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# Predicting Student Performance in a Caribbean Engineering Undergraduate Programme

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**Abstract:** *In the Caribbean context, entry into university is primarily based on Caribbean Examinations Council (CXC) qualifications, and specifically the CXC Advanced Proficiency Examination (CAPE). The goal of this work is to examine the degree to which CAPE entry-grades predict both student final-graduating and in-programme course performance in a Caribbean engineering undergraduate programme. The data set included graduation, course and entry data for 140 students who graduated from the programme between 2014 and 2016. Students in the sample had grades in the four CAPE units associated with Pure Mathematics and Physics upon entry into the programme. The data set was analysed using cross-correlation, linear regression, classification and logistic regression. We note that a significant correlation of 0.40 to 0.51 exists between the scores of the four CAPE units. However, the multiple linear regression models reflect the relatively low influence of two of the CAPE units on graduating and course GPA. Despite the poor fit of the regression models (i.e., $R^2$ of 17% for graduating GPA and $R^2$ of 7% for course GPA) we were able to demonstrate clear patterns in the success rates, based on entry bands (e.g., approximately 45% of top-scoring entrants graduate with First Class Honours degrees, whereas 12.5% of lower-scoring entrants achieved same). There was no inherent bias by gender or entry band in any of the models generated. The results suggest that the entry criteria serve as a means of predicting the probability of achieving success, rather than the actual success level.*

***Keywords:*** *Entrance qualifications, performance prediction, undergraduate engineering education*

## 1. Introduction

Globally, universities are focused on improving their student intake, whether by expanding the range of input standards they are prepared to accept, or improving access mechanisms for under-represented populations (Bridgeman et al., 2008). The increased variability in the student background requires academic institutions to be deliberate in their efforts to ensure that there is no concomitant impact on throughput/success levels due to students being unable to perform appropriately (Lee et al., 2008; Badr et al., 2016). That said, the ability of the entrance scores, based on varied criteria, to predict performance has increasingly been called into question (Barry and Chapman, 2007), with some authors suggesting that depending on the degree discipline, specific subject/pre-test scores (Othman et al., 2012), or first-year course scores provide better predictors (Badr et al., 2016; Lee et al., 2008).

In the Caribbean context, entry into university is primarily via assessments by the Caribbean Examinations Council (CXC) – specifically, CXC Advanced Proficiency Examinations (CAPE) (CXC 2015). The goal of this work is to examine the ability of CAPE entry grades to predict both student final-graduating and in-programme course performance in a Caribbean engineering undergraduate programme.

For entry into Bachelor of Science (BSc) (Engineering) - Electrical and Computer Engineering programme at The University of the West Indies, St. Augustine Campus, applicants must fulfil the University's general matriculation requirements, as well as have suitable grades in Chemistry, Pure Mathematics and Physics. Success in the programme is defined as being able to achieve Chartered Engineering status (IET, n.d.) post-BSc graduation, by entry into a matching-section Masters programme, which nominally requires a GPA $\geq$ 2.0. A highly successful student would be a student with a First Class Honors degree, which requires a GPA $\geq$ 3.6

## 2. Related Caribbean Works

Over the period 1990-2003, the College of Engineering at the University of Puerto Rico in Mayaguez (Gonzalez-Barreto and Gonzalez-Quevedo, 2005) examined the GPA that their freshmen achieved at the end of their first-year with a number of entry variables such as gender, school type (whether or public or private), high school grade-point average (GPA), performance in the Mathematics and Spanish verbal aptitude tests by the Puerto Rico and Latin America College Entrance Examination Board (CEEB), as well as three (3) other CEEB variables, namely Mathematical Knowledge, English Language Knowledge and Spanish Language Knowledge. These are components that comprise their admission criteria. The admission index (called IGS) comprises the high-school GPA, the CEEB Verbal and Mathematics aptitude scores. Prior to 1995, these three criteria contributed equally to the IGS, but thereafter, the weighting became 2:1:1. The authors attempted to determine the suitability of using such a weighting for the IGS, and to propose more optimal ones. Excluding gender and school type, models comprising subsets of the variables which served as predictors were created. The bases for comparing the quality of the models were the minimum mean square error and the Cp Mallows statistic. One of the findings is that the set of predictors comprising the best three-variable model differed from what was currently being used in the IGS, and even that "best" model was not sufficient to describe the First-Year GPA (FYGPA) variability, thus alluding to other factors contributing to the students' first year performance.

Muddeen and Mallalieu (2016) discussed steps taken by the Department of Electrical and Computer Engineering (DECE) at The University of the West Indies (UWI), St. Augustine Campus, to specifically address the declining performance in first year Engineering Mathematics as part of a comprehensive curriculum review undertaken by the department. There were no predictive models developed in this study, but rather a qualitative discussion of the factors attributing to the poor performance in Mathematics such as the entry qualifications of the students, the content of the Mathematics courses being offered to students in the department, as well as the assessment and delivery strategies employed within the Mathematics courses. The authors also described the interventions to improve the Mathematics performance, as well as the result of those interventions.

