIET et al., 2015) or the JISC in the UK (SCLATER & BAILEY, 2015) are keenly trying to advance the implementation of Learning Analytics in higher education institutions and to alleviate potential barriers, such as data privacy. Recently, policies and good practice guides are emerging to give further guidance on how to apply Learning Analytics on an institutional level (cf. OPEN UNIVERSITY UK, 2014; SCLATER, 2016; JRC, 2016).

Our rationale for applying Learning Analytics to investigate student participation and success lies mainly in its anticipated power to detect students in danger of falling behind or dropping out of a course early, so dedicated remedial actions can be taken to keep them going (GRELLER & DRACHSLER, 2012).

## **4 Issues and setting**

Since 2009, the University of Mauritius (UoM) has been running the “Diploma in Web and Multimedia Development” programme to secondary school leavers, online through their e-learning platform. Two modules in the first year are, however, offered face-to-face given that they form the core of the subject area. The course is offered on a full-time basis over four semesters with exams for each module normally being held at the end of the academic year. However, throughout the year, there are a number of assignments, and practical exercises that students have to submit as part of the continuous assessment of the course. The enrolment numbers in the programme have continuously risen over the years. Then, in 2012, it was noticed that some 30% of students failed the course in their first year. This issue triggered a data investigation through a Learning Analytics approach to try and establish the main causes for the drop-out.

In 2012, some 120 freshmen were enrolled in the programme. After the first-year exams, many of them either had at least one re-sit, had to repeat the year, or had been terminated from the course. There have been sporadic claims especially from a few of the failed students that the online mode of delivery was to their disadvantage – despite them knowing that the course was offered in a distance education online learning mode prior to registration. Given that the number of students had been steadily increasing due to the policy of widening access to tertiary education, there are a number of questions that arose with the challenge of explaining this relatively high dropout:

- Is there a correlation between HSC grades of first year students and their performance in the course?
- Is there a significant difference between the performance of the same students in the online modules when compared to modules offered in a face-to-face mode?
- Do we find gender related issues?
- Is there a link between student engagement in an online module and the performance of that same student in the exams?

Statistical analysis of interaction data from the VLE log files was used as the main method adopted for this investigation of two consecutive cohorts of students. The pool of data was already available on the e-learning platform and on the student record system of the university. Students' personal data have been kept strictly confidential, the identities of students were hidden throughout the study and their use was restricted only to the purpose of this specific research.

## 5 Phases of data analysis

An online learning platform tracks and stores a lot of data about student engagement patterns and behaviours. The first phase of the study, therefore, consisted of using data mining techniques to extract, clean, order, and put the available data into a structured format. Such data was related to the students' HSC grades, their per-

formance in the modules, their cumulative point average, and their learning interaction patterns on the VLE platform.

The second phase encompassed the analysis of the data retrieved from the online learning platform and the student record system to identify any patterns and/or correlations as per the above research questions. Available performance data from the face-to-face modules was compared to data available from the online modules to further test the hypotheses.

In a final step, phase three, the findings of the data analysis were presented to the academic community at the Centre for Innovative & Lifelong Learning, including students, in a mini-workshop to validate and discuss the findings.

## **6 Overview of the ‘Web & Multimedia’ Programme**

The programme was conceived in 2008, as the first undergraduate online programme of studies at the University of Mauritius, and was first offered in August 2009 (academic year 2009/10). To ensure the success of this first initiative, the programme was offered in a blended learning mode with an online component of 60% and face-to-face tutorials amounting to 40%. Out of the five yearly modules of the first year, three were delivered with a heavy online component and minimal face-to-face contact, while two key modules, ‘programming fundamentals’ and ‘database design’, had intensive face-to-face sessions given the practical nature of the modules, but were supported by online lecture notes on the e-learning platform. So far, the Web and Multimedia Programme have admitted seven successive cohorts of students since August 2009.

The programme is offered on the MOODLE e-Learning platform of the University and all new students on the programme are given an induction prior to the official start of the course. Each module in the first year is taught by a different academic, who is well versed in both the subject matter and the mode of delivery. The peda-

gogical structure of an online module at the University of Mauritius is conceptually represented in figure 1 (SANTALLY et al., 2012).

