A STATISTICAL MODEL TO IDENTIFY THE INFLUENCE OF MATHEMATICS ON STUDENTS' PERFORMANCE IN ENGINEERING PROGRAMS

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Degree of Master of Philosophy

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DECLARATION

"I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text."

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ABSTRACT

Mathematics plays a major role in higher education as it is particularly essential to develop the analytical thinking of students in a wide range of disciplines, especially, in engineering sciences. Therefore, exploring the student academic performance has been a crucial aspect of the educational research recently. In this study, the impact of mathematics in Level 1 and Level 2 on student engineering performance in Level 2 was investigated for seven engineering disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka under two scenarios: (i) effect of mathematics in Level 1 and Level 2 simultaneously and (ii) effect of mathematics in Level 1 and Level 2 separately by using unadjusted and adjusted Canonical Correlation Analysis (CCA). A theoretical model underlying relationship between two measurements, mathematics performance and engineering performance was developed based on literature review. The Structural Equation Modeling based on Partial Least Squares (PLS-SEM) technique was used to validate the conceptual model and proposed an index to measure the mathematical influence on student engineering performance. The first canonical variate of engineering was found to be the best proxy indicator for the engineering performance. The impact of mathematics in semester 2 is significantly higher compared with the impact of mathematics in semester 1 on engineering performance in Level 2. The mathematics in Level 1 and Level 2 jointly influenced on the engineering performance in Level 2 irrespective of the engineering disciplines and the level of impact of mathematics varies among engineering disciplines. The individual effect of mathematics in Level 2 is significantly higher compared to the individual effect of mathematics in Level 1 on engineering performance in Level 2. The mathematics in Level 1 is still important in affecting students' engineering performance in Level 2 as there is a significant effect indirectly. The results obtained in this study can be utilized in curriculum development in mathematics modules.

Keywords: canonical correlation analysis; engineering mathematics; structural equation modeling; student academic performance

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K.A.D.S.A. Nanayakkara

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LIST OF ABBREVIATIONS

Abbreviation	Description
ANOVA	Analysis of Variance
AVE	Average Variance Extracted
CCA	Canonical Correlation Analysis
CE	Civil Engineering
CH	Chemical and Process Engineering
CR	Composite Reliability
CS	Computer Science and Engineering
EE	Electrical Engineering
EN	Electronic and Telecommunication Engineering
ENG	Engineering
GPA	Grade Point Average
MAT	Mathematics
ME	Mechanical Engineering
MT	Material Science and Engineering
OLS	Ordinary Least Squares
PLS	Partial Least Squares
S1	First Semester
S2	Second Semester
S3	Third Semester
S4	Fourth Semester
SE	Standard Error
SEM	Structural Equation Modeling
VIF	Variance Inflation Factor

CHAPTER 1
INTRODUCTION

This chapter describes the background of the study, the objectives of the study and the significance of the study. Also, chapter outline of the thesis is presented.

1.1. Background

Higher education is an important tool for the socio-economic and technological development of any country as it provides the capable manpower needed to transform the resources within that country into wealth (Farooq et. al., 2011). This is achieved when higher education provides the exact quality of training and skills required in the exact quantity. Recently, many researchers have made extensive efforts in determining various aspects of student academic performance in higher education in different countries (Alfan and Othman, 2005; Al-Alwan, 2009; Hermon and Cole, 2012; Imran, Nasor, and Hayati, 2011; McKenzie and Schweitzer, 2001; Mufti and Qayum 2013).

Improving student academic performance is essential for the universities as their main objective is to provide quality education to their undergraduates with the changes in higher education. Consequently, there is an urgency to look into the effectiveness of the academic programs which will lead to discover the possible factors that assist to improve student academic performance.

Mathematics plays a major role in higher education as it is more than a tool for solving problems and it can develop intellectual maturity and logical thinking of students. The skills in mathematics would certainly assist to enhance students' knowledge in a wide range of disciplines, such as engineering, physics, biology, accounting and social science. Especially, in engineering sciences, mathematical knowledge is crucial importance to improve the analytical thinking of engineering undergraduates. Thus, students desire to pursue an engineering degree course are required to be proficient in mathematics than other students.

Engineers, particularly apply mathematics and sciences such as physics to find suitable solutions to problems or to make improvements to the status quo. Therefore, mathematics is a key foundation for the education of engineers in all disciplines. Many researchers (Sazhin, 1998; Pyle, 2001; Goold and Devitt, 2012) have revealed the importance of mathematical knowledge for engineering students to develop their logical and analytical thinking. Mathematics is a significant topic supporting a large number of engineering courses. It is important for engineering students, to hold a strong mathematical fundamental knowledge that can keep their motivation for equitable progress of their engineering programs (Othman et. al., 2012). Pyle (2001) stated that engineering as a profession requires a clear understanding of mathematics, sciences and technology. According to Harris et. al. (2015), a widely understood need for professional engineers and student 'becoming engineers' to think mathematically and to use mathematics to describe and analyze different aspects of the real world they seek to engineer. Also Sazhin (1998) explained that an engineering graduate acquires not only a practical but also abstract understanding of mathematics.

Over the years, there have been concerns about the relationship between the pre-university admission performance of students and their academic performance in the university. In many countries, the pre-university requirement for engineering degrees is based mostly on mathematics for all higher education institutions. Similarly, in Sri Lanka, admission to higher education institutions is based on the results of the General Certificate of Education Advanced Level; G.C.E. (A/L) examination. The indicator to select the engineering students to government universities is decided by the mean Z-score of the three Z-scores of Combined Mathematics, Physics and Chemistry in G.C.E. (A/L) examination (University Grants Commission – Sri Lanka, 2017).

In engineering sciences, pre-university qualification or admission criteria for university entrance have been widely studied in the literature and are commonly accepted to have a beneficial effect of pre-university mathematical knowledge on students' subsequent academic performance (Barry and Chapman, 2007; Hermon and Cole, 2012; Ismail et al., 2012; Lee et al., 2008; Othman et al., 2009).

As described above, it is clear that mathematics is a key role in engineering sciences. Therefore, developing mathematical thinking of students is a major task as it is an essential tool in engineering education. Thus, Department of Mathematics, Faculty of Engineering, University of Moratuwa provides knowledge to all the engineering departments in the university equipping undergraduates with the essential mathematical knowledge, to enhance their analytical skills so that they are capable of solving problems in engineering sciences. The Department of Mathematics has designed mathematics modules in semester 1 and semester 2, which are made compulsory for all engineering students. Further, Department of Mathematics offer variety of common modules for all engineering departments depending on their requirements from Level 2 onwards as well.

According to Sri Lankan education system, students are entering university with diverse prior knowledge and background. However, most of the students who admitted to the Faculty of Engineering, University of Moratuwa have obtained higher grades in combined mathematics in G.C.E. (A/L) examination as it is a pre-requisite for the admission to engineering degree programs. During the semester 1 students do not belong to the particular engineering department. At the end of semester 1 the students are allocated to seven engineering disciplines based on the mean marks of six common modules including mathematics. The six common modules are: Mathematics, Programming Fundamentals, Mechanics, Properties of Materials, Fluid Mechanics and Electrical Engineering. The seven engineering disciplines are: Chemical and Process Engineering, Civil Engineering, Computer Science and Engineering, Electrical Engineering, Electronic and Telecommunications Engineering, Materials Science and Engineering and Mechanical Engineering.

Department of Mathematics has identified that mathematics performance of engineering students in their undergraduate degree programs varies significantly between and within different engineering disciplines irrespective of semesters. Furthermore, the variability in mathematics marks in first two semesters are high comparatively. A few percentage of students used to fail the mathematics module in semesters, while certain percentage used to repeat the examination to upgrade their results. The staff of mathematics department strongly feels that performance of mathematics by the student, certainly have similar impact on the academic performance of students in each level (year).

1.2. Objectives of the Study

In the view of the above, the objectives of the study are:

- To determine the impact of mathematics on students' academic performance at the end of Level 2 by different disciplines of engineering programs.
- To determine the individual impact of mathematics in Level 1 and Level 2 separately on the engineering performance in Level 2.
- To develop a statistical model to determine the underlying relationships between mathematics in Level 1 and Level 2 with the engineering performance in Level 2.

1.3. Significance of the Study

It is crucial to understand the impact of mathematical knowledge that students acquired from their undergraduate engineering degree programs as it is particularly essential to develop the analytical and logical thinking of engineering students. This knowledge would be useful for educational stakeholders at different level of decision making. As such studies were not reported the findings of this study will be useful for various stakeholders at the University of Moratuwa, in particular, the academic staff of the Department of Mathematics as well as the academic staff of other engineering disciplines to make future planning such as revise the future curriculum and etc. Moreover, other government universities in Sri Lanka can make use of these results to make their decisions.

Much research effort has been devoted to student academic performance in various fields such as engineering, physics, medicine, accounting, etc. Researchers mostly concerned about the prior knowledge that obtained from secondary education. Therefore, admission criteria or entry test was used as the factors in their studies. In reference to engineering education, prior mathematical knowledge was considered as the main key factor to examine the student academic performance. However, there is a lack of studies related to examining the impact of mathematical knowledge gained from undergraduate engineering degree programs on students' academic performance.

Though the marks of different subjects can be considered as the multivariate data, no studies were found under multivariate statistical environment to examine the impact of subjects on student academic performance. Furthermore, a detailed statistical analysis of students' marks has not been carried out to determine the influence of mathematics. Hence, a suitable multivariate statistical technique can be used to determine the influence of mathematics on students' academic performance.

1.4. Outline of the Thesis

This thesis is organized into seven chapters, references and appendices. Chapter 2 consist a review of literature about the influence of mathematics as well as other subjects on students' performance. The purpose of this chapter is to establish the current available knowledge and the statistical techniques used to determine the impact of a subject on students' performance. Chapter 3 briefly describes the research methodology employed and the theories and techniques applied to the study and the theory of proposed index. Chapter 4 presents the descriptive statistics of students' mathematics and engineering performance. Apart from that bivariate correlation analysis and linear regression analysis are also reported. The overall impact of mathematics on engineering performance in Level 2 is examined in Chapter 5. Chapter 6 illustrates the individual impact of mathematics in Level 1 and Level 2 on engineering performance in Level 2 separately. Chapter 7 discovers the underlying relationships between mathematics in Level 1 and Level 2 with the engineering performance in Level 2. The final chapter describes conclusions, recommendations and suggestions for future studies.

CHAPTER 2
LITERATURE REVIEW

The aim of this chapter is to obtain an insight on the literature related to the study: different findings, knowledge and ideas have been established on the students' academic performance. This will provide guidance on which statistical analyses are used, their drawbacks and etc.

2.1. Importance of Mathematics in Higher Education

Over the years, the influence of mathematics in a variety of subjects has been challenged by learning research and the development and diversification of the curriculum. A number of research studies revealed that there is a significant influence of mathematics on students' performance in different fields (Imran, Nasor & Hayati, 2011; Aina, 2013; Hailikari, Katajavuori, & Lindblom-Ylanne, 2008; Alfan and Othman, 2005).

Othman et al. (2009) studied on Pre-University qualifications of engineering students together with their performance on their first semester Grade Point Average (GPA) and found a pre-test effect on first semester results. According to Alfan and Othman (2005) knowledge earned in mathematics prior to entering the university is crucial in assisting the students in undertaking the courses in both business and accounting program. A study conducted among physics students in four colleges of education in Nigeria by Aina (2013) found that the subject combination affects students' performance. The students, who combined mathematics with physics performed better than students who follow other subject combinations.

2.2. Importance of Mathematics in Engineering Education

Mathematical knowledge is one of the most important tools for engineers. Mathematics for the engineering student should be regarded as a language of expressing physical, chemical and engineering laws (Sazhin, 1998). To discover the role of mathematics in engineering practice, Goold and Devitt (2012) conducted a study with the focus on professional engineers in Ireland. They exposed that mathematical knowledge gained prior and during engineering education is highly essential in engineering practice as they use a high level of curriculum mathematics and mathematical thinking in their work. Therefore, mathematics plays a major role in the formation of engineers.

Some authors have studied about the relationship between pre mathematical knowledge of engineering undergraduate students and their academic performance. Lawson (2003) found that changes in basic mathematical knowledge have a direct effect to many mathematical skills that are essential for those undergraduate degree courses with a significant mathematical content. Othman et al. (2009) found that pre-university mathematical knowledge effect on the performance of the first year engineering students.

A study carried out by Imran et al. (2011) investigated the relationship between students' overall performance in engineering programs and their grades in mathematics and physical science courses. Their findings indicated that the relationship between students' overall performance in the degree program and their performance in the mathematics courses was relatively stronger compared to the physical science courses. A similar study conducted by Hermon and Cole (2012) found that pre-university mathematical knowledge is an effective predictor of academic performance in aerospace engineering.

Othman et al. (2012) conducted a research on more than 800 first year engineering undergraduates from two academic sessions in Malaysia. The main purpose of their study was to identify the mathematical concepts which are considered difficult and challenging by the first year students. The study evaluated the results of pre-test that include 15 elementary mathematical concepts and found that students from both academic sessions were lacking in certain important topics, which are the main mathematical contents required in engineering courses. A study by Nopiah et al. (2013) investigated the effectiveness of the pre-test mathematics questions in predicting the performance of the students in the subsequent engineering mathematics course.

Many authors have been reported on the use of university mathematics support with strong mathematical backgrounds. A study by Lee et al. (2008) concluded that first year engineering students' performance can be improved with the help obtained from the university mathematics learning support centre. Similarly, the benefits of mathematics support in university engineering students are well documented in several studies (Parsons and Adams, 2005; Patel and Little, 2006; Pell and Croft, 2008).

2.3. Statistical Analysis of Student Academic Performance

Pre-university qualification and admission criteria for university entrance have been widely studied by various authors in a variety of academic fields: Engineering (Ali and Ali, 2010; Hermon and Cole, 2012), Chemistry (Seery, 2009), Medicine (Ali, 2008; Hailikari, Katajavuori and Lindblom-Ylanne, 2008; Mufti and Qayum, 2013), Equine and animal studies (Huws and Taylor, 2008), Accounting (Al-Twaijry, 2010; Alfan and Othman, 2005), Finance (Grover, Heck, and Heck, 2009) and Psychology (Huws, Reddy and Talcott, 2006; Thompson and Zamboanga, 2004). Different types of statistical techniques have been applied to examine the student academic performance in past studies and most frequent techniques are discussed below.

2.3.1. Correlation Coefficient

A study has been carried out by Ali and Ali (2010) to determine the validity of entry tests in term of predicting future academic performance of the engineering students at the University of Engineering and Technology, Peshawar. The study covers 203 engineering students from six engineering disciplines: Electrical, Mechanical, Civil, Agriculture, Chemical and Mining Engineering. In their study, FSc scores (exam score at the end of grade XII), entry test scores and overall merit (combination of FSc and entry test scores) as the predictors and the academic achievements from first to final year as the response were considered. Results revealed that the FSc marks, entry test scores and overall merit were significantly and positively correlated with the academic achievement of engineering students irrespective of gender and disciplines. However, for female students and agriculture discipline, results showed a negative correlation between the predictors and the academic achievement. Ali and Zaman (2011) conducted a similar study for the students of Dental Colleges of Khyber Pukhtunkhawa, during the academic sessions 2000-2005. The study showed that entry tests are significantly correlated with the academic achievement of dental students.

Imran, Nasor and Hayati (2011) explored the association between students' overall performance in engineering programs and their grades in mathematics and physical science courses. Ten year data on students' grades of 6 courses in mathematics and 3 courses in physical science for three undergraduate engineering programs; electronics engineering, communication engineering and instrumentation and control engineering were considered in their study. Cumulative Grade Point Average (CGPA) was used as the overall performance in the program while GPA for each category of courses was calculated separately as the performance in each course category. They found that significant positive correlation in the mathematics (r=0.85, $p<0.05$) and physical science courses (r=0.75, $p<0.05$) with students' overall performance.

Nopiah et al. (2013) examined the effectiveness of the pre-test mathematics questions in predicting the performance of the diploma students of the Faculty of Engineering & Built Environment, Universiti Kebangsaan Malaysia, in the subsequent engineering mathematics course using a sample of 23 engineering diploma students from four engineering programs (Mechanical and Material Engineering, Electrical and Electronic Engineering, Civil and Structural Engineering, and Chemical and Process Engineering). They found that there is no significant correlation between the pre-test towards Vector Calculus and Linear Algebra (r=-0.160, p=0.465 and r=-0.095, p=0.668) whereas the correlation between Vector Calculus and Linear Algebra subjects showed a strong correlation with the value of 0.767.