The study by Pottinger et al. (2009) was based at The UWI, Mona Campus. The main objective was to compare the performance (in terms of GPA), social adjustment and academic challenges of students who did not have a hidden (nonphysical) disability (such as, Attention Deficit Hyperactivity Disorder (ADHD) and Psychiatric Disabilities (PD)) with those who did, particularly in their second year, given that all of the students would have met the criteria for entry into their respective programmes at the university. Besides discovering that the students with hidden disabilities did perform more poorly academically than their peers due to their learning challenges, they also discovered through their intake checklist, that regardless of having a disability, students' ability to manage time was important to achieving academic success.

Golding and Donaldson (2006*a*) conducted a study at the University of Technology, Jamaica (UTECH) and their aim was to determine the relationship between academic performance (final GPA) of students in the Bachelor of Science in Computing and Information Technology (BSCIT) Degree program and their matriculation requirements as well as their performance in first-year courses. They proposed that the results of this study be used in restructuring their admission policies. The three hypotheses they sought to test were: 1) Mathematics and English CXC and GCE O' Level grade quality do not have a direct impact on students' academic performance; 2) performance in 1st year Programming and Computer Science courses does not have an impact on students' performance; and 3) gender and age do not determine the level of students' success in Computer Science. Using simple linear regression, they found that English CXC was not a strong factor, and CXC Mathematics was a poor predictor. They were able to isolate one of their gateway courses that can help predict students' future performance, thereby rejecting the second null hypothesis. They also found that gender and age had no impact on their students' performance.

Mlambo (2011) investigated the factors that affect student performance in a specific course: "Introduction to Biochemistry" (Agri 1013). Exploratory variables included age (young, mature), gender (male, female), learning style (Visual, Aural, Read/Write, Kinesthetic, Multimodal), entry qualifications (CAPE, GCE A' Levels, Associate Degree, CXC only, Other, Diploma in Agriculture). He found that none of these factors significantly impacted academic performance in that course.

Sastry et al. (2007) described the authors' experiences in establishing and administering joint degree programmes between the University of the West Indies and the University of Trinidad and Tobago, specifically, the Bachelor of Technology Degrees in Mechanical and Electrical Engineering which targets engineering technicians and technologists, which traditionally would not likely have CAPE A' Level grades as entry qualifications. No explicit admission criteria were stated and no models were employed.

## 3. Background to the Study

The study of admission criteria for validity and as suitable predictors of university performance has been pursued at many institutions around the world (e.g., Australia (Whyte et al., 2011), Bulgaria (Kabakchieva 2013), Canada (Cyrenne and Chan, 2012), Jamaica (Golding and Donaldson, 2006), Kingdom of Bahrain (Alnasir and Jaradat, 2011), New Zealand (Shulruf et al., 2008), Thailand (Vuttipittayamongkol, 2016), the United Kingdom (Whyte et al., 2011; Kevern et al., 1999), the USA (Abele et al., 2013, Cohn et al., 2004, Maruyama, 2012, Venezia and Voloch, 2012, Sedlacek, 2003, Garton et al., 2000)), across a variety of programmes and disciplines such as Nursing (Whyte et al., 2011, Abele et al., 2013, Kevern et al., 1999), Information Technology (Golding and Donaldson, 2006), Medicine (Alnasir and Jaradat, 2011), Agriculture (Garton et al., 2000) and Business (Rothstein et al. 1994, Kuncel et al., 2007), and at both the undergraduate and graduate levels (Rothstein et al. 1994; Kuncel et al., 2007, 2001).

The main reasons for conducting these studies have been to determine how to improve (Whyte et al., 2011) or optimise (Golding and Donaldson, 2006) the student selection process for entry into the programme; to identify students who should be denied admission (Alnasir and Jaradat, 2011); to determine how to make scholarship decisions so those who would most likely succeed in college would receive the help to do so (Cohn et al., 2004); to predict those will be matched behaviorally to the programme of study (Kuncel et al., 2007); to improve recruitment, retention and to reduce wastage (Kevern et al., 1999; Kuncel et al., 2001); and to protect the field of study from weakening (Kuncel et al., 2001). In Shulruf et al. (2008), different formulations of the entrance qualifications were used to see if the profile of eligible applicants would change.