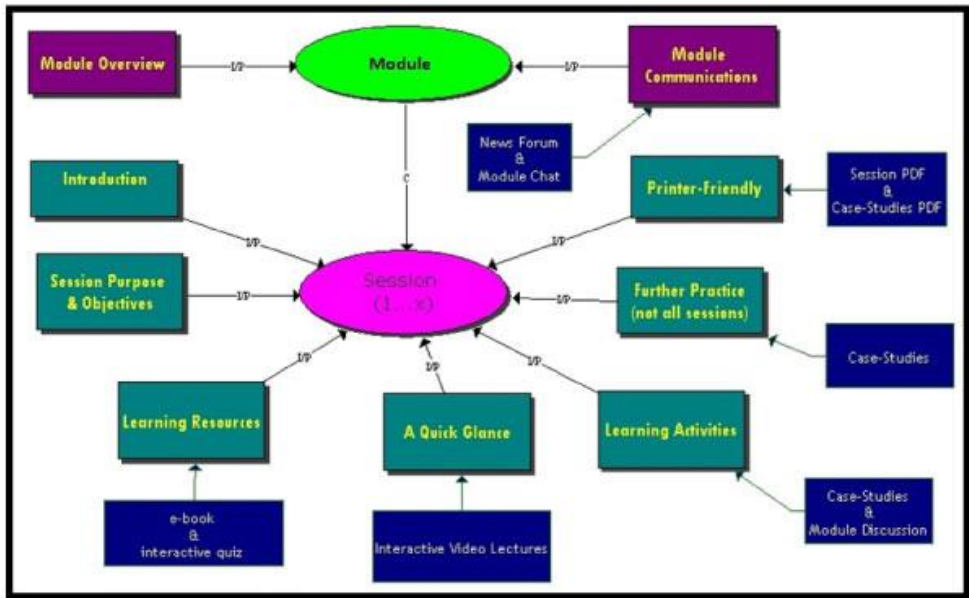


Figure 1: Pedagogical structure of an online module (SANTALLY et al., 2012)

The programme follows all quality assurance procedures of the University with respect to the general programmes of studies and is subject to external accreditation every year, to ensure academic standards are comparable to international practice. Furthermore, at the University of Mauritius, the completion of student feedback questionnaires is a mandatory process for all students. The pedagogical conception of the programme has been internationally recognised through the Commonwealth of Learning Excellence Awards in Distance Education in 2010.



## 7 Data analysis

Our study focuses on five modules and two course cohorts for the two consecutive academic years 2013-14 (AY1) and 2014-15 (AY2). Both courses (LC201 and LC302) use the same five modules: programming fundamentals (LLC1010Y), database design and development (LLC1030Y), visual communication and graphic design (LLC2010Y), dynamic scripting (LLC1090Y), and software development methodologies (LLC1020Y). The modules LLC1010Y and LLC1030Y were offered mainly face-to-face with some online materials, while modules LLC1090Y, LLC2010Y and LLC1020Y were offered mainly via online delivery. In order to classify the students in terms of their regularity and commitment to the module, attendance sheets were used for the face-to-face modules. For measuring participation in online modules, the access logs of the e-learning platform were used together with attendance sheets from face-to-face tutorials (three per year), and the completion of the self-assessment and continuous learning activities (quiz, forum, learning journals) in the e-learning platform. Three levels of regularity of participation were defined to cluster student engagement and interactions (see section on engagement analysis further below).

The total number of students were ( $n=$ ) 111 and 123 for the AY1 and AY2 respectively. The cross-tables 1 & 2 present the details of the number of students registered by module. IBM's SPSS 20 was used to run the statistical tests (FIELD, 2009), which consisted of correlation analysis using Pearson's correlation coefficient, identifying inter-quartile outliers, error plots, regression analysis, and ANOVA (analysis of variance).

Table 1: Number of students as per courses vis-a-vis modules

**Courses \* Modules \* Academic Year Crosstabulation**

Count

			Modules					Total
			Programming Fundamentals (LLC1010Y)	Database Design and Development (LLC1030Y)	Visual_Communication & Graphic Design (LLC2010Y)	Dynamic Scripting (LLC1090Y)	Software Development Methodologies (LLC1020Y)	
Academic Year 2013-2014	Courses	Diploma in Web and Multimedia Development (LC201)	30		30	30	30	120
		Diploma/BSc in Web and Multimedia Development (LC302)	81		81	81	81	324
	Total		111		111	111	111	444
Academic Year 2014-2015	Courses	Diploma in Web and Multimedia Development (LC201)	23	23	23	23	23	115
		Diploma/BSc in Web and Multimedia Development (LC302)	100	100	100	100	100	500
	Total		123	123	123	123	123	615
Total	Courses	Diploma in Web and Multimedia Development (LC201)	53	23	53	53	53	235
		Diploma/BSc in Web and Multimedia Development (LC302)	181	100	181	181	181	824
	Total		234	123	234	234	234	1059