2.3.2. Generalized Linear Models using One-way ANOVA

A study conducted by Aina, Ogundele and Olanipekun (2013) focused on the relationship between proficiency in English language and academic performance among students of science and technical education. The study was based on 60 students and students' results from First year to Third year in College of Education, Kwara State, Nigeria were used. The results revealed that the difference exists between students who failed English language and those who passed in both science and technical education. In another study Aina (2013) investigated the difference in students' academic achievement in Physics based on subject combination based by physics students from four Colleges of Education in Kwara State, Nigeria. They concluded that the academic achievement of students who combined physics with mathematics was significantly better than those who combined with chemistry. Alves, Rodrigues and Rocha (2012) found the significant difference between engineering undergraduate students' achievement on their engineering disciplines in Engineering and Industrial Management, Computer Engineering, Materials Engineering and Industrial Electronics and Computers Engineering. A study by Amin et al. (2013) showed the students with low-entrance CGPAs could still obtain the equivalent CGPAs as the high-entrance CGPA students while in Institution of Higher Education (IHE).

2.3.3. Linear Regression Models

Eng, Li and Julaihi (2010) investigated the factors influencing the course marks of underachieved Mathematics courses based on 1050 students from a public university in Sarawak, Malaysia. Marks of Pre-Calculus, Calculus-I, Mathematics-II and Engineering Mathematics-I taken as the response variables while Sijil Pelajaran Malaysia (SPM), or the Malaysian Certificate of Education Mathematics grades, SPM Additional Mathematics grades, Mathematics class size and students' gender as the predictor variables. Results revealed that SPM Mathematics was not significant in all the four models ($p>0.05$). However, SPM Additional Mathematics was recommended as the best predictor to the course marks of underachieved Mathematics courses, which is statistically not valid.

Grover, Heck, and Heck (2009) attempted to determine the level of mathematics, accounting, and economics knowledge students have upon entering the introductory finance course. The results showed that scores for the math and accounting questions on the pretest are a predictor of student performance in the introductory finance course. The scores on economics questions have no significant impact regarding course performance.

Seery (2009) examined the role of prior knowledge in the first year performance of undergraduate chemistry, aptitude and claimed a strong relationship between prior knowledge and exam performance. Furthermore, it was found that prior knowledge has a demonstrable influence on future exam performance over and above student aptitude. Hailikari, Katajavuori, and Lindblom-Ylanne (2008) found that student achievement in the pharmaceutical chemistry course can be predicted by prior knowledge from previous courses; mathematics and chemistry.

2.3.4. Clustering and Classification

In educational fields, data mining techniques: Clustering and Classification are used to enhance the understanding of the learning process of students. Rajadhyax and Shirwaikar (2012) conducted a study to find the relevant subjects in an undergraduate syllabus and the strength of their relationship. Although, there existed a general notion that mathematics subjects and programming subjects are correlated, the experiments illustrated that there does not exists a strong relationship between mathematics subjects and programming subjects. Ahmed and Elaraby (2014) applied clustering techniques to evaluate students' performance in one of the educational institutions, in Egypt and the decision tree method was used to predict the final grade of students. Similarly, predicting student performance using data mining techniques is well documented in several studies (Tair and El-Halees, 2012; Bhise, Thorat and Supekar, 2013; Pal and Pal, 2013).

2.4. Canonical Correlation Analysis (CCA)

The CCA developed by Hotelling (1936) used to identify and measure the associations among two multidimensional variables. This is appropriate in the same situations where multiple regression would be, but where are there are multiple intercorrelated outcome variables. Estimating separate equations for each output neglects the relationships among the outputs, while estimating a simultaneous equation model assumes that the relationship among the dependent variables is causal. Moreover, both separate regressions and simultaneous equation models are likely to neglect aspects of joint production technology (Gyimah-Brempong and Gyapong; 1991). Vinod (1968) argued that the presence of joint production, ordinary least squares regression (OLS), or even a simultaneous equation system, gives inconsistent estimates. Therefore, the problem with estimating a regression equation when there are two or more dependent variables is substantially solved by CCA approach.

Gyimah-Brempong and Gyapong (1991) examined the effects of socioeconomic characteristics (SEC) of communities in the production of high school education in the state of Michigan. Abedi (1991) conducted a study on academic performance to examine the efficiency of the undergraduate Grade Average Point (GPA) as a predictor of graduate academic success and compared it with other predictors. CCA was applied on three measures of graduate academic success and eight demographic and undergraduate academic variables including undergraduate GPA. It was found a weak relationship among graduate academic success and predictors and the graduate academic success was not associated with undergraduate GPA.

A study carried out in Malaysia, by Ismail and Cheng (2005) investigated the effects of school inputs, environmental inputs and gender influence in the production of a joint educational production function in mathematics and science subjects for eighth grade students. Rovai and Ponton (2005) focused on how a set of three classroom community variables (social community, learning community and mean number of postings per week) was related to a set of two students learning variables (course points and perceived learning) in a predominantly using CCA. A study carried out by Dai et al. (2011) focused on the context of student score analysis and CCA was used to investigate the relationship of scores of different classes of courses; i.e. basic courses and major courses. The study was based on course scores of the first and second academic year of 76 college students. It summarized that three mathematical basic courses were strongly related with major courses. A recent study by Sliusarenko and Clemmensen (2014), applied CCA to explore the association between the evaluation of the course and the evaluation of the teacher at the Technical University of Denmark.

Incorrect modelling may result in spurious statistical conclusions which do not reliably reflect the underlying structure of the data. Therefore, by using CCA, it is not possible to investigate the association between two sets of variables when there exists a linear effect of the third set of variables on other two variable sets.

2.5. Chapter Summary

The review of the literature confirmed several studies have been conducted by different authors in different countries to find the impact of mathematics on student academic performance. Various types of statistical approaches such as bivariate correlation, analysis of variance, regression analysis and canonical correlation analysis have been used. However, the knowledge on the influence of mathematics on different aspects is very few and there are many gaps in this area. The existing knowledge on the influence of mathematics were inadequate to find a real effect due to spurious statistical correlation among subjects. The concept of covariate in statistical analysis has not been used in any of the studies. Nevertheless, no such studies were reported in Sri Lanka.

CHAPTER 3
MATERIALS AND METHODS

3.1. Data Description

The study was conducted with all engineering students from seven different disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka for two academic years 2010/2011 and 2011/2012. Data were collected from examination division, University of Moratuwa after due permission was taken. Seven different engineering disciplines used for the study are namely; Chemical and Process Engineering (CH), Civil Engineering (CE), Computer Science and Engineering (CS), Electrical Engineering (EE), Electronic and Telecommunications Engineering (EN), Materials Science and Engineering (MT) and Mechanical Engineering (ME). The number of students enrolled in the seven departments is given in Table 3.1.

Table 3.1: Number of students enrolled in each engineering disciplines

Engineering Discipline	**Academic year**	
	2010/2011	**2011/2012**
CE	125	125
CH	80	80
CS	100	98
EE	69	100
EN	100	100
ME	100	100
MT	46	48

Students' examination marks of mathematics courses in Level 1 as well as Level 2 and all compulsory engineering courses in Level 2 were utilized for the analysis. Each Level has two semesters and semesters can be named as, Level 1: semester 1 (S1) and semester 2 (S2) and Level 2: semester 3 (S3) and semester 4 (S4).

As the curriculum of engineering departments (refer Appendix 1) are different, the analysis is carried out for each engineering discipline separately. Moreover, the mathematics modules; MA1013 (in S1), MA1023 (in S2), MA2013 and MA2023 (in S3 and MA2033 (in S4) are compulsory for all engineering disciplines except CS discipline. In addition to that, there are more mathematics modules offered in S4 for engineering disciplines, depending on their requirements. The following Table 3.2 and Table 3.3 present the mathematics modules followed by students of each engineering discipline in two academic years; 2010/2011 and 2011/2012.

Table 3.2: Mathematics modules followed – academic year 2010/2011

Level	Semester	Course Code	CH	CE	CS	EE	EN	ME	MT
Level 1	S1	MA1013	✖	✖	✖	✖	✖	✖	✖
	S2	MA1023	✖	✖		✖	✖	✖	✖
		MA1032			✖				
Level 2	S3	MA2013	✖	✖		✖	✖	✖	✖
		MA2023	✖	✖	✖	✖	✖	✖	✖
		MA2042			✖				
	S4	MA2033	✖	✖	✖	✖	✖	✖	✖
		MA2042				✖	✖	✖	
		MA2013			✖				
		MA3013		✖					✖

Table 3.3: Mathematics modules followed – academic year 2011/2012

Level	Semester	Course Code	CH	CE	CS	EE	EN	ME	MT
Level 1	S1	MA1013	✖	✖	✖	✖	✖	✖	✖
	S2	MA1023	✖	✖		✖	✖	✖	✖
		MA1032			✖				
Level 2	S3	MA2013	✖	✖		✖	✖	✖	✖
		MA2023	✖	✖		✖	✖	✖	✖
		MA2073			✖				
		MA2053			✖				
	S4	MA2033	✖	✖	✖	✖	✖	✖	✖
		MA2053				✖		✖	
		MA2063			✖				
		MA3013		✖					✖

3.2. Canonical Correlation Analysis (Unadjusted)

Canonical Correlation Analysis (CCA) is a powerful multivariate statistical technique for measuring the linear relationship between two multidimensional systems developed by Hotelling (1936). Procedurally, the two sets of observed variables are linearly combined to produce pairs of canonical variates that have maximum bivariate correlation (Johnson and Wichern, 2007). The number of variables in the smaller set of the two is equal to the maximum number of pairs of canonical variates.

Let two vectors $X = (X_1, X_2, \dots, X_p)$ and $Y = (Y_1, Y_2, \dots, Y_q)$ of random variables, and there are correlations among the variables, then CCA will find a linear combination of the X_i and Y_j which have maximum correlation with each other. The CCA computes two projection vectors, a and b such that the correlation coefficient:

$$R_c = \frac{cov(a^T X, b^T Y)}{\sqrt{var(a^T X).var(b^T Y)}} = \frac{a^T S_{XY} b}{\sqrt{a^T S_X a}\sqrt{b^T S_Y b}} \tag{1}$$

is maximized, where S_{XY} is the covariance matrix between X and Y, and S_X and S_Y are the covariance matrices of X and Y respectively. Since R_c is invariant to the scaling of vectors a and b, CCA can be formulated equivalently as,

$$max_{a,b}\, a^T S_{XY} b \tag{2}$$

subject to,

$$a^T S_X a = 1 \qquad \text{and} \qquad b^T S_Y b = 1.$$

The first pair of canonical variables or first canonical variate pair (U_1, V_1) is the pair of linear combinations of X and Y respectively, having the highest correlation between the two systems. If the optimum values of (a, b) are denoted as (a_1^T, b_1^T) and then,

$$U_1 = a_1^T X \qquad \text{and} \qquad V_1 = b_1^T Y$$

is the pair of first canonical variables.

The second pair of canonical variables is the pair of linear combinations U_2 and V_2 having unit variances, which has the highest correlation subject to U_2, being uncorrelated with U_1, and V_2, being uncorrelated with V_1 (the construction actually ensures that U_1 and V_2 are uncorrelated, as well as are U_2 and V_1). Therefore, at the k^{th} step, the canonical vectors are obtained as:

$$(a_k^T, b_k^T) = \arg\max_{a,b} a^T S_{XY} b \tag{3}$$

subject to,

$$var(U_k) = var(V_k) = 1$$
$$corr(U_k, U_l) = 0 \quad \text{for} \quad k \neq l$$
$$corr(V_k, V_l) = 0 \quad \text{for} \quad k \neq l$$

for all $\mathrm{l} = 1,2, \dots, \mathrm{k} - 1$ and $k \leq min\{p, q\}$. The process continues, until subsequent pairs of linear combinations no longer produce a significant correlation. The conceptual framework of the canonical correlation function is illustrated in Figure 3.1.

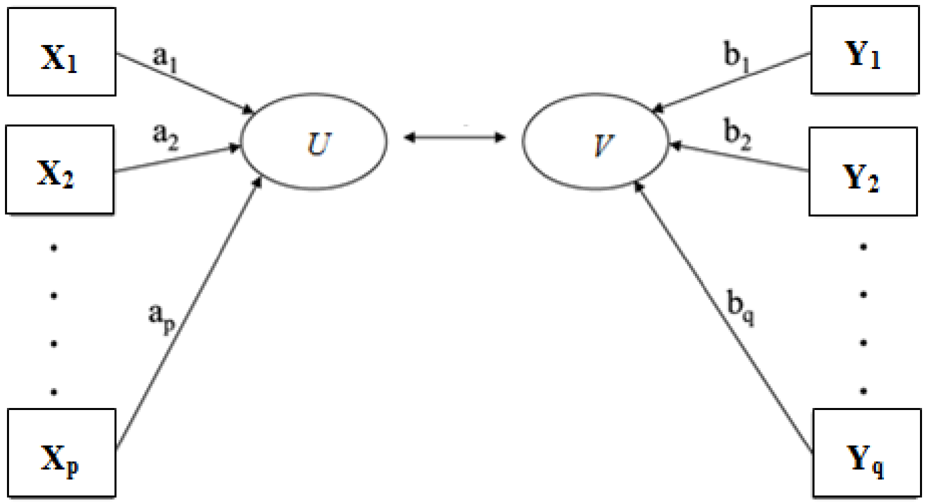


Figure 3.1: Illustration of the conceptual framework in CCA

3.2.1. Key Terms in CCA

It is necessary to review the key terms, to have a basic understanding of the analytic procedure.

- *Canonical variate:*

A linear combination of optimally weighted sum of two or more variables, and are formed for both independent and dependent variables. This is also known as linear composite. For example, new variables U_i where $U_i = \sum_{j=1}^{p} a_{ij}X_j$ on $(j = 1,2, \dots, p)$ and V_i where $V_i = \sum_{j=1}^{q} b_{ij}Y_j$ on $(j = 1,2, \dots, q)$ are canonical variates.

- *Canonical correlation:*

The bivariate correlation between the pair of canonical variates and it measures the strength of the overall relationship between the two canonical variates, with one variate representing the independent variables and the other representing the dependent variables. Thus, $C_i = Corr(U_i, V_i),\ i = min(p, q)$ is known as the canonical correlation between X and Y variable sets.

- *Canonical root:*

This represents the squared canonical correlation, which estimates the proportion of shared variance between the canonical variates of dependent and independent variables. this denoted by ${C_i}^2$.

- *Standardized canonical coefficient:*

This is similar to the standardized regression coefficients in multiple regressions that can be used as an indication of relative importance of the observed independent or dependent variables in determining its respective canonical variate.

- *Canonical loading:*

The Pearson correlation between an observed independent or dependent variable with its respective canonical variate. This is also referred as canonical structure correlations.

- *Canonical cross-loading:*

The correlation between an observed independent or dependent variable with its opposite canonical variate. As an example, the independent variables are correlated with the dependent canonical variate.

- *Redundancy index:*

The amount of variance in a canonical variate (dependent or independent) explained by the other canonical variate in the canonical function. For an example, the amount of variance in the dependent variables explained by the independent canonical variate is represented by the redundancy index of the dependent variate. Redundancy measure can be formulated as:

$$RI_{U_i,V_i} = AV(Y|V_i) * C^2_{U_i,V_i}\,, \qquad AV(Y|V_i) = \frac{\sum_{j=1}^{q} LY_{ij}^2}{q}$$

where $AV(Y|V_i)$ is the averaged variance in Y variables that is accounted for by the canonical variate V_i, LY_{ij}^2 is the loading of the j^{th} Y variable on the i^{th} canonical variate and C_{U_i,V_i} is the i^{th} canonical correlation.

3.2.2. Test of Significance for Canonical Correlation

For assessing the statistical significance of the canonical correlations, the null and alternative hypotheses are:

$$\mathrm{H_0}: \mathrm{C_1} = \mathrm{C_2} = \cdots = \mathrm{C_m} = 0,$$
$$\mathrm{H_1}: \mathrm{C_i} \neq 0 \qquad \text{at least one } i = 1,2,\dots,m$$

For testing the above mentioned hypotheses, the most widely used test statistic is Wilks' lambda, given by $\Lambda = \prod_{i=1}^{m}(1 - C_i^2)$ and under $\mathrm{H_0}$, $\beta = [\mathrm{n} - 1 - \frac{1}{2}(p + q + 1) \log \lambda \sim \chi^2_{pq}$.

