An Investigation into the Pre-enrolment Characteristics of Students to Identify Factors Predictive of Academic Performance within First Year Computing and Engineering Programmes of Study in a Higher Educational Institution

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Abstract

First year progression rates are a key performance indicator within the higher education sector. Business intelligence can inform initiatives, interventions and supports aimed at specific student cohorts in attempts to improve progression rates. This study investigates prior educational performance, particularly in the **S**cience **T**echnology **E**ngineering and Mathematics (STEM) subject categories, English and foreign languages to identify significant factors predictive of academic performance of computing and engineering first year students within the Institute of Technology Blanchardstown (ITB).

The methodology was quantitative with correlation and multiple regression employed for data analysis. First year computing (n=197) and engineering (n=247) samples were analysed for the academic terms 2013/14, 2014/15 and 2015/16. The attribute accounting for the most variance in the end of first year Grade Point Average (GPA) for the computing sample was found to be the total Leaving Certificate points attained per student. For the engineering sample, the most significant factors predictive of end of first year GPA were Mathematics points achieved in the Leaving Certificate, age and to a lesser degree total Leaving Certificate points.

The results of this analysis support the hypotheses that prior educational attainment in the Leaving Certificate is an important predictor of tertiary academic performance (R^2 = .22) and that mathematical ability is an important factor influencing academic performance in engineering programmes. Outside of Mathematics, support for the hypothesis that prior educational attainment in STEM Leaving Certificate subjects is a significant influencing factor in the academic performance of computing and engineering students, proved less conclusive. Also of note, and in contrast to previous studies, Leaving Certificate performance in English was not found to be a predictor of tertiary academic performance within either of the computing and engineering cohorts analysed.

The uniqueness of this study is the student cohort under investigation and a focus on relationships between prior educational performance in STEM Irish Leaving Certificate subjects and end of first year GPA. The study is based on computer science and engineering programmes within an Institute of Technology where historically students would be admitted with lower Leaving Certificate points than their University counterparts.

Keywords: academic performance, first year computing, pre-enrolment.

1. Introduction.

Student academic performance is an important criterion by which the performance of higher educational institutions can be evaluated (Mayston, 2003). Research into student academic performance within higher education has identified that non-progression rates peak in the first year of programmes of study followed by a steady decline in non-progression rates in subsequent years, with more than half of student attrition in the US and UK occurring within the first year (Porter, 1990; Smith and Naylor, 2001). The prediction of, and investigation into the factors influencing student academic performance has and continues to be one of the most popular goals within Learning Analytics (LA) / Educational Data Mining (EDM) (Peña-Ayala, 2014). However little research and data exists within the Irish context in relation to factors that have been found to be significant in predicting and influencing student academic performance and progression (Kelly and Marshall, 2012).

Extensive research efforts have been made in the construction of models to predict the academic performance of students (Emerson & Taylor, 2004; Kotsiantis et al., 2003; Lowis & Castley, 2008; Pittman, 2008; Jayaprakash et al., 2014). The results of these predictive models have been used to support educators in determining the need for interventions to assist students identified as being academically at risk and assist in the development of suitable intervention strategies to improve the academic performance of students and reduce dropout rates (Lowis & Castley, 2008). Studies have included a vast array of potential predictors including but not limited to: personality factors, prior educational attainment, intelligence and aptitude tests, and demographic information with no apparent consistent agreement reached as to the optimal attributes that can predict student tertiary academic performance (Gray et al., 2014; Herzog, 2005; Lassibille & Gomez, 2008; Parmentier, 1994; Touron, 1983).