Table 2: Number of students as per mode of delivery and modules

**Mode of delivery \* Modules \* Academic Year Crosstabulation**

Count

			Modules					Total
			Programming Fundamentals (LLC1010Y)	Database Design and Development (LLC1030Y)	Visual_Communication & Graphic Design (LLC2010Y)	Dynamic Scripting (LLC1090Y)	Software Development Methodologies (LLC1020Y)	
Academic Year 2013-2014	Mode of delivery	ONLINE	0		111	111	111	333
		FACE TO FACE	111		0	0	0	111
	Total		111		111	111	111	444
Academic Year 2014-2015	Mode of delivery	ONLINE	0	0	123	123	123	369
		FACE TO FACE	123	123	0	0	0	246
	Total		123	123	123	123	123	615
Total	Mode of delivery	ONLINE	0	0	234	234	234	702
		FACE TO FACE	234	123	0	0	0	357
	Total		234	123	234	234	234	1059

The marks obtained by the students were compared module-wise, course-wise, academic year-wise and gender-wise as presented by the boxplots in fig.2 and fig.3 below. The total mark represents the student's final grade for year 1 of the course as given by the tutor. The figures show that performances are only slightly better in terms of median for course LC302 compared to course LC201. Figure 2 also shows that students in AY2 did slightly better than those of AY1.