3.3. Adjusted CCA

3.3.1. Partial Canonical Correlation Analysis (Partial CCA)

The partial canonical correlation is a multivariate generalization of ordinary partial correlation, which used to assess the partial independence of two sets of variables given a third set of variables (Rao, 1969). Suppose that, there is another vector, $Z = (Z_1, Z_2, \dots, Z_r)$ of random variables and it is interested to study the relation between the vectors X and Y partialing out the linear effect of vector Z from both X and Y vectors. Partial canonical correlation represents the maximal correlation between the partial canonical variates U^* and V^* where,

$$U^* = a^{*T} e_X \quad \text{and} \quad V^* = b^{*T} e_Y,$$

of unit variance where e_X and e_Y represent the residual vectors obtained after regressing X on Z and Y on Z respectively. Mathematically this is equivalent to maximizing,

$$P_{XY.Z} = \max_{a^*, b^*} a^{*T} S_{XY.Z} b^* \tag{4}$$

subject to,

$$a^{*T} S_{XX.Z} a^* = 1 \quad \text{and} \quad b^{*T} S_{YY.Z} b^* = 1.$$

The matrices $S_{ij.Z}$ are the covariance matrices of the residual vectors e_X and e_Y.

3.3.2. Part Canonical Correlation Analysis (Part CCA)

The part canonical correlation estimates the relation between the vectors X and Y partialing out the linear effect of vector Z from vector Y but not vector X (Timm and Carlson, 1976). That is, part canonical correlation computes linear combinations of the variates e_Y and X, $U' = a'^T X$ and $V' = b'^T e_Y$, of unit variance such that the correlation between U' and V' is maximal. This is equivalent to maximizing,

$$P_{X(Y.Z)} = \max_{a', b'} a'^T S_{X(Y.Z)} b' \tag{5}$$

subject to,

$$a'^T S_{XX} a' = 1 \quad \text{and} \quad b'^T S_{YY.Z} b' = 1.$$

3.4. The Propositions

On the view of past literature (Chapter 2), it can be hypothesized that student mathematics performance influences on their academic performance in engineering programs. The proposed relationships between mathematics performance and engineering performance can be depicted graphically as shown in Figure 3.2. In order to interpret the priori theoretical relationships from a practical perspective, the degree of structural path coefficients along with their statistical significance of each structural path can be used. The relationships depicted in Figure 3.2 can be expressed as propositions.

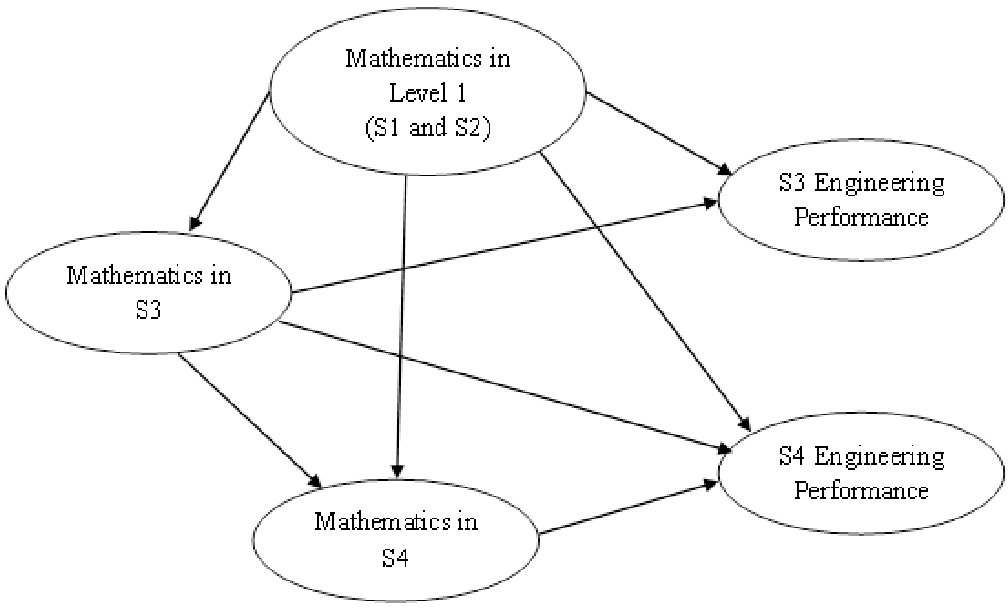


Figure 3.2: Proposed model for conceptual framework

3.5. Partial Least Squares Structural Equation Modeling (PLS-SEM)

The Structural Equation Modeling (SEM) approach using the Partial Least Squares (PLS) technique is considered as second generation multivariate data analysis technique. The first generation data analysis techniques, such as analysis of variance (ANOVA), multiple regression analysis, and factor analysis are analyzed only single relationship between the the independent and dependent variables at a time (Gefen et al., 2000). Nevertheless, PLS-SEM technique enables to model the relationships among multiple independent and dependent variables simultaneously.

PLS-SEM technique is a non-parametric method, where no strong assumptions (with respect to the distributions, the sample size and the measurement scale) are required. As there are lack of the classical parametric inferential framework, this non-parametric method allows modeling simultaneously estimate and test complex theories with empirical data based on resampling methods. An ordinary least squares (OLS) based method is the estimation procedure for PLS-SEM. This will estimate the path relationship (coefficients) in the model that maximize the explained variance of the endogenous latent variables and minimize the unexplained variances.

A structural equations model comprises of two elements, measurement model and structural model. The measurement model specifies how each construct is measured while the structural model specifies how the constructs are related to each other. A simple PLS structural equation model is depicted in Figure 3.3.

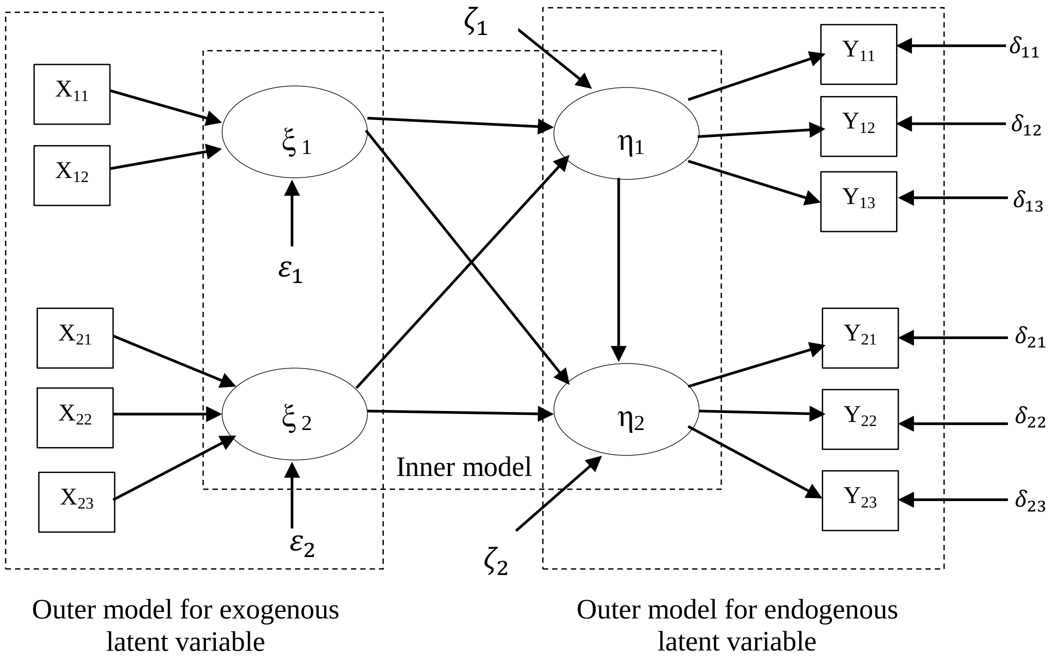


Figure 3.3: General PLS structural equation model

3.5.1. Measurement Models

The measurement model which is also referred to as the outer model represents the relationship between the construct (i.e. variables that are not directly measured) and observed variables (or indicators). Within the PLS framework, one observed variable can only be related to one construct and each construct must contain at least one observed variable. There are two different types of measurement models, namely, reflective model and formative model. According to Figure 3.3, outer model for exogenous latent variable represents a formative model while outer model for endogenous latent variable is a reflective model.

The formative measurement model is based on the assumption that indicators cause the changes in the construct. The formative measurement model can be represented as follows:

$$\xi_i = \sum_j w_{ij} X_{ij} + \varepsilon_i \tag{6}$$

where,

ξ_i – i^{th} exogenous latent variable,

X_{ij} – j^{th} observed variable of i^{th} exogenous latent variable,

w_{ij} – regression coefficient of X_{ij},

ε_i – error term of i^{th} exogenous latent variable

The reflective measurement model indicates the construct causes the measurement of the indicators. It reproduce the factor analysis model, in which each variable is a function of the underlying factor. Equation 7 presents the relationship between latent variable and its indicators mathematically.

$$Y_{kj} = \lambda_{kj} \eta_k + \delta_{kj} \tag{7}$$

where,

Y_{kj} – j^{th} observed variable of k^{th} endogenous latent variable,

η_k – k^{th} endogenous latent variable,

λ_{kj} – coefficient representing effect of η_k on Y_{kj} ,

δ_{kj} – measurement error for Y_{kj}

3.5.2. Structural Model

The structural model, (also known as the inner model) represents the relationship between constructs and observed variables that are not the indicators of constructs (Hair et al. 2016). The structural model is defined as follows:

$$\eta_k = \sum_j \beta_{kj}\eta_j + \sum_i \gamma_{ki}\xi_i + \zeta_k \qquad (8)$$

where,

β_{kj} – path coefficient linking the j^{th} predictor endogenous latent variable and k^{th} endogenous latent variable

γ_{ki} – path coefficient linking the i^{th} exogenous latent variable and k^{th} endogenous latent variable

ζ_k – error term of k^{th} endogenous latent variable

3.5.3. Assessment of Model Validation

The evaluation of estimates of PLS-SEM consist two separate processes for the measurement model and the structural model. With reference to assessment of measurement model, specific criteria associated with reflective and formative models to evaluate the reliability and validity of the construct measures are different procedures and techniques (Chin, 1998; Fornell and Larcker, 1981; Freeze and Raschke, 2007; Hair et al., 2016; Urbach and Ahlemann, 2010).

3.5.3.1. Assessment of the Reflective Measurement Models

Reflective measurement models are assessed on their internal consistency reliability and validity.

Indicator Reliability

Indicator reliability indicates the amount of variance in a measure that is due to the construct rather than to error (Fornell and Larcker, 1981). To establish indicator reliability, the squared standardized outer loadings of the indicators are considered. It is suggested that a construct should explain significant amount of each indicator's variance (at least 50%).

Internal Consistency Reliability

This is measured through Cronbach's alpha, which provides an estimate of the reliability based on the intercorrelations of the observed indicator variables and Composite Reliability (CR) which takes into account the different outer loadings of the indicator variables. Therefore, CR is a less conservative measure compared to cronbach’s alpha.

$$CR = \frac{(\sum_i \lambda_i)^2}{(\sum_i \lambda_i)^2 + \sum_i var(\delta_i)}$$

where, λ_i is the standardized outer loadings of the ith indicator variable of a specific construct, δ_i is the measurement error of ith indicator variable and $var(\delta_i) = 1 - {\lambda_i}^2$.

Construct validity describes how well the measurement items relate to the constructs and it is assessed through two main elements: convergent validity and discriminant validity.

Convergent Validity

To evaluate convergent validity on the construct level, Average Variance Extracted (AVE) critertia is considered (Fornell and Larcker, 1981). This attempts to measure the amount of variance that a construct capture from its indicators relative to the amount due to measurement error. This measure would be equivalent to the communality of a construct.

$$AVE = \frac{\sum_i {\lambda_i}^2}{\sum_i {\lambda_i}^2 + \sum_i var(\delta_i)}$$

Discriminant Validity

Discriminant validity evaluates the degree to which a construct is truly distinct from other constructs by empirical standards (Hair et al., 2016). To established the discriminant validity, two measures, cross loadings of the indicators and Fornell-Larcker criterion are considered. Cross loadings assessment allows the evaluation of discriminant validity on indicator level while Fornell-Larcker criterion assesses the discriminant validity on construct level. Fornell-Larcker criterion is more conservative method, which compares the square root of the AVE values with the latent variable correlations (Fornell and Larcker, 1981) and it suggests that a construct shares more variance with its assigned indicators than with another construct in the structural model.

3.5.3.2. Assessment of the Formative Measurement Models

Formative measurement models are assessed for their convergent validity, the significance and relevance of the indicators as well as the presence of collinearity among indicators. As there is no measurement error in foramative models, rather a disturbance term, that represents the remainder content of the construct which cannot explain by the indicators, the internal consistency reliability concept is not appropriate. (Andreev et al., 2009).

Significance and Relevance of Indicators

Formative indicator weight which represents the amount of variance in its construct that explained by the indicator, are assessed and compared to determine their relative contribution to their formative construct. Moreover, the significance level of the indicator suggests the level of validity.

Collinearity of Indicators

The variance inflation factor (VIF) is considered to check the multicollinearity among the formartive indicators and it denotes the level of an indicator’s variance is explained by the remaining indicators of the same construct (Henseler et al., 2009).

3.5.3.3. Assessment of the Structural Model

The structural model is assessed after the assessment of measurement models is established. The coefficients of determination (R^2), the magnitude and significance of path coefficients, total effects including direct and indirect effects, and the effect size (f^2) are the evaluation criteria for structural models. The effect size allows assessing the contribution of an exogenous construct to the R^2 value of an endogenous construct.

3.5.4. Bootstrapping Technique

As PLS-SEM is a non-parametric method that does not require assumptions about the data distribution, the significance tests cannot be applied to test whether the coefficients are significant. Therefore, a non-parametric bootstrapping technique is used to test the significance of various results such as path coefficients, outer weights, outer loadings and R^2 values. In bootstrapping, subsamples are randomly drawn using the resampling with replacement procedure. The subsample is then used to estimate the PLS path model and this process is repeated for all random subsamples. The estimations from the bootstrap subsamples are used to assess the significance of PLS-SEM results (Chin, 1998; Hair et al., 2016).

3.6. The Proposed Mathematical Influence Index

According to the equation 6 and equation 7, the measurement models for mathematics latent variable and engineering latent variable can be defined as:

$$(ENG)_k = \sum_{j=1}^{n_k} w_{kj} Y_{kj} + \varepsilon_k \qquad ; k = 3,4 \tag{9}$$

and

$$X_{ij} = \lambda_{ij}(MAT)_i + \delta_{ij} \qquad ; i=1,2,3;\ j=1,2,\ldots,J \tag{10}$$

where,

$(ENG)_k$	– k^{th} endogenous latent variable which represents the k^{th} semester engineering performance
Y_{kj}	– raw marks of j^{th} engineering module in k^{th} semester in Level 2
n_k	– no. of engineering modules in k^{th} semester
$(MAT)_i$	– i^{th} exogenous latent variable which represents the Level 1, S3 or S4 mathematics performance respectively
X_{ij}	– raw marks of j^{th} mathematics module in i^{th} mathematics block

Let $corr^2(X_{ij}, MAT_i)$ be the squared outer loading of j^{th} observed mathematics variable of the i^{th} mathematics latent variable (mathematics performance in i^{th} block) and R_k^2 is the coefficient of determination of k^{th} engineering latent variable (engineering performance in semester k). The mean of squared outer loadings linking each mathematics variable to the corresponding mathematics latent variable over all blocks is a special case of communality index which measures the predictive performance of the mathematics models. The coefficient of determination can be considered as an index of measuring the predictive performance of the structural model.

The mathematical influence index is defined as the geometric mean of the average communality of mathematics, (i.e. the average proportion of variance the mathematics modules can contribute to the mathematics performance), and R^2 of engineering performance (i.e. the proportion of variance in engineering performance explained by the mathematics performance). Thus, new index is defined as:

$$(index)_k = \sqrt{\left[\frac{1}{I}\sum_i \left(\frac{1}{n_i}\sum_{j=1}^{n_i} corr^2(X_{ij}, MAT_i)\right)\right] * \ R_k} \quad ; \qquad (11)$$

where, $I = \begin{cases} 2\,; & k = 3 \\ 3\,; & k = 4 \end{cases}$

This new index is used to compare the impact of mathematics on student engineering performance by their engineering disciplines.