Prior educational attainment has consistently been found to be a significant factor in student academic performance and in first year retention within the higher educational environment. From a prior educational attainment perspective, the most significant predictors in terms of retention identified through research in the US include the high school grade point average (GPA) and the scholastic aptitude test (SAT) (Schmitt et al., 2009; Bogard et al., 2012; Kabakchieva, 2012). Within the UK, student academic performance in secondary level education has been found to have a positive relationship with performance in higher education (Chapman, 1996; Hoskins et al., 1997; Peers & Johnson, 1994). While research in Ireland has identified a significant relationship between prior educational attainment within the Leaving Certificate (points achieved) and undergraduate programme completion levels (Morgan et al., 2001). Also within the Irish context a study of first year students over a three year period, 2010 – 2012 found that age, prior academic performance (particularly overall performance i.e. total Leaving Certificate points) and mathematics were statistically significant in predicting academic performance (Gray et al., 2016), while a study by the HEA published in 2010 identified prior educational attainment and in particular mathematics, and to a lesser degree English, as predictors of student academic performance within the Irish higher education sector (Mooney et al., 2010).

A multitude of student demographic characteristics have been empirically researched and cited as being significant factors in student retention with their importance attributed to how they affect students' engagement, interaction, and integration into college environments (Bean, 1980; Tinto, 1987). Within the Irish context evidence exists of variation in progression rates by age, where it has been found that students over the age of 23 are more likely to progress in level 6 and 7 programmes within the Institute of Technology (IoT) sector with the opposite found at level 8 in the university sector where students over the age of 23 are less likely to progress (Mooney et al., 2010; Liston et al., 2016). Studies have also found that academic performance models employed within Irish tertiary education can achieve reliable predictive accuracy when learners above and below the age of 21 are modelled separately (Gray et al., 2013).

Knowledge based economies depend on the quality and availability of STEM graduates and the continuous supply of same is seen as critical if Ireland is to deliver on its ambitions to be an internationally recognised hub of creativity and leadership in innovation (STEM Education Review Group, 2016). Retention is a significant issue within computer science and information technology programmes with students often struggling to master the core concepts in computer

programming. A combination of high failure rates and low progression rates have been reported internationally particularly within the early stages of computing programmes (Bennedsen & Caspersen 2007) with attrition rates reported as being as high as 50% within the first semester (Beaubouef et al., 2001; Beaubouef & Mason, 2005). First year progression rates of computing students for the period in question within the Higher Education Institute (HEI) under review range from 55% in 2013/14 to 65% in 2014/15 to 62% in 2015/16. Mathematical ability has long been identified as a significant predictor of academic performance on introductory computer science modules (Leeper & Silver, 1982; Campbell & McCabe, 1984; Evans & Simkin, 1989; Byrne & Lyons, 2001; Wilson & Shrock, 2001; Beaubouef, 2002) and to a lesser degree science subjects (Werth, 1986; Byrne & Lyons, 2001). Results from a study carried out on first year computing students in an Irish University in the academic year 2003/04 using correlation and linear regression analysis indicated that gender, Leaving Certificate Mathematics score, a student's perceived understanding of the programme of study and their comfort level were significant indicators of programming success (Bergin & Reilly, 2005).

Within engineering programmes cognitive abilities including general reasoning, verbal and spatial have been found to influence academic performance (Rothstein et al., 1994) with all three and in particular spatial ability identified as a significant factor in successful engagement within the engineering profession (Strong & Smith, 2001). From an international perspective, studies include the one carried out at Purdue University where two cohorts of engineering students were analysed for the academic years 2000/01 and 2001/02. A hierarchical multiple linear regression model was developed to evaluate the influence of cognitive, non-cognitive and environment variables on the academic success and persistence of engineering students. Consistent with previous research (Zhang et al., 2004; Bordonaro et al., 2000; Astin, 1993) they found SAT scores, high school rank and gender were found to be significant (French et al., 2005). Previous studies reported in the literature from a national perspective include that of Mooney et al. (2010) on entrance data gathered from approximately 22,000 students over a 10-year period (2000 to 2009), 1,835 of which were engineering students. This study identified specific factors relevant to progression for both the general student sample and specifically the engineering cohort. Mathematics was identified as the single most influential factor regardless of discipline echoing the findings of a study in 1979 (Moran & Crowley, 1978).

The aim of this study was to investigate prior educational performance, particularly in the STEM subject categories, English and foreign languages in the Leaving Certificate[1], to identify significant factors influencing the academic performance of computing and engineering first year new entrants[2] admitted through the CAO over a three-year period within the Institute of Technology Blanchardstown. Three hypotheses were addressed:

H1 Prior educational attainment in the Leaving Certificate is a significant predictor of tertiary academic performance.