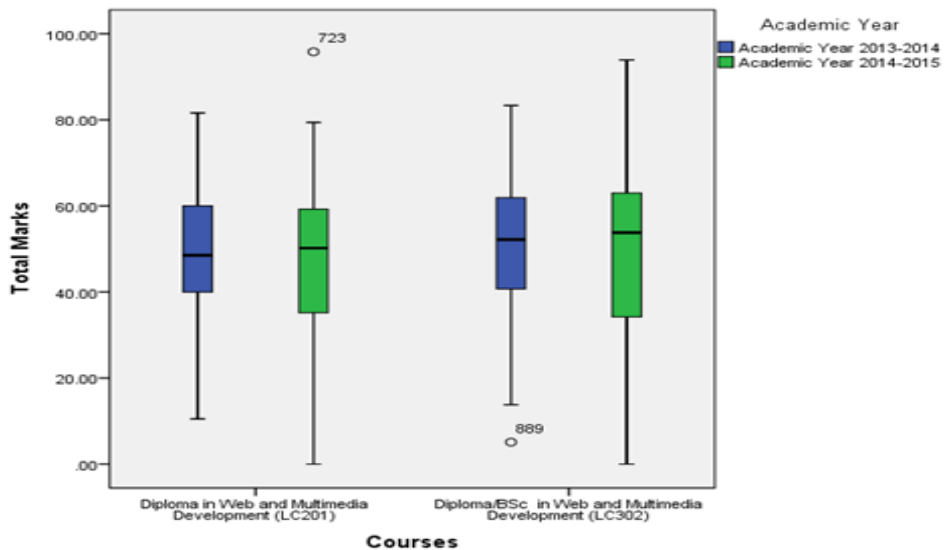


Figure 2: Boxplots for total marks per course and per Academic Year

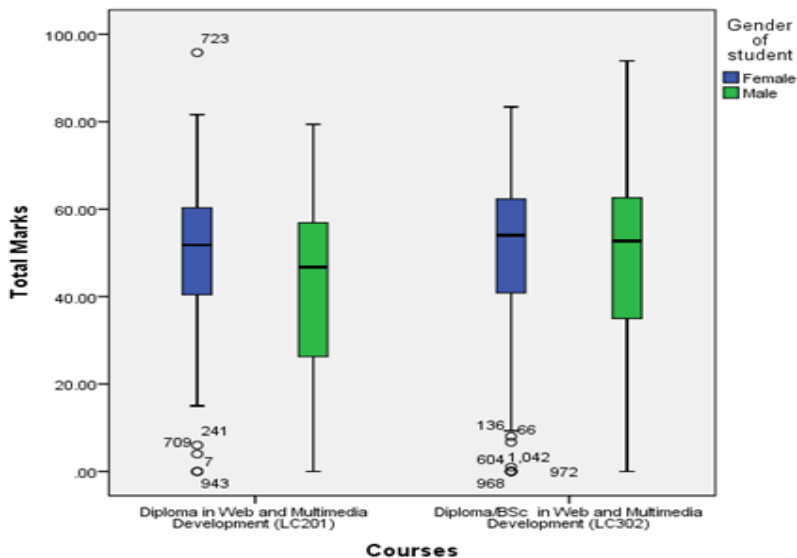


Figure 3: Boxplots for total marks per course and per Gender

Figure 3, above, shows the distribution of the overall performance by gender. It is observable that we had quite a few outlier cases particularly for girls, meaning that there is a small cluster of poor performing girls who got below 10 points in total. Also, when taking all cohorts across both courses and years, girls stood out by forming a special low-performing group. Despite this, girls' performances were more consistent, with lesser variability, and on average are doing slightly better than boys (fig.3 above). Only in one single module, 'visual communication and graphic design' (LLC2010Y), did boys produce better results.

## 7.1 Correlations

In a first step, we looked at ten different variables such as total marks, HSC score, exam marks, coursework marks, the mode of delivery, courses, academic year, results (i.e. cumulative points from assignments, tests, coursework and exams),

gender and engagement of students. These were investigated using a correlational analysis (table 3 below).

Table 3: Correlation matrix for ten variables

		Correlations									
		Total Marks	HSC Score	Examination Marks	Course Work Mark	Mode of delivery	Courses	Academic Year	Results	Gender of student	Attendance of Student
Total Marks	Correlation Coefficient	1.000	.188*	.759**	.711**	.061	.063	-.016	.730*	-.066*	.356*
	Sig. (2-tailed)	.	.000	.000	.000	.048	.042	.611	.000	.031	.000
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
HSC Score	Correlation Coefficient	.188*	1.000	.158*	.127*	-.027	-.238**	-.173*	.157*	-.042	.098
	Sig. (2-tailed)	.000	.	.000	.000	.380	.000	.000	.000	.176	.137
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Examination Marks	Correlation Coefficient	.759**	.158*	1.000	.170*	-.244**	.046	.003	.616*	-.074*	.296*
	Sig. (2-tailed)	.000	.000	.	.000	.000	.135	.916	.000	.016	.000
	N	1057	1057	1057	1056	1057	1057	1057	1057	1057	234
Course Work Mark	Correlation Coefficient	.711**	.127*	.170*	1.000	.282*	.033	-.114*	.625*	-.068*	.301*
	Sig. (2-tailed)	.000	.000	.000	.	.000	.288	.000	.000	.026	.000
	N	1057	1057	1056	1057	1057	1057	1057	1057	1057	234
Mode of delivery	Correlation Coefficient	.061	-.027	-.244**	.282*	1.000	.015	.157*	.085*	.009	.
	Sig. (2-tailed)	.048	.380	.000	.000	.	.615	.000	.006	.763	.
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Courses	Correlation Coefficient	.063	.238**	.046	.033	.015	1.000	.099*	.024	.101*	.132*
	Sig. (2-tailed)	.042	.000	.135	.288	.615	.	.001	.440	.001	.044
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Academic Year	Correlation Coefficient	-.016	-.173*	.003	-.114*	.157*	.099*	1.000	-.091*	.059	.068
	Sig. (2-tailed)	.611	.000	.916	.000	.000	.001	.	.003	.054	.300
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Results	Correlation Coefficient	.730*	.157*	.616*	.625*	.085*	.024	-.091*	1.000	-.122*	.206*
	Sig. (2-tailed)	.000	.000	.000	.000	.006	.440	.003	.	.000	.002
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Gender of student	Correlation Coefficient	-.066*	-.042	-.074*	-.068*	.009	.101*	.059	-.122*	1.000	-.221*
	Sig. (2-tailed)	.031	.176	.016	.026	.763	.001	.054	.000	.	.001
	N	1059	1059	1057	1057	1059	1059	1059	1059	1059	234
Attendance of Student	Correlation Coefficient	.355*	.098	.296*	.301*	.	.132	.068	.206*	-.221*	1.000
	Sig. (2-tailed)	.000	.137	.000	.000	.	.044	.300	.002	.001	.
	N	234	234	234	234	234	234	234	234	234	234

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

\* Correlation is significant at the 0.05 level (2-tailed).