3.7. Chapter Summary

The four multivariate techniques: Canonical Correlation Analysis (CCA), Partial CCA, Part CCA and Partial Least Squares Structural Equation Modeling (PLS-SEM) are used to achieve the objectives of this study. Of these techniques, Partial CCA and Part CCA are not being explored in many areas in applied statistics. In this study, these two methods are used to eliminate the effect of mathematics in Level 1 and in Level 2 respectively. The novel contribution of this study is to propose an index based on the results of PLS-SEM to determine the impact of mathematics on engineering performance for a given discipline and to compare the influence among the engineering disciplines.

CHAPTER 4
EXPLANATORY DATA ANALYSIS

This chapter provides the explanatory data analysis (descriptive statistics, boxplots, etc.) of both independent and dependent variables. The mathematics modules in Level 1 and the all compulsory modules in Level 2 are taken as the independent and dependent variables respectively. Furthermore, the association between mathematics marks and engineering marks is investigated using correlation coefficients and multiple regression analysis.

4.1. Descriptive Analysis of Overall Mathematics Marks in Level 1

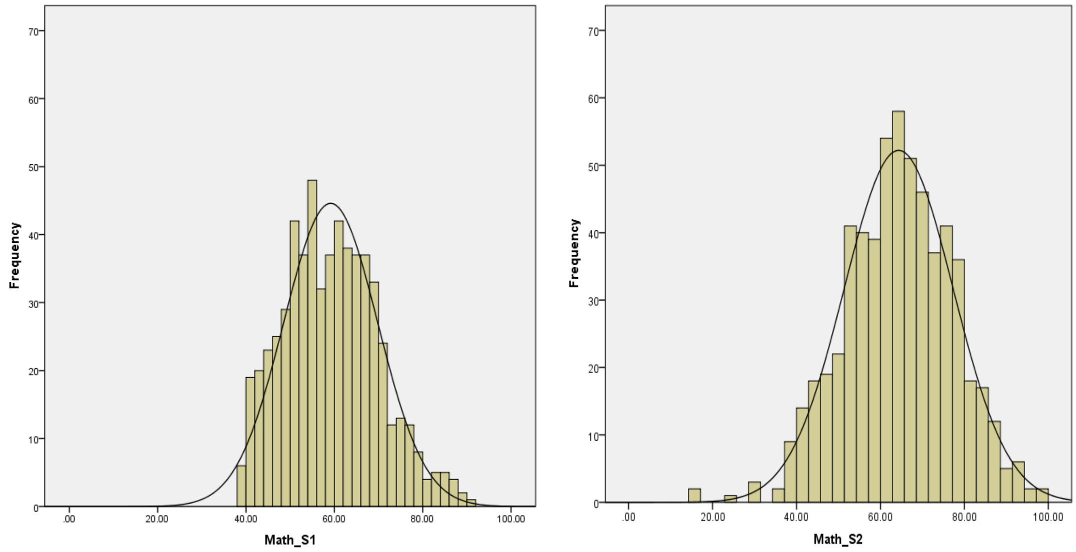
Mathematics marks in Level 1: semester 1 (S1) and semester 2 (S2) are denoted by Math_S1 and Math_S2 respectively. Table 4.1 presents the descriptive statistics of students' marks of mathematics courses in S1 and S2 (in Level 1), irrespective of engineering discipline. Math_S1 is a 3 credits mathematics module which consists of Logic and Set Theory, Vectors and Metrices, and Real Analysis. Math_S2 is also a 3 credits module which consists of Probability and Statistics, Differential Equations and Multivariate Calculus and Numerical Methods.

Table 4.1: Descriptive statistics of mathematics marks in Level 1

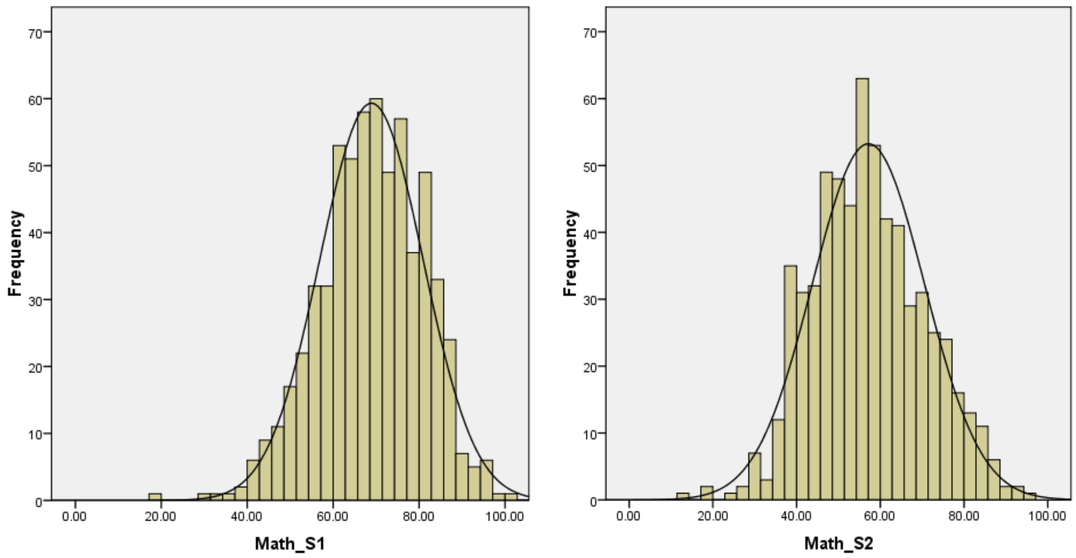
Academic year	Variable	Mean	SE of Mean	Median	Std. Dev.	Minimum	Maximum
2010/2011	Math_S1	59.2	0.44	58.8	10.6	39.5	91.3
	Math_S2	64.3	0.53	64.3	13.0	15.0	99.0
2011/2012	Math_S1	68.9	0.48	69.3	12.0	18.7	100
	Math_S2	57.2	0.54	56.4	13.4	12.6	95.4

According to Table 4.1, the average mark of Math_S2 (64.3) is higher than the average mark of Math_S1 (59.2) in 2010/2011 academic year while the average mark of Math_S1 (68.9) is higher than the average mark of Math_S2 (57.2) in 2011/2012 academic year. But, the standard error of the mean of Math_S1 is lower than that of

Math_S2 for both academic years. Furthermore, median values indicate that many students obtained higher marks for Math_S2 in 2010/2011 academic year and for Math_S1 in 2011/2012 academic year. It is clear that students' mathematics performance in two academic years is different.



(a) 2010/2011 academic year



(b) 2011/2012 academic year

Figure 4.1: Distributions of mathematics marks in S1 and S2

The distributions of mathematics marks in S1 and S2, irrespective of engineering discipline for both academic years are shown in Figure 4.1. It is clear that Math_S2 are wider spread around the mean mark than Math_S1 in both academic years.

4.2. Descriptive Analysis of Mathematics Marks by Engineering Disciplines

4.2.1. Analysis of Mathematics Marks in S1

Table 4.2 contains the descriptive statistics of mathematics marks in S1 for both academic years.

Table 4.2: Descriptive statistics of mathematics marks in S1 (Discipline wise)

Academic year	Discipline	N	Mean	SE of Mean	Std. Dev.	CV.	Min.	Max.
2010/2011	CE	117	59.7	0.66	7.1	11.94	39.8	83.5
	CH	77	50.9	0.78	6.8	14.34	39.5	71.0
	CS	96	65.1	0.95	9.3	13.42	46.5	91.3
	EE	68	60.3	0.96	7.9	13.17	44.3	84.3
	EN	98	70.9	0.77	7.7	10.81	45.2	88.8
	ME	98	52.7	0.66	6.5	12.34	39.5	68.3
	MT	41	45.0	0.77	4.9	10.96	39.5	61.3
2011/2012	CE	125	69.7	0.79	8.8	12.68	46.7	96.0
	CH	71	59.5	1.23	10.3	17.38	38.9	96.7
	CS	95	77.1	0.83	8.1	10.54	54.7	100.0
	EE	99	71.4	0.81	8.1	11.33	56.7	93.3
	EN	96	79.7	0.71	6.9	8.71	62.3	95.3
	ME	96	62.5	0.83	8.2	13.08	40.3	84.0
	MT	44	48.7	1.3	8.6	17.76	18.7	69.3

CV – Coefficient of Variation

According to the results of 2010/2011 academic year, EN discipline obtain the highest mean of mathematics marks in S1 (70.9) while MT discipline obtain the lowest mean of mathematics marks in S1 (45.0) with the least standard deviation of 4.9. The highest amount of variability relative to its mean is from CH discipline compared with other disciplines.

With reference to the results of 2011/2012 academic year, it can be seen that, mean of mathematics marks in S1 in EN discipline is 79.7 with a least standard deviation of 6.9 and the mean marks of Math_S1 in CH discipline is 59.5 with the largest standard deviation of 10.3 compared with other disciplines. Moreover, coefficient of variation confirmed that, EN discipline has the least amount of variability relative to its mean (8.71) while the highest amount of variability relative to its mean is from MT and CH disciplines. It is clear from the data that mathematics performance in S1 is relatively high in two disciplines: EN and CS. Students from MT discipline show the least mathematics performance in S1.

Furthermore, Figure 4.2 exhibits the boxplots of mathematics marks in S1 by engineering disciplines. It can be seen that few students of CE, CH and CS disciplines obtained exceptionally high marks than EN discipline. Furthermore, it is clear that performance of MT students is far below than the performance of other students in both academic years. The outliers (*) indicates values which are higher than $Q_3+1.5(Q_3-Q_1)$ and lower than Q_1 -1.5(Q_3-Q_1) where Q1 and Q3 are the first and third quartiles of the variable.

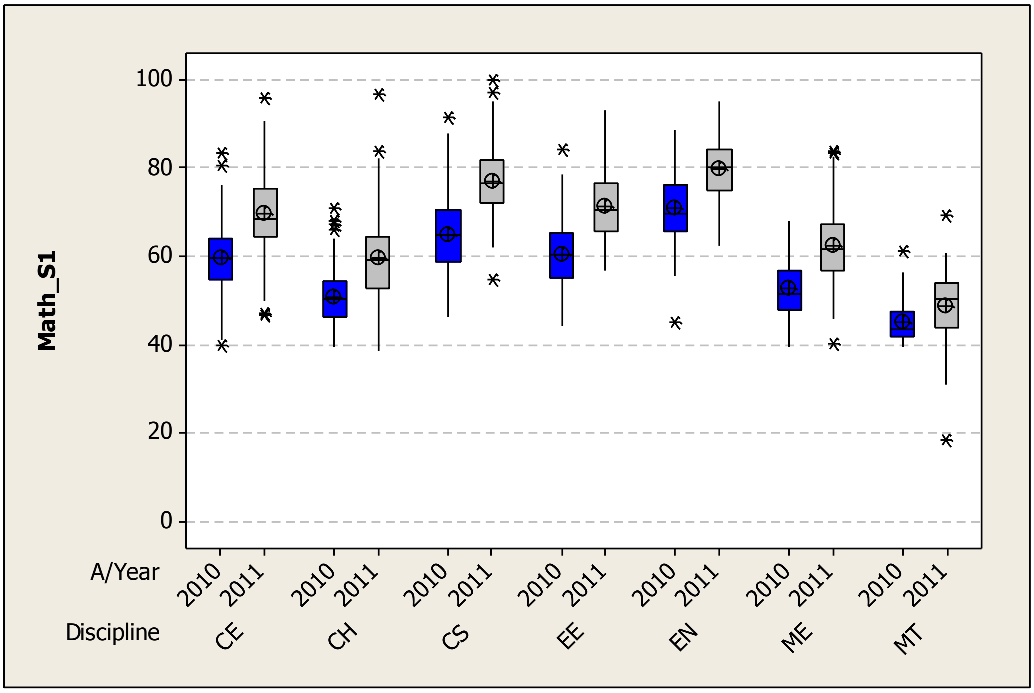


Figure 4.2: Distribution of mathematics marks in S1 by engineering discipline

4.2.2. Analysis of Mathematics Marks in S2

Descriptive statistics of students' mathematics performance in S2 for both academic years are presented in Table 4.3. With respect to the results of 2010/2011 academic year, it is clear that the highest average mark for the mathematics course in S2 is from CS discipline and the second highest average mark is from the EN discipline while the lowest average mark is from the MT discipline (48.2). The results of coefficient of variation indicate that EN discipline obtain the lowest amount of variability relative to its mean (12.12) while the highest amount of variability relative to its mean is from the MT discipline (18.65).

Table 4.3: Descriptive statistics of mathematics marks in S2 (Discipline wise)

Academic year	Discipline	N	Mean	SE of Mean	Std. Dev.	CV.	Min.	Max.
2010/2011	CE	117	63.7	0.97	10.5	16.50	15.0	91.7
	CH	77	58.8	1.14	10.0	17.02	29.5	85.0
	CS	96	74.6	1.30	12.7	17.05	28.7	98.1
	EE	68	66.1	1.16	9.6	14.47	41.0	87.0
	EN	98	73.5	0.90	8.9	12.12	53.7	99.0
	ME	98	55.8	0.95	9.4	16.88	16.0	84.0
	MT	41	48.2	1.40	9.0	18.65	25.1	71.0
2011/2012	CE	125	57.1	0.9	10.1	17.64	26.9	79.6
	CH	71	48.0	1.29	10.8	22.58	25.7	78.7
	CS	95	73.9	1.04	10.1	13.66	40.8	95.4
	EE	99	56.3	0.98	9.8	17.36	30.8	80.8
	EN	96	62.1	1.05	10.3	16.59	37.8	86.2
	ME	96	51.1	0.9	8.8	17.21	32.5	74.8
	MT	44	40.1	1.41	9.4	23.32	12.6	58.9

CV – Coefficient of Variation

By referring the results of 2011/2012 academic year in Table 4.3, it can be said that the students of the CS discipline have obtained the highest average mark (73.9) while students from MT discipline have obtained the lowest average mark (40.1) for mathematics in S2. Besides that, the highest amount of variability relative to its mean is from MT discipline (23.32) while the least amount of variability relative to its mean is from CS discipline (13.66).

The Figure 4.3 depicts the boxplots of mathematics marks in S2 by engineering disciplines. By comparing Figure 4.2 and Figure 4.3, it can be seen that the range of marks (Max–Min) in S2 is higher than that of S1 in most of the engineering disciplines.

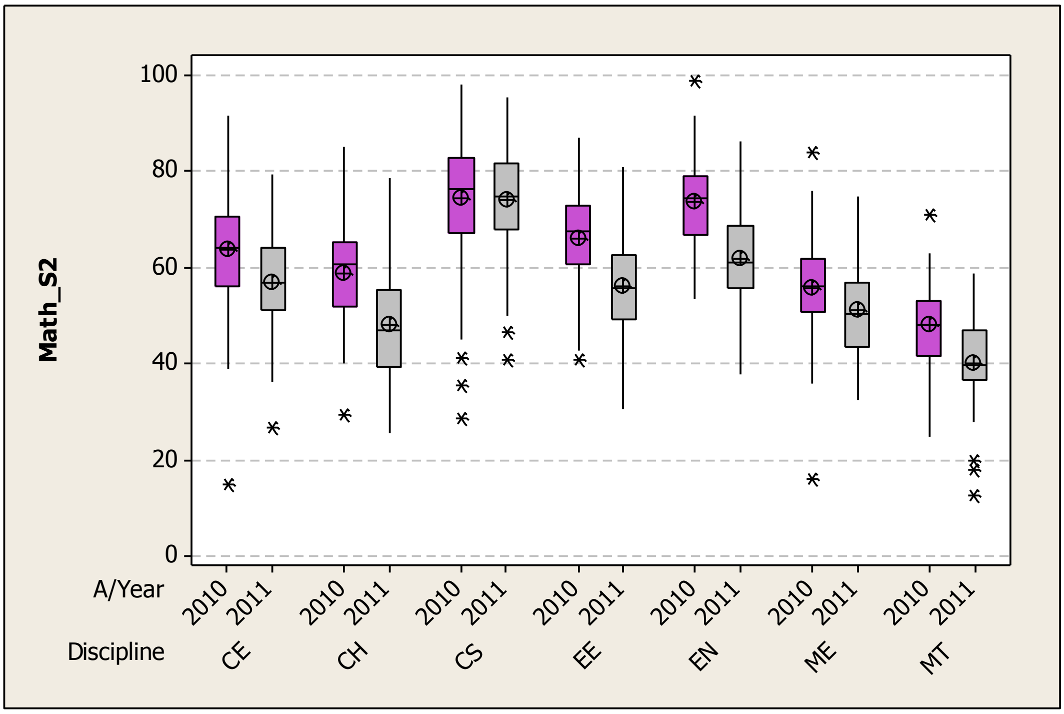


Figure 4.3: Distribution of mathematics marks in S2 by engineering discipline

4.3. Analysis of Variance (ANOVA)

In order to test the significant difference of mathematics marks among engineering disciplines, Analysis of Variance (ANOVA) was carried out for students' mathematics marks in S1 and S2 for both academic years separately. The null hypothesis tested was: there is no significant difference between mean marks of mathematics course among engineering disciplines. The summary of the ANOVAs is shown in Table 4.4. It can be seen that all F-values are highly significant (p=0.000). Thus, it can be concluded with 95% confidence that both mean marks of mathematics courses in both S1 and S2 are significantly different for both academic years.