H2 Mathematical ability is a significant factor influencing academic performance in computing and engineering programmes.

H3 Prior educational attainment in STEM Leaving Certificate subjects is a significant influencing factor in the academic performance of computing and engineering students.

This study not only explored engineering and computing student academic performance from the perspective of end of first year GPA but also factors influencing academic performance within the most failed constituent modules within engineering and computing programmes. To achieve this, a detailed exploration of the profile of first year engineering and computing students was undertaken from which relevant attributes were identified and mined to identify factors predictive of student academic performance. The uniqueness of this study is not the subject matter, nor the tool, nor algorithm employed for analysis but the focus on a higher educational institution within the Institute of Technology sector and the influence prior educational performance in the STEM subject categories has on tertiary academic performance within two STEM disciplines, namely computing and engineering.

2. Methodology.

For the purpose of this study, student academic performance is based on end of first year GPA[3] while prior educational attainment is taken as the students' performance in the Irish Leaving

[1] Final exams of the Irish secondary school system.
[2] New entrant – student entering an undergraduate higher education programme for the first time.
[3] The means by which first year academic performance is measured within the Institute of Technology Blanchardstown (ITB).

Certificate (LC) using grades achieved within the STEM subjects, foreign languages and English. STEM Leaving Certificate subjects are listed in Table 1.

Table 1: Leaving Certificate STEM subjects

Science	Biology, Chemistry, Physics, Agricultural Science, Physics & Chemistry
Technology	Technology, Graphic and Technical Design
Engineering	Engineering, Construction Studies
Mathematics	Mathematics, Applied Mathematics

An anonymised dataset incorporating first year computing and engineering student[1] pre-enrolment data for the academic years 2013/14, 2014/15 and 2015/16 was generated from a number of sources. These included the HEA survey extract file[2] from the Banner student records system, the academic programme catalogue and multiple extracts of the Banner student records system using Oracle Discoverer to provide student demographics, Leaving Certificate results and first year examination results. The dataset included new entrants aged 18 and over who were admitted through the CAO based on their Leaving Certificate points. Students admitted under alternative criteria i.e. criteria other than Leaving Certificate performance were excluded from this study.[6]

Based on the student sample profiles the following datasets were analysed for the computing and engineering cohorts.

- All students excluding those with a zero GPA
- Students aged 21 and under (as recommended by Gray et al., 2013) excluding those with a zero GPA

Summary statistics for the computing and engineering dataset samples are provided in Tables 2 and 3. The academic performance of under 21's in computing is comparable to the academic

[4] Engineering students comprised of computer engineering and mechatronic engineering programmes across NFQ levels ranging from 6-8 who undertake a common first year curriculum.

[5] Data file created on the 1st of November each year for the Higher Education Authority (HEA) containing students' registration details.

[6] Examples include schemes which admit students with disabilities and from disadvantaged backgrounds

performance of all computing students, whereas under 21's in engineering had a lower academic performance than all engineering students.

Table 2: Computing datasets - summary statistics

	Instances	GPA	Leaving Certificate Points	Total STEM Leaving Certificate Points	Age	Gender
Dataset 1	197	[0.25, 3.96] Mean: 2.18	[200, 490] Mean: 285	[5, 315] Mean: 105	<= 21: 73% >21: 27% Mean: 20	88% Male
Dataset 2 (age≤ 21)	144	[0.25, 3.96] Mean: 2.18	[200, 490] Mean: 285	[10, 315] Mean: 105	<= 21 Mean: 20	85% Male

Table 3: Engineering datasets - summary statistics

	Instances	GPA	Leaving Certificate Points	Total STEM Leaving Certificate Points	Age	Gender
Dataset 1	247	[0.13, 4.00] Mean: 1.76	[90, 450] Mean: 245	[5, 355] Mean: 107	<= 21: 72% >21: 28% Mean: 21	92% Male
Dataset 2 (age≤ 21)	178	[0.13, 3.79] Mean: 1.64	[90, 395] Mean: 240	[10, 355] Mean: 110	<= 21 Mean: 20	94% Male