Some researchers, however, have suggested that the motives for conducting such studies on entrance qualifications be more developmental, for example, to identify students who may be at risk of failing (Whyte et al., 2011; Crede and Kuncel, 2008), so that additional assistance may be given to these prospective students prior to entering the programme (Abele et al., 2013). The results of these studies can aid students to determine for themselves their own level of readiness for college and may help them improve in this regard (Maruyama, 2012). These studies can inform effective strategies to help students transition successfully to the college/university environment (Venezia and Voloch, 2012). Also, by using the results of these analyses, counseling and teaching staff can proactively identify ways to address learning differences and challenges among students of an incoming cohort (Crede and Kuncel, 2008; Garton et al., 2000).

Triggers for these studies included, for example, programmes facing an increase in the number of applicants (Golding and Donaldson, 2006) vying for a limited number of places. On the other hand, another trigger would have been high attrition rates encountered by particular programmes (Abele et al., 2013) possibly due to a lack of alignment between the demands of high school and college/university (Venezia and Voloch, 2012). Another trigger could be unexpected student failures in spite of these same students having good entrance qualification scores (Crede and Kuncel, 2008).

Although the main interest among the studies is admission criteria, their objectives varied. For example, Whyte et al. (2011) wanted to predict the probability of student success in a number of subjects given the entrance qualifications and other factors. However, Abele et al. (2013) wanted to identify those courses that can predict student success. In the work done by Cohn et al. (2004), it was the degree to which SAT scores, high-school GPA and class rank could predict success in college that was examined. Cyrenne and Chan (2012) wanted to examine the usefulness of high school grades as a predictor of university performance, and Maruyama (2012) wanted to determine if the ACT scores are satisfactory indicators of college readiness at the aggregate level. In Shulruf et al. (2008), alternative models for university entrance were explored.

## 4. Methodology and Findings

The goal of this work is to examine the degree to which CAPE entry-grades predict:

- Student final-graduating GPA (i.e., the predicted value and whether it will exceed 2.0)
- In-programme course performance, and
- Time from entry to graduation

for students in the B.Sc. Electrical and Computer Engineering programme. The methodology used in the study is based on methods described in Bridgeman et al. (2008), Barry and Chapman (2007), Badr et al. (2016), and Lee et al. (2008). The statistical computing software, R version 3.1.3 (2015-03-09) (R Core Team, 2015) was used to carry out the analysis. Specifically, the major functions used were **lm** and **cor.test** from the **stats** package to perform the linear regression and correlation analyses; **regsubsets** from the **leaps** (Lumley and Miller 2004) to perform the model reduction; and **clm** from the **ordinal** package (Christensen, 2015) to perform the logistic regression.

The input data set was based on graduation, course and entry data for 140 students who graduated from the program between 2014 and 2016.These students had Caribbean Advanced Proficiency Examinations (CAPE) grades in Pure Mathematics and Physics upon entry into the programme. The highest grade in any CAPE unit is one, and this assigned a score of five points; the second-highest is two and this assigned a score of four points and so on. The lowest score of one point is assigned a grade of five. The average score of Physics Unit 1 and Physics Unit 2 is added to the average score of Pure Mathematics Unit 1 and Pure Mathematics Unit 2 to determine the overall entry score for each student. Additional Mathematics may also be considered but it is not a mandatory qualification. The data set is summarised in Table 1.

91.7% of the students graduated with a GPA greater than 2.00 and 27.9% graduated with a GPA greater than 3.60. The ratio of male to female graduating students was 2.9 to 1, whereas the ratio of male to females graduating with a GPA greater than 3.60 narrowed to 2.25 to 1. It should be noted that no student who entered the programme having an entry score greater than ten (10) points graduated with a GPA less than 2.00. In fact, a higher proportion of the students in this “greater than 10 point” entry-band graduated with a GPA greater 3.60 (i.e., 29/65), than in any other entry- band (i.e., 7/56, and 3/19).

**Table 1.** Summary table: Input data-set students graduating between 2013/14 to 2015/16

| | **Entry Score** | | | | | | | | | **Full** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **>10 points** | | | **>8 and <10 points** | | | **≤ 8points** | | | | | |
| Gender | Male | Female | Overall | Male | Female | Overall | Male | Female | Overall | Male | Female | Overall |
| No. of students | 44 | 21 | 65 | 44 | 12 | 56 | 16 | 3 | 19 | 104 | 36 | 140 |
| Average Graduating GPA | 3.42 | 3.58 | 3.48 | 2.94 | 2.96 | 2.95 | 2.82 | 2.91 | 2.83 | 3.12 | 3.32 | 3.17 |
| Average ECNG 2001 GPA | 2.85 | 3.42 | 3.03 | 2.69 | 2.39 | 2.63 | 2.33 | 2.67 | 2.37 | 2.70 | 3.01 | 2.78 |
| No. of students with GPA<2.00 | 0 | 0 | 0 | 2 | 0 | 2 | 2 | 0 | 2 | 4 | 0 | 4 |
| No. of students with GPA>3.60 | 18 | 11 | 29 | 1 | 6 | 7 | 3 | 0 | 3 | 27 | 12 | 39 |

For each entry-band, females, though fewer in number, scored higher graduating GPAs than their male counterparts, on average. The same could be said for their performance in the course ECNG 2001: Communication Systems I, except for the "8 to 10 point" entry-band.