Table 4.4: ANOVA for mathematics performance in Level 1

Category	Source of variation	Sum of Squares	df	Mean Square	F	Sig.
2010/2011 (Math_S1)	Between Groups	34571 (51%)	6	5761.815	103.592	0.000
	Within Groups	32705 (49%)	588	55.62		
	Total	67275	594			
2010/2011 (Math_S2)	Between Groups	38802 (39%)	6	6467.011	61.936	0.000
	Within Groups	61396 (61%)	588	104.415		
	Total	100198	594			
2011/2012 (Math_S1)	Between Groups	46459 (51%)	6	7743.113	109.081	0.000
	Within Groups	43940 (49%)	619	70.985		
	Total	90398	625			
2011/2012 (Math_S2)	Between Groups	51277 (46%)	6	8546.181	86.800	0.000
	Within Groups	60946 (54%)	619	98.458		
	Total	112223	625			

Parenthesis indicates percentage values with respect to the total sum of squares

The percentage sum of squares between groups for S1 is 51% for both years. This indicates that variability of mathematics marks in S1 is almost same between disciplines and within disciplines. In contrast between the groups sum of squares in S2 has absorbed 38% and 46% of the total variability during 2010 and 2011 respectively. This implies within discipline variability of mathematics marks is higher for S2.

It should be noted that pairwise comparisons between engineering disciplines are not investigated as it does not make more sense for the objectives of this study.

4.4. Descriptive Analysis of Mathematics Marks in Level 2

The mathematics modules followed in semester 3 (S3) and semester 4 (S4) in Level 2 vary according to the requirement of engineering discipline as described in Section 3.1. The results of important descriptive statistics of students’ mathematics performance in Level 2 with respect to their engineering disciplines for two academic years are presented in Table 4.5 and Table 4.6.

Table 4.5: Descriptive Statistics for mathematics performance in Level 2 – 2010/2011

Discipline		**S3**			**S4**			
		MA2013	**MA2023**	**MA2042**	**MA2033**	**MA2042**	**MA3013**	**MA2013**
CE	Mean ± SE	65.0±0.8	59.5±1.2		62.8±1.0		80.2±0.4	
	Minimum	42.3	25.0		20.0		55.1	
	Maximum	87.6	95.0		86.0		89.0	
EN	Mean ± SE	72.0±0.8	71.2±1.3		76.8±1.0	83.8±0.7		
	Minimum	51.6	39.9		46.0	46.5		
	Maximum	92.8	97.0		95.0	98.1		
ME	Mean ± SE	55.9±1.0	55.6±1.0		62.4±1.0	71.3±1.1		
	Minimum	28.4	30.9		39.0	43.3		
	Maximum	77.0	81.3		88.0	97.2		
EE	Mean ± SE	69.6±1.0	61.5±1.5		66.1±1.6	77.1±1.2		
	Minimum	46.5	38.5		38.0	49.5		
	Maximum	86.1	93.5		92.0	95.2		
MT	Mean ± SE	51.4±1.4	43.8±1.7		49.5±1.5		68.9±1.8	
	Minimum	31.3	21.0		35.0		46.0	
	Maximum	69.4	68.4		75.0		90.9	
CS	Mean ± SE		63.8±1.2	73.8±0.9	72.4±1.1			64.5±1.0
	Minimum		43.5	53.4	48.0			40.8
	Maximum		100.0	93.2	95.0			84.2
CH	Mean ± SE	61.6±1.1	51.7±1.3		58.8±1.3			
	Minimum	36.9	24.5		37.0			
	Maximum	80.2	83.0		87.0			

Table 4.6: Descriptive Statistics for mathematics performance in Level 2 – 2011/2012

Discipline		S3				S4			
		MA2013	MA2023	MA2073	MA2053	MA2033	MA2053	MA2063	MA3013
CE	Mean ± SE	77.6±0.8	62.4±1.0			71.9±0.8			67.1±0.8
	Minimum	39.6	37.6			48.0			44.6
	Maximum	93.4	91.5			95.4			85.3
EN	Mean ± SE	81.5±1.0	71.4±1.2			77.8±1.1			
	Minimum	53.5	43.2			55.0			
	Maximum	98.6	96.2			99.2			
ME	Mean ± SE	67.4±1.0	56.6±1.2			62.4±0.9	73.9±1.1		
	Minimum	23.8	19.4			41.8	42.9		
	Maximum	86.7	84.9			90.4	95.2		
EE	Mean ± SE	78.6±0.9	66.7±1.2			70.9±1.0	86.1±0.6		
	Minimum	52.2	40.0			46.3	61.8		
	Maximum	97.6	89.1			91.8	97.2		
MT	Mean ± SE	56.7±2.3	45.8±2.1			56.4±1.6			65.0±1.1
	Minimum	21.5	14.4			38.2			48.5
	Maximum	88.8	77.6			88.6			78.6
CS	Mean ± SE			64.9±1.0	58.4±1.3	73.2±1.2		66.0±1.2	
	Minimum			45.6	23.5	42.3		43.2	
	Maximum			89.3	95.2	98.0		92.7	
CH	Mean ± SE	67.0±1.6	56.7±1.6			64.7±1.4			
	Minimum	32.4	26.4			34.0			
	Maximum	92.0	81.8			97.0			

Based on the results of Table 4.5 and Table 4.6, it is clear that students from EN discipline show the best performance in mathematics in S3 and S4 whereas the students from MT discipline show the least performance in mathematics in S3 and S4 for both academic years. It should be noted that CS discipline is offered special modules by the Department of Mathematics.

4.5. Comparison of GPA with Average / Weighted Average Marks

In order to determine the students' overall academic performance in Level 2, the university standard criteria, Grade Point Average (GPA) is calculated. To avoid the interval scale in marks which used in GPA calculations, the students' mean marks and weighted mean marks are also calculated. The weights were assigned based on the number of credits. These three statistics are computed as follows:

$$mean_i = \frac{\sum_{j=1}^{n} m_{ij}}{n}$$

$$(weighted\ mean)_i = \frac{\sum_{j=1}^{n} c_j m_{ij}}{\sum c_j}$$

$$(GPA)_i = \frac{\sum_{j=1}^{n} c_j g_{ij}}{\sum c_j}$$

where, m_{ij} – raw mark of the j^{th} subject by the i^{th} student

n – number of subjects

c_j – number of credits of the j^{th} subject

g_{ij} – grade point of the j^{th} subject by the i^{th} student

In order to test whether raw marks can be used in this study as a proxy variable for student performance, correlation analysis was carried out among the above three performance indicators. The results are shown in Table 4.7 and Table 4.8.

The coefficients of correlation reveal that there is very strong positive significant linear relationship (> 0.9) between GPA with mean marks in Level 2 as well as GPA with weighted mean marks in Level 2, irrespective of the engineering disciplines for both academic years. This confirms that either mean marks or weighted mean marks can be considered as a proxy estimator for the student actual academic performance.

Table 4.7: Correlation between GPA and average performance - 2010

Discipline	Mean		Weighted Mean	
	S3	S4	S3	S4
CE	0.990	0.983	0.990	0.983
CH	0.987	0.974	0.991	0.983
CS	0.978	0.983	0.984	0.984
EE	0.978	0.989	0.983	0.991
EN	0.980	0.978	0.981	0.977
ME	0.972	0.980	0.990	0.986
MT	0.992	0.986	0.992	0.991

Table 4.8: Correlation between GPA and average performance - 2011

Discipline	Mean		Weighted Mean	
	S3	S4	S3	S4
CE	0.979	0.975	0.979	0.975
CH	0.983	0.984	0.971	0.980
CS	0.984	0.981	0.987	0.980
EE	0.948	0.867	0.952	0.877
EN	0.987	0.987	0.988	0.983
ME	0.974	0.976	0.986	0.986
MT	0.994	0.988	0.994	0.993

4.6. Association between Mathematics in Level 1 and Overall Performance in Level 2

In order to determine the association between marks of mathematics modules in Level 1 (Math_S1 and Math_S2) and average marks of the all modules in S3 and S4 as well as overall average marks in Level 2, correlation analysis was performed by engineering disciplines separately and the results are shown in Table 4.9 and Table 4.10.

Table 4.9: Correlation between mathematics marks and student performance -2010

Criterion	Predictors	CE (N=117)	EN (N=98)	ME (N=98)	EE (N=68)	MT (N=41)	CH (N=77)	CS (N=96)
Mean_S3	Math_S1	0.368**	0.468**	0.348**	0.284*	0.283	0.340**	0.362**
	Math_S2	0.536**	0.581**	0.499**	0.513**	0.703**	0.515**	0.605**
Mean_S4	Math_S1	0.165*	0.419**	0.228*	0.339**	0.147	0.394**	0.351**
	Math_S2	0.399**	0.430**	0.305**	0.463**	0.677**	0.572**	0.527**
Mean_ Level 2	Math_S1	0.295**	0.475**	0.326**	0.339**	0.217	0.387**	0.385**
	Math_S2	0.518**	0.554**	0.454**	0.522**	0.710**	0.576**	0.612**

**. Correlation is significant at the 0.01 level (1-tailed)

*. Correlation is significant at the 0.05 level (1-tailed)

Table 4.10: Correlation between mathematics marks and student performance -2011

Criterion	Predictors	CE (N=125)	EN (N=96)	ME (N=96)	E-E (N=99)	MT (N=44)	CH (N=71)	CS (N=95)
Mean_S3	Math_S1	0.314**	0.332**	0.238*	0.461**	0.393**	0.483**	0.482**
	Math_S2	0.485**	0.631**	0.575**	0.606**	0.556**	0.603**	0.501**
Mean_S4	Math_S1	0.342**	0.224*	0.233*	0.372**	0.198	0.446**	0.492**
	Math_S2	0.490**	0.617**	0.613**	0.600**	0.482**	0.600**	0.507**
Mean_ Level 2	Math_S1	0.360**	0.307**	0.253*	0.439**	0.308*	0.486**	0.507**
	Math_S2	0.534**	0.659**	0.634**	0.635**	0.541**	0.630**	0.524**

**. Correlation is significant at the 0.01 level (1-tailed)

*. Correlation is significant at the 0.05 level (1-tailed)

Considering the results of correlation coefficients in Table 4.9, the correlation between mathematics marks in Level 1 and students' overall performance for all disciplines are statistically significant at the 0.05 level except the linear relationships between mathematics module in S1 and students' performance of MT discipline.

The results of correlation analysis in Table 4.10, shows significant correlation between mathematics marks and students' performance for all disciplines at the 0.05 level except the linear relationship between mathematics course in S1 and average marks of S4 (Mean_S4) of MT discipline. Moreover, the correlation between mathematics course in S2 and students' overall performance are stronger compared with the correlation between mathematics course in S1 and students' overall performance for all disciplines in both academic years.

4.7. Analysis of Academic Performance by Engineering Disciplines

Additionally, Pearson correlation analysis was carried out, in order to examine the linear relationship between variables of the two sets; mathematics and engineering modules separately as well as between the variables in both mathematics and engineering sets for each discipline. The results of correlation analysis for two semesters in Level 2 by engineering discipline for two academic years are presented in Appendix 2.

It can be concluded that the most pairs are significant and positively correlated ($p<0.05$) within the each variable set and between the variable sets for all engineering disciplines. This indicates that there is a strong significant impact from the mathematics in Level 1 and Level 2 on the engineering modules in Level 2 irrespective of disciplines.

4.8. Multiple Linear Regression Analysis

As correlation analysis reveals the students' mathematics modules in Level 1 have significant positive relationship with their overall academic performance in Level 2, it is required to determine to what extent the mathematics in S1 and S2 contribute significantly to the variation in student overall academic performance in Level 2.

Stepwise regression analysis was carried out separately for three students' overall academic performance outcomes: average marks of S3 (Mean_S3), average marks of S4 (Mean_S4) and overall average of S3 and S4 (Mean_Level 2), by engineering disciplines and the summary of fitted models for two academic years are presented in Table 4.11, Table 4.12 and Table 4.13 respectively.

Table 4.11: MLR model Summary for S3 (Discipline wise)

Academic Year		**CE**	**CH**	**CS**	**EE**	**EN**	**ME**	**MT**
2010/2011	Constant	44.174	37.860	43.294	45.344	11.822	31.372	19.371
	Math_S1	-	-	-	-	0.337	0.208	-
	Math_S2	0.311	0.410	0.313	0.322	0.448	0.301	0.714
	ANOVA F statistic	46.26	27.11	54.40	23.57	34.63	19.04	38.16
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Std. Error of the Estimate	5.17	6.89	5.24	5.19	6.44	5.62	6.57
	R-sq	28.7	26.5	36.7	26.3	42.2	28.6	49.5
	R-sq (adj)	28.1	25.6	36.0	25.2	40.9	27.1	48.2
2011/2012	Constant	48.312	36.304	20.001	39.535	39.101	38.460	39.396
	Math_S1	0.111	-	0.320	0.212	-	-	-
	Math_S2	0.227	0.579	0.279	0.297	0.484	0.447	0.455
	ANOVA F statistic	22.12	39.36	25.58	39.38	62.30	46.53	18.76
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Std. Error of the Estimate	4.59	8.37	6.04	4.24	6.15	5.62	6.44
	R-sq	26.6	36.3	35.7	45.1	39.9	33.1	30.9
	R-sq (adj)	25.4	35.4	34.3	43.9	39.2	32.4	29.2

Dependent Variable: Mean_S3

According to the results of 2010/2011 academic year in Table 4.11, R^2 values for all seven models, illustrated that the fitted models explained 26% to 50% of the variation in students' academic performance in S3. F statistics of ANOVA output imply that all seven fitted models are significant at the 0.05 level. However, Math_S1 predictor variable is significant at the 0.05 level only in two fitted models and that is for EN and ME disciplines. Besides that, Math_S2 has the significant influence on students' academic performance in S3 compared to Math_S1 in all engineering disciplines. Furthermore, residual analysis confirmed that all the fitted models are adequate.

Similarly, the model summary of students' overall performance in S3 for 2011/2012 academic year in Table 4.11 indicates that Math_S2 has the significant influence on students' academic performance in S3 compared to Math_S1 in all engineering disciplines. Moreover, the mathematics module in S1 is significant at the 0.05 level in three fitted models only and that is for CE, EE and CS disciplines.

Table 4.12: MLR model Summary for S4 (Discipline wise)

Academic Year		**CE**	**CH**	**CS**	**EE**	**EN**	**ME**	**MT**
2010/2011	Constant	53.530	34.523	48.339	44.561	40.569	51.756	26.246
	Math_S1	-	-	-	-	0.216	-	-
	Math_S2	0.266	0.465	0.282	0.323	0.238	0.220	0.662
	ANOVA F statistic	21.83	36.53	36.16	18.04	17.56	9.86	33.01
	P-value	0.000	0.000	0.000	0.000	0.000	0.002	0.000
	Std. Error of the Estimate	6.45	6.72	5.81	5.95	5.09	6.50	6.55
	R-sq	16.0	32.8	27.8	21.5	27.0	9.3	45.8
	R-sq (adj)	15.2	31.9	27.0	20.3	25.5	8.4	44.5
2011/2012	Constant	42.516	34.337	18.664	43.086	42.945	37.328	41.265
	Math_S1	0.156	-	0.350	0.135	-	-	-
	Math_S2	0.275	0.657	0.300	0.290	0.386	0.478	0.453
	ANOVA F statistic	23.98	38.72	26.83	31.81	57.81	56.72	12.71
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.001
	Std. Error of the Estimate	5.54	9.58	6.39	4.14	5.10	5.44	7.78
	R-sq	28.2	35.9	36.8	39.9	38.1	37.6	23.2
	R-sq (adj)	27.0	35.0	35.5	38.6	37.4	37.0	21.4

Dependent Variable: Mean_S4

By referring Table 4.12, it can be seen that all seven fitted models are significant at the 0.05 level. R^2 values denote that the fitted models explained 9% to 46% of the variation in students' academic performance in S4 in 2010/2011 academic year while the fitted models explained 23% to 40% of the variation in students' academic performance in S4 in 2011/2012 academic year. Furthermore, the impact of mathematics module in S2 (Math_S2) is significantly higher compared to mathematics module in S1 (Math_S1) for all engineering disciplines in both academic years. Moreover, residual analysis confirmed the adequacy of all fitted models in both academic years.