Dataset attributes are listed in Tables 4 and 5. Data transformations to generate attributes in Table 5 are discussed below. Grade Point Average (GPA) is the means by which first year academic performance is measured. It is the aggregate of 11 modules in computing and 12 in engineering, range [0,4]. GPA is calculated as a weighted average of grades achieved with weights determined by the number of ECTS credits per module. A student with a GPA of less than 2.0 is considered to have failed first year. Distribution of GPA for each of the student samples was verified as being approximately normal using histograms. Students with a GPA of zero were excluded on the basis that first year modules are assessed by both continuous assessment and final exam, with zero indicating non-engagement on the programme.

Table 4: Initial attributes included in the datasets

Attribute	Description
Student_Id	Anonymised student identification number
English_Score	Leaving Certificate points achieved per student in English
LC_Points	Total Leaving Certificate points achieved per student
GPA	End of first year GPA score
Age	Age of student upon admission
Gender	Male / Female
Nationality	Country listed on student passport
Module1	Student grade achieved in most failed first year module
Module2	Student grade achieved in second most failed first year module

Table 5: Generated attributes for data exploration, visualisation and mining purposes

Attribute	Description
STEM_Science	Total Leaving Certificate points achieved per student in Science subjects: Biology, Chemistry, Physics, Agricultural Science, Physics & Chemistry
STEM_Technology	Total Leaving Certificate points achieved per student in Technology subjects: Technology, Design & Communication Graphics
STEM_Engineering	Total Leaving Certificate points achieved per student in Engineering subjects: Engineering, Construction Studies
STEM_Mathematics	Total Leaving Certificate points achieved per student in Mathematic subjects: Mathematics, Applied Mathematics
STEM_Total	Total Leaving Certificate points achieved per student in all STEM subjects taken
No_Stem_subj_taken	Number of STEM subjects taken per student
Language_Score	Total Leaving Certificate points achieved per student in Foreign Languages
No_Languages	Number of Foreign Language subjects taken per student

Given that Mathematics is a compulsory subject it is of interest to note that 40% of the computing student sample took only one other STEM subject while 38% took two STEM subjects in addition to Mathematics. The standard of mathematics was relatively low, 186 (94%) students achieved 45 points or below equivalent to a D3 in Honours level Mathematics or a B1 in Ordinary level Mathematics in the Leaving Certificate. 79 (40%) students did not take a science subject in their Leaving Certificate examination, and 96 (49%) students took only one science subject, 53% of

which took Biology, by far the most popular science subject but has little mathematical content. Following an analysis of the first year module examination scores, 'Fundamentals of Programming 2' (COMP H1031) and 'Mathematics for Computing' (COMP H1028) were identified as being most problematic for first year computing students.

Again, given that Mathematics is a compulsory subject, it is of interest to note that 20% of the engineering student sample took only one other STEM subject while the majority 54% took two STEM subjects in addition to Mathematics. The standard of mathematics was relatively low, 234 (95%) students achieved 45 points or below equivalent to a D3 in Honours level Mathematics or a B1 in Ordinary level Mathematics in the Leaving Certificate. Looking at science subjects specifically, 47 (19%) students did not take a science subject in their Leaving Certificate examination, and 142 (57%) students took only one science subject, 79 of which took Biology. A total of 51 (21%) students took two science subjects with only 8 (3%) of students taking three science subjects. Following an analysis of the first year module examination scores, 'Digital Electronics' (EENG H1013) and 'Programming 1' (EENG H1019) were identified as being most problematic for first year engineering students.

2.1 Methods.

Using Rapidminer version 5.3 (Ritthoff et al., 2001), computing and engineering cohorts were analysed to identify factors significant in influencing end of first year GPA. Correlation was employed to examine the strength of a relationship between two variables without implying causation, and regression examined how much of the variance in the dependent variable can be attributed to the independent factors/variables. For the purpose of this stud,y regression analysis was used to investigate the effect of multiple independent variables, in this instance student pre-enrolment data, have on a dependent variable, the end of first year GPA, from which the quantitative relationship can be determined. Optimal attribute subsets were explored using hierarchical regression, forward selection and backward elimination.