In comparison, the datasets used for the studies in the literature (Bridgeman et al., 2008; Barry and Chapman, 2007; Badr et al., 2016; Lee et al., 2008) are either larger, or involve a different number of cohorts, where Bridgeman et al.(2008) looked at 3 cohorts of students across multiple programmes and 26 colleges. Badr et al.( 2016) looked at 6 cohorts of students (200 students) from a single programme, and Lee et al.( 2008) examined a single cohort of students (133 students) from a single program. This suggests that the methods used are not dependent on the specific programme, and/or the number of cohorts involved, and that the quantity of data available for this study is sufficient.

Lee et al. (2008) and Barry and Chapman (2007) outlined the creation of linear regression models to establish the significance of predictive factors in course performance models. In this work, linear regression models were developed for both graduating GPA and achievement level in a mathematically-based second-level course (ECNG 2001) using the CAPE Pure Mathematics and Physics grades as the predictors. The models are summarised in Table 2 where the individual coefficients, their respective p-values and levels of significance are provided. It has become almost standard practice to use traditional regression analysis in studies of similar type to characterise the relationship between an outcome that serves as a measure of student performance and a set of controlled variables or predictors (e.g., entrance scores). Besides, Lee et al. (2008) and Barry and Chapman (2007), other studies that employed linear regression include Vuttipittayamongkol (2016), Shulruf et al., (2008), Whyte et al., (2011), Cohn et al., (2004), Alnasir and Jaradat (2011), and Rothstein et al. (1994).

For the graduating GPA the regression model was $0.05P_2 + 0.17P_1 + 0.20M_2 - 0.03M_1 + 1.40$, where $P_1$ denotes the Physics Unit 1 grade, $P_2$, Physics Unit 2 grade, $M_1$, Pure Mathematics Unit 1 grade and $M_2$, Pure Mathematics Unit 2 grade. The p-value of 5.254e-05 for the overall model suggests that the overall relationship between the graduating GPA and the regressors taken together was statistically significant. However, the p-values for the individual regressors suggest that Pure Mathematics Unit 1 and Physics Unit 2 were not found to be statistically significant, whereas that of Pure Mathematics Unit 2 and Physics Unit 1 were. The coefficient of determination ($R^2$) was 17%, meaning that the regressors under study only accounted for 17% of the variability in graduating GPA. For the ECNG 2001 course GPA, the regression model seemed to not have as good a fit. In fact, the coefficient of determination was 7% and the p-value was borderline (i.e. 0.03772). The only variable with a significant coefficient was Pure Mathematics Unit 2.

**Table 2.** Multiple linear regression models for course and graduating GPA

| | **Variable** | **Coefficient** | **Standard error** | **t** | ***Pr*** **(> \|*t*\|)** | **Significance** |
|---|---|---|---|---|---|---|
| Graduating GPA | Intercept | 1.40624 | 0.47345 | 2.970 | 0.00352 | 0.01 |
| | Maths Unit 1 | -0.03469 | 0.11579 | -0.300 | 0.76495 | nil |
| | Maths Unit 2 | 0.19941 | 0.08100 | 2.462 | 0.01508 | 0.05 |
| | Physics Unit 1 | 0.17322 | 0.08302 | 2.087 | 0.03881 | 0.05 |
| | Physics Unit 2 | 0.05065 | 0.08780 | 0.577 | 0.56501 | nil |
| | R-squared: 0.1674; Adjusted R-squared: 0.1427; p-value:5.254e-05 | | | | | |
| Course GPA | Intercept | 0.94871 | 0.94426 | 1.005 | 0.3168 | nil |
| | Maths Unit 1 | 0.03828 | 0.23093 | 0.166 | 0.8686 | nil |
| | Maths Unit 2 | 0.33591 | 0.16154 | 2.079 | 0.0395 | 0.05 |
| | Physics Unit 1 | -0.21224 | 0.16557 | -1.282 | 0.2021 | nil |
| | Physics Unit 2 | 0.23329 | 0.17511 | 1.332 | 0.1850 | nil |
| | R-squared: 0.07203; Adjusted R-squared: 0.04454; p-value:0.03772 | | | | | |

To examine the relationships further, the cross-correlations among the variables and between each variable and the outcome (i.e., graduating GPA and ECNG 2001 course GPA) were determined. These are listed in Table 3. All the variables posted significant correlations with graduating GPA. However, Physics Unit 2 and Pure Mathematics Unit 1 were not as strong in correlation as the other two variables. Only the grade in CAPE Pure Mathematics Unit 2 was reasonably (and positively) correlated with the performance in ECNG 2001.