The table shows that there are strong relationships between the total marks and the examination marks, coursework marks and results, as expected. There also exists a weak positive relationship to student engagement. Furthermore, despite a very weak relationship, there is a positive significant correlation probability to students' HSC scores. A significant p-value is also found in the weak relationship between total marks, exam marks, coursework marks, results and student engagement data.

Table 4: Correlation matrix for normalised variables

		Correlations					
		Total Marks	Normalised Exam marks on 100%	Normalised Coursework marks on 100%	HSC Score	Attendance of Student	Gender of student
Total Marks	Pearson Correlation	1	.888**	.870**	.214*	.563**	-.122*
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	1059	1057	1057	1059	936	1059
Normalised Exam marks on 100%	Pearson Correlation	.888**	1	.580**	.206**	.462**	-.084*
	Sig. (2-tailed)	.000		.000	.000	.000	.006
	N	1057	1057	1056	1057	935	1057
Normalised Coursework marks on 100%	Pearson Correlation	.870**	.580**	1	.169*	.521**	-.129**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	1057	1056	1057	1057	935	1057
HSC Score	Pearson Correlation	.214**	.206**	.169**	1	.119*	-.022
	Sig. (2-tailed)	.000	.000	.000		.000	.465
	N	1059	1057	1057	1059	936	1059
Attendance of Student	Pearson Correlation	.563**	.462**	.521**	.119*	1	-.157**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	936	935	935	936	936	936
Gender of student	Pearson Correlation	-.122*	-.084*	-.129**	-.022	-.157**	1
	Sig. (2-tailed)	.000	.006	.000	.465	.000	
	N	1059	1057	1057	1059	936	1059

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

Next, we normalised six of the ten variables: total marks, exam marks, coursework marks, HSC score, engagement and gender (table 4 above). With this approach, the following information became evident: As expected, the total marks and both normalised exam and coursework show again a very strong positive relationship. Normalised student engagement data comes to a moderate positive relationship (0.563), but still with high significance ( $p < .01$ ), while HSC scores are only weakly positively connected to the total marks.

Normalised exam marks (0.462) and normalised coursework marks (0.521) hold a moderate but significant positive linear relationship to the participation and engagement of students (cf. the section further below). Though only very weakly correlated, the normalised total marks, normalised exam marks, and normalised coursework are significantly negatively correlated with gender – meaning that slightly higher scores are obtained by girls (0) compared to boys (1).

## 7.2 Confidence intervals and Analysis of Variance

We stuck to a 95% confidence interval and 5% significance level ( $p < .05$ ) for all our inferential tests. Figure 4 (below) shows the confidence interval (CI) for total marks, normalised exam marks and normalised coursework per each module. We notice a significant disparity between the three markings with normalised coursework (highest), normalised exam marks (lowest), and, following from this logically, the total marks in between the two, re-occurring across each module.