Table 4.13: MLR model Summary for Level 2 (Discipline wise)

Academic Year		**CE**	**EN**	**ME**	**EE**	**MT**	**CH**	**CS**
2010/2011	Constant	48.545	36.521	45.819	44.920	25.114	38.135	23.026
	Math_S1	-	-	-	-	0.291	0.181	-
	Math_S2	0.290	0.432	0.298	0.323	0.341	0.247	0.686
	ANOVA F statistic	42.15	31.89	15.05	24.77	39.69	37.15	56.17
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Std. Error of the Estimate	5.05	5.34	5.26	5.08	6.19	6.20	4.91
	R-sq	26.8	40.2	24.1	27.3	50.4	33.1	37.4
	R-sq (adj)	26.2	38.9	22.5	26.2	49.2	32.2	36.7
2011/2012	Constant	45.615	35.330	19.280	41.301	40.690	37.970	40.252
	Math_S1	0.132	-	0.335	0.174	-	-	-
	Math_S2	0.249	0.618	0.290	0.293	0.443	0.460	0.454
	ANOVA F statistic	29.88	71.97	63.32	42.23	17.41	45.49	29.76
	P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Std. Error of the Estimate	4.42	5.24	4.96	3.84	6.67	8.31	5.84
	R-sq	32.9	43.4	40.3	46.8	29.4	39.7	39.3
	R-sq (adj)	31.8	42.8	39.7	45.7	27.7	38.9	37.9

Dependent Variable: Mean_Level 2

Considering the results in Table 4.11 and Table 4.12, it can be said that the overall academic performance in S3 is more predictable than overall academic performance in S4 from mathematics modules in S1 and S2 (in Level 1) in some engineering disciplines.

With respect to the results in Table 4.13, it is clear that the amount of variance in students' overall academic performance in Level 2 (i.e. Mean_Level 2) that can be explained by the corresponding fitted model is varied from 24% to 50% in 2010/2011 academic year and 29% to 43% in 2011/2012 academic year. F statistics and residual analysis implies that the fitted models are significant at 0.05 level and adequate for both academic years. Furthermore, the impact of mathematics module in S2 (Math_S2) is significantly higher compared to mathematics module in S1 (Math_S1) for all engineering disciplines in both academic years.

According to these results, it can be concluded that mathematics in S1 and S2 in Level 1 are good predictors to the students' academic performance in Level 2.

4.9. Chapter Summary

The descriptive analysis carried out to identify the patterns of mathematics and engineering variables. Based on the descriptive analysis of mathematics in S1 and S2, it can be seen that the highest mathematics performance is from students in EN and the lowest mathematics performance is from students in the MT discipline for both academic years. A similar approach is carried out for mathematics in Level 2 and found the consistent results. ANOVA was conducted to compare mathematics performance in S1 and S2 among engineering disciplines and it is found that mathematics performance in S1 and S2 are significantly different among engineering disciplines for both academic years. It can be identified that student in MT discipline obtained the least engineering performance in S3 and S4 for both academic years.

According to the correlation analysis, it is found that there is a strong positive significant correlation between GPA with mean marks in Level 2 as well as GPA with weighted mean marks in Level 2, irrespective of the engineering disciplines for both academic years. Furthermore, the overall performance in Level 2 is significantly correlated with mathematics in S1 and S2 for all disciplines except MT discipline and it can be seen that correlation with mathematics in S2 is higher compared to mathematics in S1 for both academic years. Besides that, correlation analysis is carried out to identify the linear relationship between mathematics and engineering modules separately as well as between the variables in both mathematics and engineering sets for each discipline. It is found that the most pairs are significant and positively correlated within the each variable set and between the variable sets for all engineering disciplines. The regression analysis suggests that the impact of mathematics in S2 was significantly higher than the impact of mathematics in S1 on the overall performance in Level 2 irrespective of the engineering disciplines for both academic years. Hence, the next chapter examines the overall impact of mathematics in Level 1 and Level 2 on engineering performance in Level 2.

CHAPTER 5
COMBINED IMPACT OF MATHEMATICS IN LEVEL 1 AND LEVEL 2

The results of Pearson correlation analysis in Chapter 4, confirmed that there is a strong significant relationship between the variables of mathematics and engineering sets separately as well as between the variables in both sets for each discipline. This confirms the validity of data for the use of Canonical Correlation Analysis (CCA) in order to examine the relationship between mathematics performance in Level 1 and Level 2 with the engineering performance of undergraduates in Level 2.

The marks of two mathematics modules in Level 1 (MA1013 and MA1023) and the marks of mathematics in each semester in Level 2 (MA2013 and MA2023) are taken as the predictor set of variables. The number of mathematics modules in Level 2 is varied from three to four depending on the engineering disciplines. The marks of all compulsory engineering modules in two semesters (Semester 3 and 4) in Level 2 are taken as the dependent set of variables. The dependent variables are varied among engineering discipline (refer Appendix 1).

The result of Chemical and Processing Engineering (CH) discipline is extensively discussed while the inferences based on results of remaining engineering disciplines are highlighted. The analysis was done for two semesters S3 and S4 in Level 2 separately in two academic years: 2010/2011 and 2011/2012.

5.1. Combined Impact on CH Student Engineering Performance

5.1.1. Academic Year 2010/2011 - S3 of CH Students

By the end of S3 undergraduates of CH discipline have followed two mathematics modules in Level 1 (S1 and S2), two mathematics modules in S3 and seven engineering modules in S3. Therefore, the number of variables in the dependent set and predictor set is seven and four respectively. Table 5.1 presents the results of CCA for S3.

Table 5.1: Results of canonical correlations - performance of CH in S3 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.791584	0.764661	0.042831	0.626605
2	0.366145	0.239713	0.099330	0.134062
3	0.221443	0.037990	0.109083	0.049037
4	0.168348	.	0.111457	0.028341

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.6781	1.5233	0.8769	0.8769	0.29876697	3.40	28	239.39	<.0001
2	0.1548	0.1033	0.0809	0.9578	0.80013702	0.87	18	189.99	0.6205
3	0.0516	0.0224	0.0269	0.9848	0.92401182	0.55	10	136	0.8530
4	0.0292		0.0152	1.0000	0.97165886	0.50	4	69	0.7335

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.29876697	3.40	28	239.39	<.0001
Pillai's Trace	0.83804511	2.61	28	276	<.0001
Hotelling-Lawley Trace	1.91368098	4.43	28	155.5	<.0001
Roy's Greatest Root	1.67813081	16.54	7	69	<.0001

The results in Table 5.1 indicate that there are four canonical variate pairs in this particular model as the number of canonical variate pairs is equal to the number of variables in the smaller set. It can be seen that out of four canonical variate pairs only the first canonical variate pair is statistically significant ($p < 0.001$) according to F value of Likelihood ratio (that is, Wilks' Lambda test statistic). It implies that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. In other words, the remaining three canonical variant pairs are not significantly important to describe the variability of the two sets. The four multivariate statistics also confirmed that there is a significant linear relationship between the students' mathematics performance in Level 1 and S3 with their engineering performance in S3.

The first canonical correlation of 0.792 ($p < 0.05$) indicates a significant strength of strong linear relationship between mathematics performance in Level 1 (MA1013 and MA1023) and S3 (MA2013 and MA2023) and engineering performance in S3. It denotes that the linear function of mathematics marks of the four modules (overall mathematics performance) significantly influences a linear function of marks of seven engineering modules (overall engineering performance of CH). Furthermore, the squared canonical correlation of 0.6268 (Table 5.1) indicates that 62.7% of the observed variability of the engineering performance of CH can be explained by the mathematics performance. This confirms that there is a significant impact on engineering performance at S3 from the mathematics performance in Level 1 and S3 in Level 2. At this point, it should be noted that the performance in mathematics in S3 were not taken in to consideration for the engineering performance in S3.

The correlation between the dependent variables (engineering measurements) and the corresponding canonical variables and that between independent variables (mathematics measurements) and the corresponding canonical variables are called 'canonical loadings'. Similarly, the correlation between engineering measurements and the canonical variables of the mathematics measurement and that between mathematics measurements and the canonical variables of the engineering measurements are called 'canonical cross loadings'. Table 5.2 provides the canonical loadings and canonical cross loadings for CH data in S3 (2010).

The canonical loadings that the MA1013 mathematics variable ($r = 0.4697$) indicates that the MA1013 mathematic variable is weakly correlated with its first canonical variate of mathematics measurements while the remaining three mathematics variables are highly correlated (> 0.7) with their first canonical variate of mathematics measurements. It can also be seen that MA1013 mathematics variable has a weak relationship ($r = 0.372$) with the first canonical variate of engineering measurements, remaining three mathematics variables are moderately correlated ($0.5 < r < 0.7$). Hence, it can be hypothesized that the impact MA1013 mathematics variable is weakly related with students' engineering performance in S3 compared to the impact of other mathematics variables.

Table 5.2: Canonical loadings and canonical cross loadings – performance of CH in S3 (2010)

Canonical Loadings

Correlations Between the Engineering Measurements and Their Canonical Variables

	ENG1	ENG2	ENG3	ENG4
CH2042	0.8181	-0.1700	0.1458	-0.2278
CH2052	0.8301	0.3331	0.0144	-0.0186
EE2802	0.8655	-0.0572	-0.0566	0.2374
EN2852	0.3718	0.1453	-0.1830	-0.1766
ME1822	0.3071	-0.6018	0.4754	-0.0149
ME2012	0.7932	0.0255	0.0717	-0.2967
ME2122	0.4500	0.3567	0.6736	0.0884

Correlations Between the Mathematics Measurements and Their Canonical Variables

	MAT1	MAT2	MAT3	MAT4
MA1013	0.4697	-0.4508	-0.6715	0.3540
MA1023	0.7103	0.0151	-0.4985	-0.4967
MA2013	0.7645	0.5063	-0.1849	0.3536
MA2023	0.8064	-0.4198	0.4151	0.0344

Canonical Cross Loadings

Correlations Between the Engineering Measurements and the Canonical Variables of the Mathematics Measurements

	MAT1	MAT2	MAT3	MAT4
CH2042	0.6476	-0.0623	0.0323	-0.0383
CH2052	0.6571	0.1220	0.0032	-0.0031
EE2802	0.6851	-0.0209	-0.0125	0.0400
EN2852	0.2943	0.0532	-0.0405	-0.0297
ME1822	0.2431	-0.2204	0.1053	-0.0025
ME2012	0.6279	0.0093	0.0159	-0.0499
ME2122	0.3563	0.1306	0.1492	0.0149

Correlations Between the Mathematics Measurements and the Canonical Variables of the Engineering Measurements

	ENG1	ENG2	ENG3	ENG4
MA1013	0.3718	-0.1650	-0.1487	0.0596
MA1023	0.5623	0.0055	-0.1104	-0.0836
MA2013	0.6052	0.1854	-0.0410	0.0595
MA2023	0.6383	-0.1537	0.0919	0.0058

The Canonical Redundancy analysis (CRA) is a method to extract and summaries the variation in a set of response variables (engineering measurements) that can be explained by a set of explanatory variables (mathematics measurements). The canonical redundancy indices reflect the effectiveness of canonical analysis in capturing variances of the observed variables by canonical variate pairs. Table 5.3 depicts the results of the canonical redundancy analysis for S3.

Table 5.3: Canonical redundancy analysis – performance of CH in S3 (2010)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.4531	0.4531	0.2839	0.2839
2	0.0935	0.5466	0.0125	0.2965
3	0.1061	0.6527	0.0052	0.3017
4	0.0337	0.6864	0.0010	0.3026

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.4899	0.4899	0.3070	0.3070
2	0.1590	0.6489	0.0213	0.3283
3	0.2265	0.8754	0.0111	0.3394
4	0.1246	1.0000	0.0035	0.3430

The proportion of the first opposite canonical variable (redundancy measure of engineering) denotes that the first canonical variate of mathematics performance accounted for 28.4% of the total variance of student engineering performance in S3. Furthermore, proportion of own canonical variable of mathematics measurements and that of engineering measurements indicate that the explainable variability of performance in mathematics by its first canonical variate is 48.9%, while the proportion of variance in student engineering performance explained by its first canonical variate is 45.3%. Thus, it can be concluded that CCA is effective for the data set used to capture variances of the predictor variables by the first canonical pair.

5.1.2. Academic Year 2010/2011 - S4 of CH Students

As in the Section 5.1.1 dependent set is the engineering modules in S4 and it consists of five engineering variables. Mathematics variables in both S1(MA1013) and S2 (MA1023) in Level 1 as well as in both S3 (MA2013 and MA2023) and S4 (MA2033) in Level 2 are the predictor set. This set also has five variables. Thus, the number of canonical variate pairs in this case is five. As in Section 5.1.1, the results of CCA are summarized in Table 5.4 to Table 5.6.

Table 5.4: Results of canonical correlations - performance of CH in S4 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.740065	0.708968	0.051883	0.547696
2	0.277003	.	0.105906	0.076731
3	0.248936	.	0.107600	0.061969
4	0.096492	.	0.113640	0.009311
5	0.043605	.	0.114490	0.001901

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.2109	1.1278	0.8830	0.8830	0.38733556	2.91	25	250.4	<.0001
2	0.0831	0.0170	0.0606	0.9436	0.85636041	0.68	16	208.38	0.8139
3	0.0661	0.0567	0.0482	0.9918	0.92753028	0.59	9	168.08	0.8071
4	0.0094	0.0075	0.0069	0.9986	0.98880566	0.20	4	140	0.9393
5	0.0019		0.0014	1.0000	0.99809858	0.14	1	71	0.7141

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.38733556	2.91	25	250.4	<.0001
Pillai's Trace	0.69760727	2.30	25	355	0.0005
Hotelling-Lawley Trace	1.37137407	3.61	25	155.3	<.0001
Roy's Greatest Root	1.21090057	17.19	5	71	<.0001

The results in Table 5.4 show that only the first of five canonical variate pairs is statistically significant ($p<0.001$). It implies that a significant amount of variability of predictor and dependent sets can be explained by the first canonical variate pair. Furthermore, multivariate statistics revealed that the canonical correlation is significantly different from zero ($p<0.001$) indicating that there is a significant linear relationship between linear combination of five mathematics modules and linear combination of five engineering modules. The first canonical correlation of 0.740 (Table 5.4) indicates that the students' mathematics performance in both Level 1 and Level 2 has a strong linear relationship with their engineering performance in S4. The squared canonical correlation indicates that the first canonical variate of mathematics accounted for 54.8% of the variance in the first canonical variate of engineering performance. These results clearly confirm that there is a significant impact of mathematics in both Level 1 and Level 2 on CH students' engineering performance in S4.