There were two (2) other interesting observations. The first was that there was very high correlation between ECNG 2001 performance and the graduating GPA. The second was that there were comparatively significant positive correlations among the predictor variables, i.e., CAPE units, than between these individual CAPE units and the graduating GPA. The correlation among the predictor variables ranged from 41% to 54% with the highest being between Physics Unit 1 and Physics Unit 2, and the second highest being between Pure Mathematics Unit 1 and Pure Mathematics Unit 2 (51%). This multi-collinearity can significantly increase the standard errors of the coefficients which, in turn, can reduce the overall effectiveness of the regression model.

Badr et al. (2016) outlined the creation of a predictive-model based tool to predict performance in a specific course using data-mining methods to identify the relevant performance predictors, and quantify their influence. The data-reduction process was used to identify the most relevant factors for each outcome. In this work, a model reduction technique is employed. This is particularly useful to alleviate the effects of the aforementioned multi-collinearity. Correlated predictors provide redundant information. Therefore, removing a subset of these can improve the model's performance. The reduced models are summarised in Table 4. Utilising the **regsubsets** function in R, model selection by exhaustive search is performed (rather than by forward/backward stepwise or sequential replacement). All four (4) predictor variables were initially considered, and the "best" three-variable model, two-variable model and single-variable model were obtained. In this case, "best" meant the model having the highest adjusted $R^2$ value. The "best" reduced model for the graduating GPA involved only two predictors (specifically Pure Mathematics Unit 2 and Physics Unit 1) with an adjusted $R^2$ of 15.27%. These candidate models for the ECNG 2001 course GPA had only one significant single predictor (specifically Pure Mathematics Unit 2), and the adjusted $R^2$ was consistently very low.

Badr et al. (2016) utilised a data-normalisation process that involved classifying the input and output factors to improve model robustness. Graduating GPA can be classified as "Highly Successful"/"Not Highly Successful", and the input grades can be classified as "Good" (above four points) and "Bad" (four or less points). Here, a student is deemed "Highly Successful" if he/she achieves a graduating GPA of 3.60 or above (see Tables 5 and 6). The counts by unique combinations of predictor values found in the actual data set are shown in Table 7. Note that "Good" is denoted as simply "G" and "Bad" as "B". For example, 29 students entering

**Table 3.** Correlations with their p-values among potential predictors and outcomes

| | GPA | ECNG2001 | Physics Unit 1 | Physics Unit 2 | Maths Unit 1 | Maths Unit 2 |
|---|---|---|---|---|---|---|
| **GPA** | 1 | 0.625901 p-value =2.22e-16 | 0.338825 p-value =4.22e-16 | 0.279905 p-value=0.00081 | 0.220709 p-value=0.008782 | 0.354682 p-value=1.71e-05 |
| **ECNG 2001** | | 1 | 0.048409 p-value=0.570046* | 0.181869 p-value=0.03151* | 0.121432 p-value=0.152941* | 0.234095 p-value=0.005373 |
| **Physics Unit 1** | | | 1 | 0.539861 p-value=5.85e-12 | 0.479893 p-value=1.98e-09 | 0.460096 p-value=1.07e-08 |
| **Physics Unit 2** | | | | 1 | 0.409959 p-value=4.9e-07 | 0.496512 p-value=4.41e-10 |
| **Maths Unit 1** | | | | | 1 | 0.514071 p-value=8.23e-11 |
| **Maths Unit 2** | | | | | | 1 |

**Table 4.** Model reduction for course and graduation GPA linear regression models

| | Model | Intercept | Physics Unit 1 | Physics Unit 2 | Math Unit 1 | Math Unit 2 | Adjusted $R^2$ | p-value |
|---|---|---|---|---|---|---|---|---|
| Graduating GPA | Original | 1.40624 | 0.17322 | 0.05065* | -0.03469* | 0.19941 | 0.1427 | 5.254e-05 |
| | Three-variable | 1.3188 | 0.1667 | 0.0483* | | 0.1913 | 0.148 | 1.61e-05 |
| | Two-variable | 1.39363 | 0.18453 | | | 0.20528 | 0.1527 | 4.345e-06 |
| | One-variable | 1.8422 | | | | 0.2887 | 0.119 | 1.71e-05 |
| ECNG2001 GPA | Original | 0.94871* | -0.21224* | 0.23329* | 0.03828* | 0.33591 | 0.04454 | 0.03772 |
| | Three-variable | 1.0452* | -0.2050* | 0.2359* | | 0.3449 | 0.05137 | 0.01713 |
| | Two-variable | 0.768* | 0.145* | | | 0.294 | 0.0468 | 0.0139 |
| | One-variable | 1.125* | | | | 0.360 | 0.048 | 0.00537 |