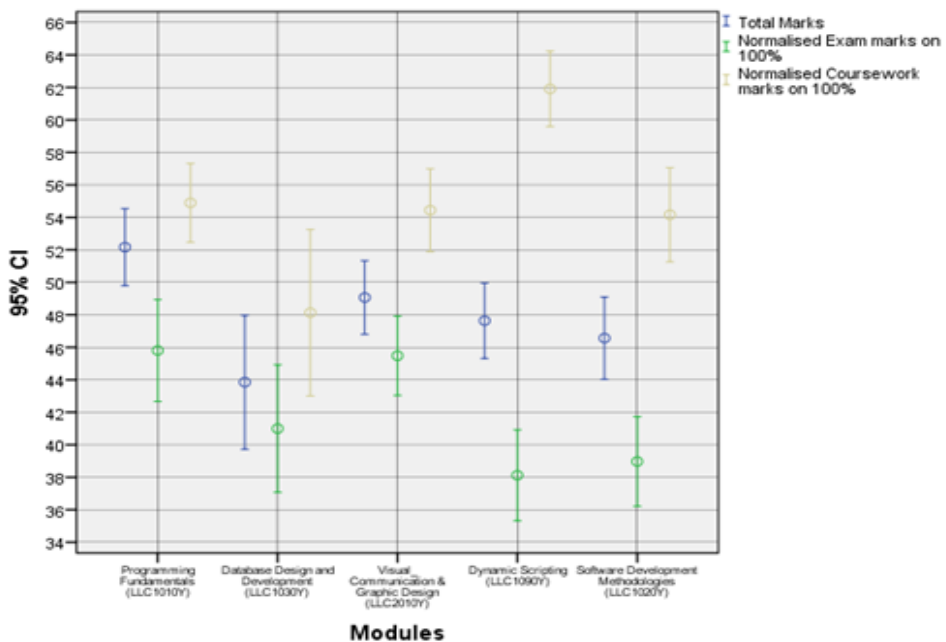


Figure 4: Error plots (Confidence Interval) for the marks

When comparing online to face-to-face delivery, the former represented by LLC2010Y, LLC1090Y, and LLC1020Y, we see that the normalised coursework

for online mode is clearly higher on average in terms of performance than the alternative mode of teaching and assessment. Looking at the efficiency of learning, we noticed that, on average, the achieved total marks are not significantly different from the online delivery, but that online marks tend to be higher on coursework than on exam marks vis-a-vis F2F teaching. From this we might conclude that online delivery favours continuous assessment by coursework, while in F2F teaching, more focus was given to summative examinations. The remarks from this investigation are further supported by the one-way ANOVA (table 5).

Table 5: One-way Analysis of Variance (ANOVA) for marks by mode of delivery

		<b>ANOVA</b>				
		Sum of Squares	df	Mean Square	F	Sig.
Total Marks	Between Groups	531.366	1	531.366	1.441	.230
	Within Groups	389899.606	1057	368.874		
	Total	390430.972	1058			
Normalised Exam marks on 100%	Between Groups	2575.158	1	2575.158	5.386	.020
	Within Groups	504378.267	1055	478.084		
	Total	506953.425	1056			
Normalised Coursework marks on 100%	Between Groups	4213.858	1	4213.858	9.272	.002
	Within Groups	479467.738	1055	454.472		
	Total	483681.596	1056			

In table 5, the ANOVA confirms the findings of the above confidence analysis that while there are no significant differences by mode in the total marks of the modules, they diverge significantly in exam marks and even more in coursework. A gender analysis using ANOVA also confirmed a significant difference of means and that girls perform better.



Table 6: One-way ANOVA Table for results by mode of delivery

**Descriptives**

Results

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
ONLINE	702	.74	.438	.017	.71	.77	0	1
FACE TO FACE	357	.82	.386	.020	.78	.86	0	1
Total	1059	.77	.422	.013	.74	.79	0	1

**ANOVA**

Results

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.358	1	1.358	7.658	.006
Within Groups	187.497	1057	.177		
Total	188.856	1058			

Results in terms of pass (score of 1) and fail (score of 0) is significantly different on average by mode of delivery. Face-to-face has significantly higher success rates in terms of passes than online mode of delivery (table 6 above).

### 7.3 Influence of student engagement and online activities on performance

In this part of the analysis, the impact of student participation and engagement, indexed as ‘not regular’, ‘regular’ and ‘very regular’, as a measure of involvement in the online courses are taken with respect to their final results at the end of the academic year.

We classified student engagement as the sum of all interactions within the online learning environment (incl. login to platform, submissions, self-assessment tests, forum participation and resource access, etc.). Interactions like login to platform,

and resource access were given an importance rating of 1, while self-assessment tests and forum participation carried an importance rating of 2, and assignment submissions a rating of 3. From this, we divided the group of students into three categories: not regular – regular – very regular. We used a simple index to classify regularity. Those who fell between 0-35 % of total activities submitted were classified as ‘not regular’; those between 35-60 % were classified as ‘regular’; and, finally, students above this percentage were classified as ‘very regular’.

It came as no surprise that the level of regularity directly corresponded to the performance in total marks, exam marks and coursework. However, like in figure 4 above, the triads were again distributed in the very same manner, i.e. exam marks always lowest and coursework always highest, for all three student categories.