Model performance was based on R^2, the proportion of variance in the dependent attribute (GPA) explained by the independent attributes, and adjusted R^2, which adjusts this statistic to compensate for increases in R^2 due to the introduction of additional attributes leading to further model complexity. A threshold of statistical significance of $p <= .05$ was adopted as often used in studies for predicting student academic performance (Ting & Man, 2001, Thompson & Zamboanga, 2004; Marsh et al., 2008).

3. Results.

Correlation between independent attributes and GPA for each of the computing and engineering samples is provided in Table 6. For the computing sample total Leaving Certificate points, total points accrued in STEM subjects and STEM Mathematics points returned the highest correlation with GPA. Also of note was the high correlation (r=0.56) between total Leaving Certificate points and STEM Mathematics.

For the engineering sample STEM Mathematics points and total Leaving Certificate points returned the highest correlation with GPA. Of note is the significance of age within the engineering sample given that the age distribution in both discipline samples is quite similar. Also of note and similar to the computing student sample was the high correlation (0.56) between total Leaving Certificate points and STEM Mathematics.

Significant pre-enrolment attributes accounting for variance in end of first year GPA of computing and engineering students for each of the datasets analysed is presented in Table 7 overleaf. The best linear regression model based on computing dataset 1 'All students excluding zero GPAs' (n=197) was achieved using backward elimination with M5 Prime attribute selection returning an R^2 of .222 ($\overline{R^2}$ .20) identifying total Leaving Certificate points as the most significant attribute influencing GPA followed by total STEM points attained by students in the Leaving Certificate.

The best linear regression model based on computing dataset 2 'Students aged 21 and under excluding zero GPAs' (n=144) was achieved using forward selection with M5 Prime attribute selection returning an R^2 of .267 ($\overline{R^2}$ .26) thereby accounting for 26% of the variance in GPA. Total Leaving Certificate points again returned as the most significant attribute influencing GPA followed by STEM Mathematics.

Table 6: Correlation between independent attributes and GPA

Computing			Engineering		
LC_Points	0.39	(p<.001)	STEM_Mathematics	0.36	(p <.001)
STEM_Total	0.34	(p<.001)	LC_Points	0.32	(p <.001)
STEM_Mathematics	0.33	(p<.001)	Age	0.23	
STEM_Science	0.24		STEM_Science	0.23	
No_Stem_subj_taken	0.20		STEM_Total	0.22	
STEM_Engineering	0.12		Language_Score	0.12	
Language_Score	0.09		STEM_Technology	0.08	
Age	0.07		English_Score	0.07	
STEM_Technology	0.06		No_Stem_subj_taken	0.03	
English_Score	0.04		No_Languages	0.01	
No_Languages	-0.01		STEM_Engineering	-0.03	

Table 7: Attributes accounting for the most variation in end of first year GPA

	Computing				Engineering			
	Dataset 1 (n=197)		Dataset 2 (n=144)		Dataset 1 (n=247)		Dataset 2 (n=178)	
	All students with Zero GPA's removed		Aged 21 and under with Zero GPA's removed		All students with Zero GPA's removed		Aged 21 and under with Zero GPA's removed	
	R^2 = .22	$\overline{R^2}$ = .20	R^2 = .27	$\overline{R^2}$ = .26	R^2 = .22	$\overline{R^2}$ = .21	R^2 = .16	$\overline{R^2}$ = .15
	Std. Coefficient	Significance	Std. Coefficient	Significance	Std. Coefficient	Significance	Std. Coefficient	Significance
LC_Pts	0.314	****	0.304	****	0.170	**	0.190	**
STEM_Total	0.141	*						
STEM_Maths			0.177	**	0.272	****	0.213	**
Age					0.227	****		

The best linear regression model based on engineering dataset 1 ‘All students excluding zero GPAs’ (n=247) was achieved using forward selection with M5 Prime attribute selection returning an R^2 of .222 ($\overline{R^2}$ .21) with STEM Mathematics the most significant attribute influencing GPA

followed by Age which in turn was found for this dataset to be more significant than total Leaving Certificate points.