**Table 5.** Normalised model for "Highly Successful" vs "Not Highly Successful" students - all predictors

| **Categorical Predictors:** | **Estimate** | **Std. Error** | **z value** | ***Pr*(<\|t\|)** | **Significance** |
|---|---|---|---|---|---|
| CAPE Physics Unit 1 | 0.166 | 0.398 | 0.42 | 0.677 | — |
| CAPE Physics Unit 2 | 0.87 | 0.432 | 2.01 | 0.044 | 0.05 |
| CAPE Pure Math Unit 1 | 0.108 | 0.471 | 0.23 | 0.819 | — |
| CAPE Pure Math Unit 2 | 0.723 | 0.443 | 1.63 | 0.102 | — |
| **Threshold coefficients:** | **Estimate** | **Std. Error** | **z value** | | |
| NO\|YES | 1.632 | 0.351 | 4.65 | | |
| **Model quality:** | **Log-likelihood** | **AIC** | **Condition number on Hessian Matrix** | | |
| | -73.7 | 157.4 | 16 | | |
| **Model prediction:** | **Accuracy** | **No Information Rate (NIR)** | **P-Value [Acc >NIR]** | **Sensitivity** | **Specificity** |
| | 0.721 | 0.721 | 0.543 | 1 | 0 |

**Table 6.** Normalised model for "Highly Successful" vs "Not Highly Successful" students - single predictor

| **Categorical Predictors:** | **Estimate** | **Std. Error** | **z value** | ***Pr*(<\|t\|)** | **Significance** |
|---|---|---|---|---|---|
| CAPE Physics Unit 2 | 1.201 | 0.367 | 3.27 | 0.0011 | 0.01 |
| **Threshold coefficients:** | **Estimate** | **Std. Error** | **z value** | | |
| NO\|YES | 1.35 | 0.26 | 5.19 | | |
| **Model quality:** | **Log-likelihood** | **AIC** | **Condition number on Hessian Matrix** | | |
| | -75.92 | 155.84 | 5.6 | | |
| **Model prediction:** | **Accuracy** | **No Information Rate (NIR)** | **P-Value [Acc >NIR]** | **Sensitivity** | **Specificity** |
| | 0.721 | 0.721 | 0.543 | 1 | 0 |

**Table 7.** Counts by combinations of predictor values for actual and predicted outcomes

| **Physics 1** | **Physics 2** | **Pure Math 1** | **Pure Math 2** | **Highly Successful** | | | |
|---|---|---|---|---|---|---|---|
| | | | | **Actual** | | **Predicted** | |
| | | | | **NO** | **YES** | **NO** | **YES** |
| B | B | B | B | 9 | 2 | 11 | 0 |
| B | B | B | G | 5 | 1 | 6 | 0 |
| B | B | G | B | 9 | 1 | 10 | 0 |
| B | B | G | G | 11 | 0 | 11 | 0 |
| B | G | B | B | 4 | 0 | 4 | 0 |
| B | G | B | G | 1 | 1 | 2 | 0 |
| B | G | G | B | 4 | 0 | 4 | 0 |
| B | G | G | G | 4 | 3 | 7 | 0 |
| G | B | B | B | 0 | 0 | 0 | 0 |
| G | B | B | G | 3 | 0 | 3 | 0 |
| G | B | G | B | 5 | 0 | 5 | 0 |
| G | B | G | G | 3 | 1 | 4 | 0 |
| G | G | B | B | 1 | 0 | 1 | 0 |
| G | G | B | G | 2 | 0 | 2 | 0 |
| G | G | G | B | 4 | 1 | 5 | 0 |
| G | G | G | G | 36 | 29 | 65 | 0 |
| | | | | 101 | 39 | 140 | 0 |

with "Good" grades in these four units were "Highly Successful", whereas 36 were "Not Highly Successful" (see the last rows of Table 7.)

The normalised model for "Highly Successful"/"Not Highly Successful" prediction is summarised in Table 5. To perform this logistic regression, the cumulative link model with logit link (**clm**) function in the ordinal package in R was used. It can be seen that the sole statistically significant predictor was CAPE Physics Unit 2. This contrasts with the predictors identified in the linear regression models obtained earlier. Another logistic regression was run but with CAPE Physics Unit 2 as the only predictor. The significance of the coefficient increased, but the overall fit marginally improved, i.e., the Akaike Information Criteria (AIC) drops from 157.4 to 155.84 and the log-likelihood ratio of -73.7 to -75.92. However, the accuracy of both models was low at 72.1%. The counts by unique combinations of predictor values for the predicted outcome can be found alongside that for actual data in Table 7. The models never predicted a positive outcome. This may be attributed to the skewness of the data set which had a higher proportion of negative outcomes than positive ones for each combination of input. Based on