Table 5.5: Canonical loadings and canonical cross loadings – performance of CH in S4 (2010)

Canonical loadings

Correlations Between the Engineering Measurements and Their Canonical Variables

	ENG1	ENG2	ENG3	ENG4	ENG5
CH2062	0.7930	-0.2200	-0.5596	-0.0928	-0.0330
CH2072	0.5457	-0.1046	0.3609	-0.7163	-0.2188
CH2082	0.8962	0.2256	0.0022	0.2550	-0.2843
CH3092	0.8534	-0.4268	0.2373	0.0297	0.1800
CH3102	0.8621	0.1257	0.0550	-0.0863	0.4801

Correlations Between the Mathematics Measurements and Their Canonical Variables

	MAT1	MAT2	MAT3	MAT4	MAT5
MA1013	0.4855	-0.6104	-0.1222	-0.5601	-0.2510
MA1023	0.7460	-0.0852	-0.5591	-0.1485	0.3188
MA2013	0.7289	0.3530	-0.1827	-0.1514	-0.5365
MA2023	0.7159	0.0960	0.5655	-0.2746	0.2883
MA2033	0.7184	-0.3730	0.0131	0.5556	-0.1896

Canonical cross loadings

Correlations Between the Engineering Measurements and the Canonical Variables of the Mathematics Measurements

	MAT1	MAT2	MAT3	MAT4	MAT5
CH2062	0.5868	-0.0609	-0.1393	-0.0090	-0.0014
CH2072	0.4039	-0.0290	0.0899	-0.0691	-0.0095
CH2082	0.6633	0.0625	0.0006	0.0246	-0.0124
CH3092	0.6316	-0.1182	0.0591	0.0029	0.0078
CH3102	0.6380	0.0348	0.0137	-0.0083	0.0209

Correlations Between the Mathematics Measurements and the Canonical Variables of the Engineering Measurements

	ENG1	ENG2	ENG3	ENG4	ENG5
MA1013	0.3593	-0.1691	-0.0304	-0.0540	-0.0109
MA1023	0.5521	-0.0236	-0.1392	-0.0143	0.0139
MA2013	0.5394	0.0978	-0.0455	-0.0146	-0.0234
MA2023	0.5298	0.0266	0.1408	-0.0265	0.0126
MA2033	0.5316	-0.1033	0.0033	0.0536	-0.0083

The results in Table 5.5 clearly indicate that all five mathematics modules positively influence on engineering performance at different level of intensity as all the canonical cross loadings of five engineering measurements are greater than zero and the first mathematics canonical variate (MAT1) varied from 0.4039 (CH2072) to 0.6633 (CH2082). The canonical cross loadings of five mathematics measurements with the first engineering canonical variate (ENG1) varied from 0.3593 (MA1013) to 0.5521 (MA1023) are all positive and significant.

Table 5.6: Canonical redundancy analysis – performance of CH in S4 (2010)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.6403	0.6403	0.3507	0.3507
2	0.0616	0.7019	0.0047	0.3554
3	0.1006	0.8024	0.0062	0.3616
4	0.1190	0.9215	0.0011	0.3627
5	0.0785	1.0000	0.0001	0.3629

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.4704	0.4704	0.2576	0.2576
2	0.1306	0.6010	0.0100	0.2677
3	0.1362	0.7371	0.0084	0.2761
4	0.1486	0.8857	0.0014	0.2775
5	0.1143	1.0000	0.0002	0.2777

According to the results in Table 5.6 it confirms that the proportion of variance in engineering performance in S4 explained by the first canonical variate of mathematics in both S3 and S4 is 35.1%. It can be concluded that mathematics performance in Level 1 and Level 2 has a significant impact on the performance of CH engineering students in S4.

5.1.3. Academic Year 2011/2012- S3 of CH Students

The mathematics measurements and as well as the engineering measurements are the same as in Section 5.1.1 which was done for academic year 2019/2011 of S3 CH students. Table 5.7 presents the results of canonical correlation and multivariate statistics for data of 2011/2012 academic year in S3 in Level 2 for CH students.

Table 5.7: Results of canonical correlations – performance of CH in S3 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.815817	0.799804	0.039973	0.665558
2	0.252979	.	0.111874	0.063998
3	0.239124	.	0.112689	0.057180
4	0.015687	.	0.119493	0.000246

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.9901	1.9217	0.9390	0.9390	0.29506605	5.93	16	193.11	<.0001
2	0.0684	0.0077	0.0323	0.9713	0.88226373	0.91	9	155.91	0.5138
3	0.0606	0.0604	0.0286	0.9999	0.94258780	0.98	4	130	0.4235
4	0.0002		0.0001	1.0000	0.99975392	0.02	1	66	0.8990

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.29506605	5.93	16	193.11	<.0001
Pillai's Trace	0.78698262	4.04	16	264	<.0001
Hotelling-Lawley Trace	2.11932342	8.22	16	120.13	<.0001
Roy's Greatest Root	1.99005503	32.84	4	66	<.0001

The results in Table 5.7 indicated that out of four canonical variate pairs only the first canonical variate pair is statistically significant (r=0.816, $p < 0.05$) confirming that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. The four multivariate statistics tests also confirmed that the first canonical correlation is significantly different greater than zero. These results indicate that the strength of the linearity between mathematics and engineering performance is high. Thus, it can be concluded that first pair of canonical variate, a linear combination of the mathematics measurements and a linear combination of the engineering measurements has a correlation coefficient of 0.816. The value of squared canonical correlation of 0.616 suggests that the proportion of the variance in the canonical variate of engineering performance explained by the canonical variate of the mathematics performance in Level 1 is 66.6%. The corresponding value for 2010//2013 is 62.7%.

Table 5.8 provides the results canonical loadings and canonical cross loadings for S3 in Level 2 of 2011/2012 batch.

Table 5.8: Canonical loadings and canonical cross loadings – performance of CH in S3 (2011)

Canonical Loadings

Correlations Between the ENG Variables and Their Canonical Variables

	ENG1	ENG2	ENG3	ENG4
CH2013	0.8881	-0.4521	-0.0370	-0.0737
CH2023	0.7981	-0.0594	0.5731	-0.1763
CH2033	0.9466	0.2312	-0.0683	0.2141
ME2122	0.4665	-0.5283	0.3550	0.6142

Correlations Between the MAT Variables and Their Canonical Variables

	MAT1	MAT2	MAT3	MAT4
MA1013	0.5603	0.6370	0.2326	0.4757
MA1023	0.7791	0.5114	-0.1364	-0.3359
MA2013	0.9256	-0.1829	-0.2122	0.2544
MA2023	0.8653	-0.0913	0.4928	0.0057

Canonical Cross Loadings

Correlations Between the ENG Variables and the Canonical Variables of the MAT Variables

	MAT1	MAT2	MAT3	MAT4
CH2013	0.7246	-0.1144	-0.0088	-0.0012
CH2023	0.6511	-0.0150	0.1370	-0.0028
CH2033	0.7723	0.0585	-0.0163	0.0034
ME2122	0.3805	-0.1337	0.0849	0.0096

Correlations Between the MAT Variables and the Canonical Variables of the ENG Variables

	ENG1	ENG2	ENG3	ENG4
MA1013	0.4571	0.1611	0.0556	0.0075
MA1023	0.6356	0.1294	-0.0326	-0.0053
MA2013	0.7552	-0.0463	-0.0507	0.0040
MA2023	0.7059	-0.0231	0.1178	0.0001

The values canonical loadings indicate that the first canonical variate of engineering performance is highly correlated ($r > 0.75$) with all engineering modules with exceptional for the module ME2122. Thus, this implies that much of the shared variance of all engineering modules is captured by its first canonical variate. Similarly, in mathematics measurements all mathematics modules are strongly correlated (>0.75) with its first variate with exceptional for MA1013. These results confirm that there is a significant impact from mathematics in Level 1 and S3 on the CH Engineering performance in 2011/2012 batch as well.

Based on the values of canonical cross-loadings (Table 5.8), it can be said that all engineering measurements are highly correlated (>0.60) with the first canonical variate of mathematics performance except the engineering measurement ME 2122 while all mathematics measurements are also highly related (>0.60) with the first canonical variate of engineering performance except MA1013 mathematics variable. These results confirm that there is a significant impact from mathematics in Level 1 and S3 on the CH Engineering performance in 2011/2012 batch as well.

Table 5.9: Canonical Redundancy Analysis – performance of CH in S3 (2011)

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.6349	0.6349	0.4225	0.4225
2	0.1351	0.7700	0.0086	0.4312
3	0.1151	0.8851	0.0066	0.4378
4	0.1149	1.0000	0.0000	0.4378

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.6316	0.6316	0.4204	0.4204
2	0.1773	0.8089	0.0113	0.4317
3	0.0901	0.8990	0.0052	0.4369
4	0.1010	1.0000	0.0000	0.4369

The results of the canonical redundancy analysis are provided in Table 5.9. The results of cumulative proportions for opposite canonical variables in engineering measurements indicate that the proportion of variance explained by the first canonical variate of mathematics performance is 42.3% of engineering performance in S3. Furthermore, the amount of variance in engineering performance in S3 explained by its first canonical variate is 63.5%, while 63.2% of the variance in mathematics performance is explained by its first canonical variate.

5.1.4. Academic Year 2011/2012 – S4 of CH Students

As in Section 5.1.2, the dependent set contains five engineering variables and the predictor set contains five mathematics variables. As in Section 5.1.2, the corresponding three tables with respect to canonical correlation carried out for the data in S4 for the academic year 2011/2012 are summarized in Tables 5.10 – Table 5.12 respectively.

Table 5.10: Results of canonical correlations - performance of CH in S4 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.811597	0.788620	0.040794	0.658690
2	0.413333	0.322201	0.099103	0.170844
3	0.203386	0.020121	0.114579	0.041366
4	0.146095	.	0.116972	0.021344
5	0.018812	.	0.119481	0.000354

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.9299	1.7238	0.8767	0.8767	0.26540791	3.92	25	228.11	<.0001
2	0.2060	0.1629	0.0936	0.9703	0.77761638	1.02	16	190.05	0.4381
3	0.0432	0.0213	0.0196	0.9899	0.93784118	0.46	9	153.48	0.9021
4	0.0218	0.0215	0.0099	0.9998	0.97830983	0.35	4	128	0.8417
5	0.0004		0.0002	1.0000	0.99964610	0.02	1	65	0.8799

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.26540791	3.92	25	228.11	<.0001
Pillai's Trace	0.89259832	2.83	25	325	<.0001
Hotelling-Lawley Trace	2.20125183	5.27	25	140.6	<.0001
Roy's Greatest Root	1.92989156	25.09	5	65	<.0001

According to the results (Table 5.10) it can be seen that only the first pair of canonical variate is statistically significant ($p < 0.001$) confirming that only the first variate is able to capture significant amount of variability of the predictor set and dependent variable set. This further shows the significance impact from mathematics performance on the engineering performance in Level 2 for the 2011/2012 CH students. The first canonical correlation is found to be equal to 0.812 which implies a strong relationship between mathematics in both Level 1 and Level 2 with their engineering performance in S4. The squared canonical correlation indicates that 65.9% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics.

Table 5.11: Canonical loadings and canonical cross loadings – performance of CH in S4 (2011)

Canonical loadings

Correlations Between the ENG Variables and Their Canonical Variables

	ENG1	ENG2	ENG3	ENG4	ENG5
CH2043	0.8905	-0.2166	-0.1659	-0.0642	0.3584
CH2053	0.9132	-0.0306	0.1482	-0.1896	-0.3275
CH2063	0.8948	-0.0614	0.2879	0.2925	-0.1648
CH2073	0.8781	0.2739	-0.1960	0.1879	-0.2833
CH2083	0.8991	0.3623	0.2295	0.0406	0.0773

Correlations Between the MAT Variables and Their Canonical Variables

	MAT1	MAT2	MAT3	MAT4	MAT5
MA1013	0.5408	-0.4021	0.1600	-0.4541	0.5603
MA1023	0.7407	-0.5074	-0.1409	-0.3141	-0.2747
MA2013	0.8152	0.3668	-0.0678	-0.4428	-0.0176
MA2023	0.7962	0.0458	-0.4970	-0.0473	0.3386
MA2033	0.9664	0.0817	0.2156	0.1105	0.0263

Canonical cross loadings

Correlations Between the ENG Variables and the Canonical Variables of the MAT Variables

	MAT1	MAT2	MAT3	MAT4	MAT5
CH2043	0.7227	-0.0895	-0.0337	-0.0094	0.0067
CH2053	0.7411	-0.0126	0.0301	-0.0277	-0.0062
CH2063	0.7262	-0.0254	0.0586	0.0427	-0.0031
CH2073	0.7126	0.1132	-0.0399	0.0275	-0.0053
CH2083	0.7297	0.1497	0.0467	0.0059	0.0015

Correlations Between the MAT Variables and the Canonical Variables of the ENG Variables

	ENG1	ENG2	ENG3	ENG4	ENG5
MA1013	0.4389	-0.1662	0.0325	-0.0663	0.0105
MA1023	0.6011	-0.2097	-0.0287	-0.0459	-0.0052
MA2013	0.6616	0.1516	-0.0138	-0.0647	-0.0003
MA2023	0.6462	0.0189	-0.1011	-0.0069	0.0064
MA2033	0.7843	0.0338	0.0438	0.0161	0.0005

Table 5.11 provides the canonical loadings and canonical cross loadings for S4. The canonical loadings reflect that both engineering and mathematics variables are strongly correlated (>0.70) with their first canonical variate except MA1013

mathematics variable. Hence, it can be concluded that a considerable amount of variance in mathematics except MA1013 variable, is captured by its first canonical variate. By referring the canonical cross-loadings, it can be said that all engineering variables are significantly and strongly correlated (>0.70) with the first canonical variate of mathematics performance. Furthermore, all mathematics variables have a significant impact on the first canonical variate of engineering. The impact is the highest from MA2033 and the lowest from MA1013.

Table 5.12: Canonical Redundancy Analysis – performance of CH in S4 (2011)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.8014	0.8014	0.5279	0.5279
2	0.0516	0.8530	0.0088	0.5367
3	0.0447	0.8977	0.0018	0.5385
4	0.0325	0.9302	0.0007	0.5392
5	0.0698	1.0000	0.0000	0.5392

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.6147	0.6147	0.4049	0.4049
2	0.1125	0.7272	0.0192	0.4241
3	0.0687	0.7959	0.0028	0.4270
4	0.1031	0.8990	0.0022	0.4292
5	0.1010	1.0000	0.0000	0.4292

Table 5.12 presents the results of the canonical redundancy analysis for S4. The redundancy index of engineering exhibits that the explainable variability of student engineering performance in S4 is 52.8% by the first canonical variate of mathematics. It can be concluded that the first canonical variate of mathematics is a good predictor of student engineering performance in S4. In addition to that, 80.1% of the variance in engineering performance is explained by its first canonical variate while the proportion of variance in mathematics performance explained by its first canonical variate is 61.5%.

5.2. Combined Impact on CE Student Engineering Performance

In order to determine the impact of mathematics on students' engineering performance of the remaining engineering disciplines, similar analyses as explained in Section 5.1.1 – Section 5.1.4 were carried out separately for each engineering disciplines. For each discipline, the analyses were carried out for all four cases: (i) 2010/2011 – S3, (ii) 2010/2011 – S4, (iii) 2011/2012 – S3 and (iv) 2011/2012 – S4.

For CE discipline, the independent set contains marks of six different engineering modules (Table 5.13) and predictor set contains marks of four mathematics modules for S3 and marks of six mathematics modules for S4 (Table 5.13). The detailed output for CE disciplines under those four scenarios are shown in Appendix 2. It was found that only the first canonical variate pair is significant for all four scenarios and thus Table 5.13 provides summary results focusing on the first pair of canonical variate.

5.2.1. Academic Year 2010/2011- S3 of CE Students

According to the results in Table 5.13 it is clear that the students' mathematics performance has a moderately strong impact on their engineering performance in S3 in the academic year 2010/2011 ($r = 0.592$, $p < 0.001$). About 35% of engineering performance can be explained by the mathematics performance. Furthermore, it can be seen that the impact of MA1023 module (in S2) is higher compared with other mathematics modules. The canonical redundancy index of engineering suggests that 13.5% of the total variance of engineering performance in S3 can be explained by the first canonical variate of mathematics.