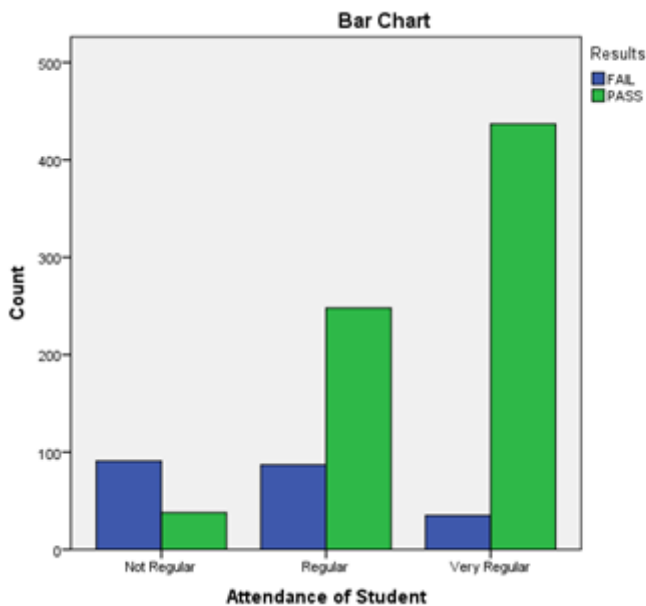


Figure 5: Bar chart for results (Pass and Fail) by participation/engagement level

A simple bar chart of success or failure shows that pass or fail at the end of the year strongly correlates with the intensity of a student's participation rate (fig. 5 above).

Table 7: Regression analysis for marks versus engagement

Mode of Delivery	Engagement (0 = Not regular, 1 = Regular, 2 = Very regular)	Correlation Coefficient	Trend coefficient
Overall (Both Online and Face-to-face)	Total marks	0.563	14.6
	Normalised Exam marks	0.462	14.2
	Normalised Coursework marks	0.521	14.7
Online	Total marks	0.618	15.9
	Normalised Exam marks	0.508	14.9
	Normalised Coursework marks	0.595	17.1
Face-to-face	Total marks	0.361	9.9
	Normalised Exam marks	0.315	11.4
	Normalised Coursework marks	0.329	9.2

The following regression analysis of marks versus engagement (table 7) showed that the total marks of both delivery methods in general increased by an average rate of 14.6 points from one engagement category level to the next. The linear correlation coefficient between the different modes of assessment and the engagement level is positive and moderate. However, the correlation coefficient for online modules are higher than those of face-to-face (almost double) for the three assess-

ment modes with higher trend coefficients. Given that the mean assignment marks obtained in online modules (including those from continuous learning activities) were significantly higher than those in the face-to-face modules, we take it that the performance of students is more sensitive to the regularity of students in online modules than in face-to-face modules.

## 8 Results and Findings

From our analysis, we observe that the final marks obtained for the three online modules do not differ significantly, while there does exist a significant difference between the two face-to-face modules. This can perhaps be explained with the online modules having a predefined uniform instructional structure whereas the two face-to-face modules, taught by different lecturers, could be subject to different teaching styles, and also different weightage of assignments and exams.

Taking the analysis of engagement data, the results (pass or fail) clearly demonstrate that the pass rate increases, and, as a consequence, failure rate decreases as the regularity of students increases. The linear correlation coefficient between the different modes of assessment and the engagement level is positive and moderate. Therefore, the regularity aspect both in face-to-face and online participation plays an important part in defining overall student success.

On the other hand, the correlation coefficient for online modules is higher than those of face-to-face (almost double) for the three assessment modes with higher trend coefficients. This shows that the learning progress of students is influenced to a greater extent by the regularity of their learning activities in online modules than in face-to-face modules. Despite the fact that student feedback highlights the wish for more face-to-face support sessions, attendance sheets indicate that the majority do not turn up when such sessions are offered.

There exists a significant disparity between the three markings, namely normalised coursework (highest), normalised exam marks (lowest) and the total marks or final grade (middle). Normalised coursework for online delivery is significantly the

highest on average in terms of performances when compared to the other mode of teaching as well as assessment types (exams and overall total marks). Also, when looking at assessment types by module (face-to-face and online), again normalised coursework comes out highest on average for all the modules while normalised exam marks are the lowest. This can be explained in a few different ways as was discussed during the feedback workshop with academics and students when presenting the results (third phase of the project). The first response by academics was that the face-to-face modules and the online modules did not necessarily carry the same weight for assignments and exams. For example, the LLC1010Y module (Programming Fundamentals), which was face-to-face, had a coursework component accounting to 70% of the module mark. It was a highly practical module. On the other hand, the online modules had the same assignments as in previous years, and these were mainly group assignments. There was a possibility that students could go through previous assignments and already form an idea of what is expected. Therefore, they would be able to score higher marks in the coursework components. It has also been noted that written exams were based on the theoretical components of the modules, and that students showed poorer outcomes in written exams because they had some difficulty expressing themselves in English, which is not their first language.