**Table 8:** Over-/Under prediction according to full linear regression model

| | Entry Score | | | | | | | | | Full | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | >10 points | | | >8 and <10 points | | | ≤ 8points | | | | | |
| | Male | Female | Overall | Male | Female | Overall | Male | Female | Overall | Male | Female | Overall |
| Graduation GPA | 0.0658 | 0.229 | 0.119 | -0.151 | -0.234 | -0.168 | 0.0966 | 0.0579 | 0.0905 | -0.021 | 0.0607 | -2.28e-16 |
| ECNG 2001 GPA | -0.0738 | 0.494 | 0.11 | -0.0827 | -0.459 | -0.163 | 0.0526 | 0.392 | 0.106 | -0.0581 | 0.168 | -3.72e-16 |

these observations, using a normalised model may be ineffective. Bridgeman et al. (2008) examined whether there was bias in the prediction models (e.g. by gender, background and the nature of the course) by examining the prediction error for sub-groups of the population.

According to Bridgeman et al. (2008), if the actual performance of a sub-group is consistently better than their predicted performance then there is under-prediction, and a group that actually performed worse than predicted is over-predicted. Calculated as the mean of the difference between actual and predicted values, a substantially negative number implies over-prediction and a positive number implies under-prediction. The prediction errors by gender and entry score groups are summarised in Table 8.

Bridgeman et al. (2008) examined the relative impact of related factors by examining the percentage of successful students within each band of entry grades. The percentage of "Highly Successful" students by the range of entry score are summarised in Table 9. It demonstrates that the proportion of students achieving "Highly Successful" status is different for students with entry scores of ten versus those with less than ten. For example, of those students who had entry scores greater than ten (i.e., 65 (see Table 1)) 44% of them graduated with GPAs greater than 3.60, and 100% of them had a graduating GPA greater than 2.00. However, of the 56 students who had entry scores within the range of eight to ten points, only 12.5% of them graduated with a GPA greater than 3.60. The differences in percentages across entry-score bands is much starker when considering the "Highly Successful" threshold (i.e., GPA of 3.60) than for the "Successful" threshold (i.e., GPA of 2.00).

**Table 9:** Percentage of "Highly successful" and "Successful" students by the range of entry score

| Entry Score | % Highly Successful | % Successful |
|---|---|---|
| 10 | 44.6 | 100 |
| >8 and <10 | 12.5 | 96.4 |
| <8 | 15.8 | 89.5 |
| Overall | 27.9 | 97.1 |

## 5. Discussion

There is a need to reflect on the true purpose for entrance standards and thresholds in higher education. Are they variously:

1. A proxy for student's knowledge of pre-requisite content?
2. A way to determine a student's ability to learn?
3. A means to predict student success?

In this work, inspired by the work of Maruyama, (2012), Golding and Donaldson,(2006), Bridgeman et al.(2008), the entrance standards and thresholds of the Department were questioned with regard to their underlying assumptions as well as their ability to fulfil all three functions identified above.

For most entrants, CAPE grades were exclusively examined, and high-school performance ignored. These grades in themselves have been reported as reliable measures of student knowledge (Griffith, 2017), with no discernible bias reported between gender (CXC, 2015). The entry score is based solely on grades achieved in four specific CAPE units: Pure Mathematics Unit 1, Pure Mathematics Unit 2, Physics Unit 1, and Physics Unit 2. The grade achieved for an entire unit is considered without looking at the performance in the individual components comprising each unit. The units are treated in isolation, without considering the simultaneous workload or other subjects undertaken by the student.

In this study, it was found that a significant correlation of 0.40 to 0.51 existed between the grades of the four units (see Table 3). Despite this, the multiple linear regression models (full and reduced) (see Table 4) reflect the relatively low influence of two of the CAPE Units on graduating and course (ECNG 2001) GPA. That there are high correlations among the CAPE units in spite of them covering differing content may indicate that there could be some common underlying aspects (e.g., mode of delivery, assessment format and strategies) that not only assist the students in mastering the content but also the examination process itself. These could be vastly different at the University.

Further the linear regression models (shown in Table 2), the cross-correlations (shown in Table 3) and the reduced models (shown in Table 4) for both graduating GPA and course GPA based on the CAPE grades have low (adjusted) coefficient of determination ($R^2$), suggesting that there may be a disconnect between expectations of pre-requisite knowledge and the grades which were intended to act as proxies for that knowledge. One may even be tempted to conclude that, particularly for the ECNG 2001 course, the theory covered by the CAPE Pure Mathematics and Physics syllabus may be irrelevant. On the contrary, it may be that this course demands not only a strong handle of prerequisite knowledge which these CAPE units do provide, but also much higher order cognitive usage of this knowledge. Probably CAPE Pure Mathematics Unit 2 comes closest to this demand or maybe the course ECNG 2001 draws most heavily on knowledge gained in Pure Mathematics Unit 2. Across these models, the low $R^2$ may also indicate that there are other factors not identified in this study that contribute significantly to a student's success in the programme, probably (e.g., his/her study-skills, socio-economic status, to name a few).