The best linear regression model based on engineering dataset 2 ‘Students aged 21 and under excluding zero GPAs’ (n=178) was achieved using forward selection with M5 Prime attribute selection returning an R^2 of .162 ($\overline{R^2}$ .15) thereby accounting for just 15% of the variance in GPA. STEM Mathematics was returned as the most significant attribute influencing GPA followed by total Leaving Certificate points.

This study supports previous findings that identified prior educational attainment and, in particular mathematics, as predictors of student academic performance within the Irish higher education sector (Mooney et al., 2010). However, in this study English was not found to be a predictor of tertiary academic performance within either of the computing and engineering cohorts analysed.

3.1 Failed modules.

Having identified factors influencing GPA, further analysis was carried out to identify the most commonly failed first year modules in computing and engineering programmes with regression analysis run to investigate factors influencing results in each module. ‘Fundamentals of Programming 2’ and ‘Mathematics for Computing’ were identified as the most commonly failed modules within the computing cohort with STEM Mathematics returned as the most significant attribute predictive of performance on each module. ‘Digital Electronics’ and ‘Programming 1’ were identified as the most commonly failed modules within the engineering cohort with STEM Mathematics again returned as the most significant attribute predictive of performance on each module.

4. Discussion.

The prediction of, and investigation into, factors influencing academic performance continues to be one of the most popular goals within Educational Data Mining. The aim of this study was to

investigate prior educational performance, particularly in the STEM subject categories, English and foreign languages in the Leaving Certificate, to identify significant factors accounting for variance in the end of first year GPA, thereby predictive of academic performance of computing and engineering first year new entrants within the Institute of Technology Blanchardstown for the academic terms 2013/14, 2014/15 and 2015/16.

For the computing sample under review, the most significant factor influencing the end of first year GPA was found to be the total Leaving Certificate points attained, which in turn had a high correlation with STEM Mathematics. For the engineering sample under review, the most significant factors influencing the end of first year GPA were STEM Mathematics points achieved in the Leaving Certificate, age and to a lesser degree total Leaving Certificate points. Total Leaving Certificate points was identified as a significant factor within each discipline, and in a combined sample of both engineering and computing students, supporting hypothesis H1 that prior educational attainment in the Leaving Certificate is a significant predictor of tertiary academic performance. The results of this analysis supported hypothesis H2, that mathematical ability is a significant factor influencing academic performance in computing and engineering programmes. This support is based on both correlation results for both computing and engineering and regression results predicting GPA. In particular, STEM Mathematics was the most significant factor in predicting grades for the most commonly failed modules in both computing and engineering, namely modules in programming and mathematics.

Outside of STEM Mathematics, support for hypothesis H3 that prior educational attainment in STEM Leaving Certificate subjects is a significant influencing factor in the academic performance of computing and engineering students, proved less conclusive. The total Leaving Certificate points attained per student in STEM subjects i.e. STEM Total was identified as significant for the computing sample only, which is surprising given the expected relevance of the STEM engineering and STEM technology subjects to the engineering curriculum. The results of this analysis based on the cohort samples analysed would appear to suggest that any investigation into factors influencing tertiary academic performance should be discipline specific. The attributes total Leaving Certificate points and STEM Total were identified as significant for the computing sample while STEM Mathematics, age and total Leaving Certificate points were identified as significant for the engineering sample. Age was not found to be a significant factor influencing GPA across any of the computing datasets analysed. However, age was identified as a significant factor within the engineering datasets and the combined dataset including both the

computing and engineering samples. Further analysis will be required to support this inference that analysis must be discipline specific given that research would suggest that age is always a factor with older students performing better and may point to an anomaly in the sample analysed.

In relation to published literature the results of this study support previous findings discussed in the introduction that prior educational attainment in the Leaving Certificate is an important predictor of tertiary academic performance and that mathematical ability is an important factor influencing academic performance in engineering programmes. Also of note, and in contrast to previous studies, Leaving Certificate performance in English was not found to be a predictor of tertiary academic performance within either of the computing and engineering cohorts analysed.