With respect to the performance of the students in the face-to-face modules as compared to the online modules, normalised total marks are not significantly different on average. From this we can infer that there is no influence on overall student performance with respect to the mode of delivery of the module. However, when we compared only exam marks, there was a significant difference for mean normalised exam marks as well as mean normalised coursework marks between face-to-face and online mode of delivery.

## 9 Discussion

In our analysis, we looked at student assessment and engagement data from the University of Mauritius student record system and learning platform using a Learn-

ing Analytics approach. From this, we see differences in the achievements by gender, where girls on average perform slightly better than boys, but also form a separate group of outlying low-performing learners that perhaps need special attention to bring them in line with the mainstream students. Future Learning Analytics research will want to look at signs of disengagement from the VLE datasets to be able to detect students in danger of dropping out of the course at an early stage.

Other results also showed that achievements can be weakly linked to the level of Higher School Certificate (HSC) results, which is in accordance with the study by LAMERES & PLUMB (2014), who also compared the regression of pre-course grades with course achievements. Hence the students' general academic ability, the mode of delivery, the assessment modalities, the courseware design and other factors such as students' own commitment to the course and participation in mandatory learning activities like assignments, and presentations all play their part in successful course completion. However, for online delivery our study shows that the deeper the level of engagement and interaction with the learning platform is, the higher are the chances of reaching the learning outcomes. Therefore, in this context, real-time Learning Analytics looking at engagement components can highlight early signs of warning to lecturers with respect to students who are potentially at risk. Factors like frequency of platform access, exchange of messages on forums, timely assignment submissions are elements that could consider forming an initial system of monitoring.

During the feedback gathering process with academics, diverging views were expressed by the staff who service the modules in question. The majority of them acknowledge that our students may still be reliant to some extent on the 'spoon-feeding' culture, and, therefore, are not autonomous and self-directed enough. One academic who teaches a face-to-face module even went as far as saying that first year students had to be taught mainly in face-to-face mode, but the majority of lecturers believed that students have to be steered towards becoming independent learners from the first moment on, and, therefore, the right blend of face-to-face and online modules was a good approach. Academics further suggested that a more blended approach could help address some issues. The results of the study, there-

fore, bring out issues from the pedagogical perspective in the context of traditional universities' adoption of educational models based on intensive online delivery. The key question, we find, is one of policy and of strategic vision where traditional universities must decide to adopt either fully online models or a blended mode of teaching and learning through a fully integrated, technology-supported flexible approach. In the first instance, they will rely more on mediated communication through social media, and online communication and collaboration tools, while with the latter, they will focus more on new pedagogies such as the inverted classroom.

The component of face-to-face lectures remains still solidly anchored in students' perception as the way to manage their learning, although it has been noticed that there is little added value from these sessions for the outliers. However, maintaining this component, although at longer intervals for face-to-face meeting, can help to address some elements of disengagement, provided that these sessions are made mandatory. Based on our findings, the inverted classroom solution seems to be a viable and pedagogically sound alternative to better address the demand for student engagement in online courses.

Finally, the issue of course design should be addressed. The courses are currently engineered around learning content; that is, they are content-centric. Our results show that those who are disengaged would not be reading learning materials in the first instance. Therefore, shifting towards activity-based learning designs can be a useful approach to focus on competency-based outcomes rather than content consumption. This also implies a review of the current student assessment and evaluation practices, given that poor performance in supervised written exams had a significant effect in determining the overall performance of students in a particular module.

## 10 Conclusions and future outlook

It can however be concluded that the new modality of online learning by itself is not a reason for students' lack of success or failure, but that there is a need to probe into the current pedagogical practices and student support framework to identify any shortcomings that need to be addressed for future improvements.

The findings from our study are mainly used to improve the current pedagogical model in online programmes and to identify how the academic team can modify their current interaction model with students to better support them in their learning.

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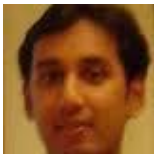
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