Furthermore, some pre-requisite content has more impact on performance than others. The negative correlation between the Pure Mathematics Unit 1 grade and graduating performance, suggests that students may in fact need to "unlearn" some of what they have been taught prior to entering the programme. CXC has reported that students have challenges with certain topics in Calculus (CXC, 2013) and these same topics align with the pre-requisite knowledge of the syllabus. Muddeen and Mallalieu (2016) have previously reported the Department's efforts to address the underlying Mathematics issues reflected by this observation, and the observation that while Pure Mathematics Unit 2 is the strongest predictor of graduating GPA (see Table 2), it is much less significant than the influence of a single course within the programme, ECNG 2001 (see Table 3).

The ability of the linear regression models shown in Table 2 to over and under predict performance were examined by gender and entry score for both graduating GPA and course GPA in Table 8. There does not seem to be any consistently inherent bias in the model by either factor.

For the students whose performance was reviewed in this study (see Table 1), slightly under half entered the programme with the maximum CAPE derived entry score of 10 points. However even with the high entry scores, only half of this group were "highly successful" at graduation. This strengthens the argument that there are other factors that may be impacting a student's performance which may not have been previously evident to either the student or the Department but which nevertheless should be addressed earlier in the programme.

College readiness was discussed by Venezia and Voloch(2012). They suggested that the discontinuity in academic performance that exists between high school and post-secondary institutions is due the lack of content alignment between high school performance and college entrance exams. Further work by Bridgeman et al. (2008, 2004) and Lee et al. (2008), highlighted significant differences in university success rates by entrance bands, while corroborating the discontinuity in performance. This is substantiated by the prediction models explored in this work for the BSc (Eng) Electrical and Computer Engineering programme, where despite poor linear and logistic regression models (see Tables 2 and 5) we were able to demonstrate clear patterns in the success rates (see Table 9). This suggests that at this time the entry criteria serve as a means of predicting probability of achieving success, rather than the actual success level.

These observations suggest that the use of the grades to derive entry score is neither a proxy for pre-requisite content, nor as a means of discerning a student's ability to manage his/her learning process.

## 6. Conclusion and Future Work

Kuncel et al. (2007) mentioned that the admission systems can be divided into two parts: the first being the predictors or measures used to forecast future student performance (which was primarily addressed in this paper), and the second being the method by which the predictors are actually combined to make the admission decisions. With regard to the former, additional admission criteria, whether high-school performance (Bridgeman et al., 2008), or entrance examinations, essays, interviews (Alnasir and Jaradat, 2011; Mercer and Puddey, 2011), would be worthy of consideration. With regard to the latter, given the predictive models bias to specific CAPE units, a weighted entry score model (rather than the present equal weighting) could also be considered.

In the literature, non-academic factors, such as personality (Rothstein et al., 1994, Crede and Kuncel, 2008), learning styles (Garton et al., 2000), extra-curricular activities (Vuttipittayamongkol, 2016), time-management (Macan et al., 1990; Pottinger et al., 2009), study skills (Crede and Kuncel, 2008), motivation (Alnasir and Jaradat, 2011; Crede and Kuncel, 2008) and socio-economic status (Whyte et al., 2011, Lei and Li, 2015; Maruyama, 2012; Sackett et al., 2009; Shulruf et al., 2008; Schulz, 2005; Sirin, 2005), and class attendance (Cohall and Skeete, 2012) have all been treated with when determining how best to predict graduating performance at entry. A future study would attempt to ascertain which, if any, of these factors may be additional contributors to the students' graduating performance in this undergraduate programme.

This work focused on those students who entered the BSc (Eng) Electrical and Computer Engineering programme via the most common route (that is with CAPE passes), however approximately 20% students enter by a variety of other means. A comprehensive means of addressing multiple entry routes (CAPE included) needs to be investigated. One of the first tasks would be to formally explore the knowledge gaps (if any) between each entry route and the prerequisite knowledge required for the programme's courses.

In this paper, the effectiveness of existing admission criteria for an undergraduate engineering programme has been questioned. The results suggest that the entry criteria can predict success, rather than actual success level. Based on the results of this analysis, closer attention to performance within the individual units may be required in order to predict academic success in this programme. The reported success rates among graduates, in spite of the relatively low correlations between CAPE qualification and graduating GPA, as well as regression models with low $R^2$, suggest that there are other major (unexplained) factors that contribute significantly to students' success.

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