4.1 Future work.

Given that both the computing and engineering samples for the time period in question are predominantly male and aged 21 and younger, it would be interesting to extend the time period thus allowing age and gender to be further explored using a larger sample size. Also it would be of interest to revisit this analysis at a point in the future to review the effect the introduction of any intervention initiatives such as the mapping of Leaving Certificate mathematics topics to first year syllabi and the introduction of mathematical competency tests at induction to assess gaps in student knowledge.

4.2 Concluding remarks.

The focus of this study was to investigate prior educational performance in the Irish Leaving Certificate and the influence it can have on the end of first year GPA in relation to computer science and engineering programmes within an Institute of Technology. To achieve this, a detailed exploration of the profile of first year engineering and computing students was undertaken from which relevant attributes were identified and mined to identify factors predictive of student academic performance. The methodology was quantitative with correlation and multiple regression employed for data analysis. First year computing and engineering samples were analysed with datasets including those containing all students and those aged 21 and under to identify factors significant in influencing end of first year GPA for the academic terms 2013/14, 2014/15

and 2015/16. Model performance was based on R^2 with a threshold of statistical significance of p <= .05 adopted as is often used in studies for predicting student academic performance.

The progression rates of both disciplines are low. In relation to Leaving Certificate subjects taken it could be inferred that the engineering sample's subject selection, in contrast to the computing sample, was less strategically based on maximum point accumulation and more based on Science, Technology and Engineering subjects that one would expect to prove useful in their tertiary engineering education. However, with regard to the end of first year GPA performance this has not translated into better results with 52% of the engineering sample failing first year as opposed to 36% of the computing sample. The engineering sample's educational attainment in the Leaving Certificate from the viewpoint of mathematical ability and total points attained is lower than the computing sample contributing to higher failure rates.

Poor progression rates in computing can be attributed in part to prior educational performance in the Leaving Certificate with 27% attaining 250 points or less. Poor progression rates also appear to be influenced by their pre-enrolment mathematical competency i.e. low STEM Mathematics points in the Leaving Certificate with 18% of the computing sample attaining 15 or less points, equivalent to a D1 in Ordinary level and 94% of the sample attaining 45 points or below equivalent to a B1 in Ordinary level. As evident from the analysis in relation to the most commonly failed modules, computer programming is challenging for students, and prior academic proficiency in mathematics was the most significant predictor of programming grades.

Poor progression rates in engineering can also be attributed in part to pre-enrolment mathematical competency with 39% of the engineering sample attaining 15 points or less, equivalent to a D1 in Ordinary level. Prior educational performance in the Leaving Certificate was also predictive of first year GPA and 59% attained 250 points or less. Based on the results of this analysis the question must be asked, are we setting engineering students up to fail given that we have identified Leaving Certificate point totals and STEM Mathematics as being predictive of academic performance in programmes of engineering?

To address this, and given the importance of mathematical competency to both disciplines, we suggest a re-examination of the required mathematical competency required for engineering

and computing programmes. Mathematics competencies could be analysed prior to admission and as part of the induction process to inform follow up assistance and supports.

Higher Educational Institutions need to be more proactive and make timely use of the data at their disposal to further support the learning experience of our primary stakeholders. Institutional and sectoral performance profiles generated by the Higher Education Authority (HEA) are retrospectively historical, behind the current academic period by on average two years with initiatives aimed at identified performance issues more reactive in nature.

Business intelligence can inform initiatives, interventions and supports aimed at specific student cohorts in attempts to improve progression rates. This can be achieved through the definition of policy, strategy and adoption of learning analytics to facilitate the timely capture, analysis and dissemination of data to feed key performance indicators focused on retention/progression. The effective use of virtual learning environments early in the first semester can be targeted to enable the timely record of engagement and student performance facilitating the analysis and dissemination of data to highlight possible 'at risk' students. Online assessment tasks implemented to gauge student uptake in key concepts/knowledge can be further supported with in-built recommender systems to further support any identified learner shortfall.

Without timely intervention and mathematical support, computing and engineering students will continue to struggle.

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