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Table 5.13: Important statistics related to the first pair of canonical variate – CE student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation (CC)	0.592				0.623				0.724				0.766			
Squared CC	0.351				0.388				0.524				0.587			
Wilks' Lambda (p-value)	0.585 (<.0001)				0.551 (<.0001)				0.355 (<.0001)				0.364 (<.0001)			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE2012	0.123	0.449	0.266	CE2012	0.686	0.895	0.558	CE2112	0.587	0.919	0.665	CE2112	0.388	0.830	0.636
	CE2022	-0.269	0.397	0.235	CE2022	0.175	0.168	0.105	CE2122	0.063	0.665	0.481	CE2122	0.229	0.766	0.587
	CE2032	0.822	0.952	0.564	CE2032	-0.085	0.042	0.026	CE2132	0.113	0.750	0.543	CE2132	0.260	0.786	0.602
	CE2042	0.245	0.700	0.415	CE2042	0.354	0.724	0.451	CE2142	-0.097	0.488	0.353	CE2142	0.086	0.622	0.476
	CE2052	0.097	0.515	0.305	CE2052	0.131	0.496	0.309	CE3012	0.442	0.862	0.624	CE3012	0.320	0.766	0.587
	CE2062	0.088	0.545	0.323	CE2062	0.085	0.472	0.294								
Variance extracted	38.62				30.39				56.61				57.29			
Redundancy	13.55				11.81				29.64				33.66			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.032	0.548	0.324	MA1013	0.027	0.428	0.266	MA1013	-0.167	0.196	0.142	MA1013	-0.062	0.374	0.287
	MA1023	0.804	0.931	0.551	MA1023	0.433	0.765	0.477	MA1023	0.054	0.454	0.328	MA1023	0.099	0.602	0.461
	MA2013	0.346	0.564	0.334	MA2013	0.335	0.758	0.473	MA2013	0.047	0.291	0.211	MA2013	0.125	0.612	0.469
	MA2023	0.076	0.504	0.298	MA2023	0.468	0.862	0.537	MA2023	0.329	0.453	0.328	MA2023	0.263	0.693	0.531
									MA2033	0.695	0.876	0.634	MA2033	0.287	0.736	0.564
									MA3013	0.377	0.629	0.455	MA3013	0.572	0.865	0.663
Variance extracted	43.47				52.12				28.26				44.10			
Redundancy	15.25				20.26				14.80				25.90			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

5.2.2. Academic Year 2010/2011- S4 of CE Students

The canonical correlation of S4 in academic year 2010/2011 implies that there is a strong linear relationship between students' mathematics performance and their engineering performance in S4 (0.724). The impact of two mathematics modules in S4 (MA2033 and MA3013) on the engineering performance in S4 is higher than that of other mathematics modules. The redundancy measure of engineering denotes that the proportion of variance explained by the first canonical variate of mathematics performance is 29.6% of engineering performance in S4.

5.2.3. Academic Year 2011/2012- S3 of CE Students

Based on the results of CCA for S4 in academic year 2011/2012 in Table 5.17, it can be said that the linear relationship between students' mathematics performance and their engineering performance in S3 is moderately strong (0.623). However, most of the engineering variables are weakly correlated with their canonical variate as well as the canonical variate of mathematics (<0.30). Moreover, the lowest impact of mathematics on engineering performance in S3 is from the MA1013 mathematics module. The first canonical variate of mathematics accounted for 11.8% of the total variance of engineering performance in S3.

5.2.4. Academic Year 2010/2011- S4 of CE Students

The results of CCA for S3 in academic year 2011/2012 in Table 5.17 illustrate that the students' mathematics performance is strongly correlated with their engineering performance in S4 (0.766). The highest impact of mathematics and the lowest impact of mathematics on CE student performance in S4 are from the MA3013 mathematics module in S4 and the MA1013 mathematics module in S1 respectively. The canonical redundancy measure of engineering denotes that the first canonical variate of mathematics can be explained 33.6% of the total variance of engineering performance in S4.

5.3. Combined Impact on Student Performance in Other Disciplines

As detailed analyses were shown for both disciplines: CH discipline (Section 5.1) and CE discipline (Section 5.2) only summary tables similar to Table 5.13 are given for other five disciplines. As for CH and CE it was found that only the first canonical covariate is significant in other five disciplines also. It concluded with 95% confidence that a significant amount of variability of predictor and dependent sets can be explained by the first canonical variate pair as revealed by the Wilks' lambda test statistics. The summary results for the five disciplines: CS, EE, EN, ME and MT are shown in Tables 5.14 to 5.18 respectively.

5.3.1. Impact on Student Performance in CS

With respect to Table 5.14, the canonical correlation exhibits that there is a significant linear relationship between students' mathematics performance and their engineering performance for both academic years in S3 and S4 as the first canonical variate between mathematics measurements and engineering measurements for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) are 0.688 ($p < 0.0001$), 0.679 ($p < 0.0001$), 0.748 ($p < 0.0001$) and 0.758 ($p < 0.0001$) respectively. The percentages of variability of engineering performance explained by the linear function of mathematics for the four cases are 47%, 59%, 56% and 57% respectively.

Based on standardized coefficients in S3 (2010/2011) it can be concluded that all the mathematics modules have positive moderately impact on engineering performance in S3 except MA1013 mathematics module in S1. The impact from MA1013 is significantly lower compared with other three mathematics modules. Similar trend was observed for S3 (2011/2012) as although all mathematics modules showed positive impact on student engineering performance in S3, the impact from MA1013 is significantly lower compared with other three modules. Based on standardized coefficients in S4 (2010/2011) the mathematics modules MA1013 and MA2023 showed negative impact on engineering performance in S3 compared to other mathematics modules. However, based on the results in S4 (2011/2012) it can be concluded that all six mathematics modules have positive impact on the engineering performance.

The redundancy measure of engineering indicates that the first canonical variate of mathematics performance accounted for 29% of the total variance of engineering performance in S3 (2010/2011). The corresponding percentages for other three are 30%, 29% and 40% respectively for S3 (2011/2012), S4(2010/2011) and S4 (2011/2012).

5.3.2. Impact on Student Performance in EE

The results in Table 5.15 showed that in all four cases: S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) the students' mathematics performance is strongly and significantly correlated with their corresponding engineering performance. The squared canonical correlation varied from 53% in S3 (2010/2011) to 71.4% in S4 (2010/2011). In all cases the standardized coefficients of mathematics measurements are all positive with exceptional for MA2023 in S4 (2010/2011) and MA1013 in S4 (2011/2012). As for CH, CE and CS the impact from S2 mathematics (MA1023) is always higher than S1 mathematics (MA1013). Furthermore by comparison of mean of the standardized coefficients for mathematics modules in Level 2 and Level 1 in S4, it was found the mean coefficient for Level 2 is higher than that of Level 1. Thus it can be hypothesized that the impact from mathematics modules in Level 2 on the engineering performance in Semester 2 is significantly higher than that from mathematics in Level 1.

The canonical redundancy measure of engineering indicates that the first canonical variate of mathematics can be explained 21.9%, 24.7%, 36.7% and 41.1% respectively of the total variance of engineering performance in S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012).

5.3.3. Impact on Student Performance in EN

According to the results in Table 5.16 it is clear that students' mathematics performance has strong impact on their engineering performance in all four cases in EN. The first canonical correlations between mathematics performance and engineering performance are 0.815, 0.834, 0.783 and 0.700 respectively for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) and therefore corresponding squared canonical correlation are 66.5%, 69.6%, 61.3% and 49.0%. It is very difficult explain why it is significantly low in S4 (2011/2012). The squared correlation was found higher for both S3 than both S4 only in EN disciplines. Thus, it can be concluded that the impact of mathematics in Level 1 and S3 on engineering performance of EN in S3 is higher compared with the impact of mathematics in Level 1 and Level 2 on engineering performance of EN in S4. to the impact of mathematics in S1 and S2.

The standardized coefficients are all positive for the four cases with exceptional for MA1013 for S4 (2011/2012) indicating all mathematics modules have some sort of positive impact on students' performance in engineering. The canonical redundancy index of engineering suggests that almost 40.0% of the total variance of engineering performance in S3 irrespective of academic year (2010/2011 or 2011/2012) can be explained by the first canonical variate of mathematics. The corresponding percentage for S4 is around 27%.

5.3.4. Impact on Student Performance in ME

The results in Table 5.17 showed that in all four cases: S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) the students' mathematics performance is significantly correlated with their corresponding engineering performance. The squared canonical correlation varied from 47% in S3 (2010/2011) to 59% in S3 (2011/2012). In all cases the standardized coefficients of mathematics measurements are all positive with exceptional for MA1013 in S3 (2011/2012) and MA2013 in S4 in both 2010/2011 and 2011/2012. As for CH, CE and CS the impact from S2 mathematics (MA1023) is always higher than S1 mathematics (MA1013).

The canonical redundancy measure of engineering indicates that the first canonical variate of mathematics can be explained 18.3%, 21.9%, 22.9% and 30.3% respectively of the total variance of engineering performance in S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012).

5.3.5. Impact on Student Performance in MT

According to the results in Table 5.18 it is clear that students' mathematics performance has strong impact on their engineering performance in all four cases in MT. The first canonical correlations between mathematics performance and engineering performance are 0.807, 0.739, 0.881 and 0.738 respectively for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) and therefore corresponding squared canonical correlation are 65.1%, 54.5%, 77.7% and 54.4%. The squared correlation was found higher for both S3 than both S4 and it can be concluded that the impact of mathematics in Level 1 and S3 on engineering performance of MT in S3 is higher compared with the impact of mathematics in Level 1 and Level 2 on engineering performance of MT in S4 to the impact of mathematics in S1 and S2.

The redundancy measure of engineering indicates that the first canonical variate of mathematics performance accounted for 28% of the total variance of engineering performance in S3 (2010/2011). The corresponding percentages for other three are 13%, 45% and 14% respectively for S3 (2011/2012), S4(2010/2011) and S4 (2011/2012).

Table 5.14: Important statistics related to the first pair of canonical variate – CS student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.760				0.764				0.756				0.855			
Squared canonical correlation	0.577				0.584				0.571				0.730			
Wilks' Lambda	0.372				0.333				0.333				0.231			
P-value	<.0001				<.0001				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE1822	0.209	0.652	0.495	CE1822	0.174	0.662	0.506	CS3022	0.343	0.848	0.641	CS3022	0.033	0.697	0.595
	CS2032	0.016	0.668	0.507	CS2032	0.447	0.894	0.683	CS3032	0.070	0.671	0.507	CS3032	0.350	0.881	0.753
	CS2042	0.354	0.797	0.605	CS2042	-0.009	0.589	0.450	CS3042	0.307	0.738	0.558	CS3042	0.090	0.716	0.612
	CS2062	0.245	0.715	0.543	CS2062	0.281	0.816	0.624	CS3242	-0.166	0.296	0.224	CS3242	0.031	0.498	0.426
	EN2022	0.339	0.757	0.575	EN2022	0.334	0.754	0.576	EN2062	0.418	0.850	0.642	EN2062	0.551	0.928	0.793
	ME1822	0.214	0.653	0.496	ME1822	0.018	0.544	0.416	ME1802	0.178	0.723	0.546	ME1802	0.114	0.675	0.577
Variance extracted	50.28				51.89				50.77				55.66			
Redundancy	29.02				30.31				28.99				40.64			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.028	0.416	0.316	MA1013	0.058	0.573	0.438	MA1013	-0.038	0.459	0.347	MA1013	0.018	0.560	0.479
	MA1032	0.416	0.774	0.588	MA1032	0.325	0.654	0.500	MA1032	0.370	0.736	0.556	MA1032	0.291	0.636	0.544
	MA2023	0.281	0.639	0.486	MA2053	0.417	0.833	0.637	MA2023	-0.055	0.414	0.313	MA2053	0.259	0.763	0.652
	MA2042	0.596	0.856	0.650	MA2073	0.465	0.875	0.669	MA2042	0.258	0.605	0.457	MA2073	0.025	0.681	0.582
									MA2013	0.414	0.758	0.573	MA2033	0.324	0.835	0.713
									MA2033	0.389	0.766	0.578	MA2063	0.369	0.868	0.742
Variance extracted	47.83				55.4				40.84				53.6			
Redundancy	27.61				32.36				23.31				39.14			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 5.15: Important statistics related to the first pair of canonical variate – EE student performance

	Semester 3			
	Academic Year 2010/2011			
CC	0.731			
Squared CC	0.535			
Wilks' Lambda	0.352			
P-value	0.0001			
		(1)	(2)	(3)
Engineering performance	EE2012	0.534	0.841	0.615
	EE2022	0.160	0.711	0.520
	EE2033	0.183	0.486	0.355
	EN2012	0.006	0.679	0.496
	EN2022	0.238	0.645	0.472
	ME2012	0.304	0.701	0.512
	CE1822	-0.105	0.221	0.161
Variance extracted	40.95			
Redundancy	21.89			
		(1)	(2)	(3)
Mathematics performance	MA1013	0.057	0.439	0.321
	MA1023	0.326	0.690	0.505
	MA2013	0.536	0.843	0.617
	MA2023	0.383	0.776	0.568
Variance extracted	49.57			
Redundancy	26.5			

	Semester 3			
	Academic Year 2011/2012			
CC	0.741			
Squared CC	0.550			
Wilks' Lambda	0.390			
P-value	<.0001			
		(1)	(2)	(3)
Engineering performance	CE1822	0.096	0.458	0.339
	EE2013	0.217	0.752	0.558
	EE2023	0.290	0.698	0.518
	EE2033	0.199	0.674	0.500
	EN2012	0.113	0.588	0.436
	EN2022	0.058	0.603	0.447
	ME2012	0.419	0.847	0.628
Variance extracted	44.94			
Redundancy	24.7			
		(1)	(2)	(3)
Mathematics performance	MA1013	0.104	0.555	0.411
	MA1023	0.337	0.758	0.562
	MA2013	0.172	0.729	0.541
	MA2023	0.610	0.920	0.682
Variance extracted	56.48			
Redundancy	31.04			

	Semester 4			
	Academic Year 2010/2011			
CC	0.845			
Squared CC	0.714			
Wilks' Lambda	0.181			
P-value	<.0001			
		(1)	(2)	(3)
Engineering performance	EE2042	0.303	0.731	0.618
	EE2052	0.225	0.610	0.515
	EE2072	0.092	0.745	0.630
	EE2083	0.389	0.840	0.709
	EE2132	0.190	0.734	0.620
	EE3072	0.154	0.641	0.542
	ME2842	0.012	0.691	0.584
Variance extracted	51.34			
Redundancy	36.65			
		(1)	(2)	(3)
Mathematics performance	MA1013	0.032	0.445	0.376
	MA1023	0.181	0.602	0.509
	MA2013	0.237	0.612	0.517
	MA2023	-0.070	0.547	0.462
	MA2032	0.724	0.938	0.793
	MA2042	0.134	0.677	0.572
Variance extracted	42.86			
Redundancy	30.6			

	Semester 4			
	Academic Year 2011/2012			
CC	0.796			
Squared CC	0.633			
Wilks' Lambda	0.251			
P-value	<.0001			
		(1)	(2)	(3)
Engineering performance	EE2043	-0.170	0.379	0.302
	EE2053	0.199	0.411	0.327
	EE2063	0.184	0.592	0.471
	EE2073	0.511	0.855	0.680
	EE2083	0.341	0.786	0.625
	ME2842	0.252	0.673	0.536
Variance extracted	41.07			
Redundancy	26.02			
		(1)	(2)	(3)
Mathematics performance	MA1013	-0.067	0.415	0.331
	MA1023	0.300	0.755	0.601
	MA2013	0.017	0.619	0.492
	MA2023	0.367	0.772	0.614
	MA2033	0.394	0.854	0.680
	MA2053	0.316	0.543	0.432
Variance extracted	45.75			
Redundancy	28.98			

(1)– Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 5.16: Important statistics related to the first pair of canonical variate – EN student performance

	Semester 3							
	Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.815				0.834			
Squared canonical correlation	0.665				0.696			
Wilks' Lambda	0.299				0.238			
P-value	<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)
	EE2092	0.300	0.881	0.718	EE2092	0.455	0.871	0.727
	EN2012	0.438	0.880	0.718	EN2012	0.204	0.660	0.550
	EN2022	0.209	0.755	0.616	EN2022	0.231	0.713	0.595
	EN2052	-0.072	0.572	0.466	EN2052	-0.191	0.588	0.491
	EN2062	0.301	0.778	0.634	EN2062	0.468	0.893	0.745
Variance extracted	61.05				56.90			
Redundancy	40.58				39.59			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.201	0.587	0.478	MA1013	0.025	0.373	0.311
	MA1023	0.201	0.693	0.565	MA1023	0.124	0.698	0.582
	MA2013	0.466	0.858	0.699	MA2013	0.373	0.838	0.699
	MA2023	0.411	0.834	0.680	MA2023	0.629	0.941	0.785
Variance extracted	56.35				55.38			
Redundancy	37.45				38.53			

	Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.783				0.700			
Squared canonical correlation	0.613				0.490			
Wilks' Lambda	0.298				0.410			
P-value	<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)
	EN2072	0.479	0.831	0.650	EN2072	0.612	0.823	0.646
	EN2142	0.020	0.619	0.485	EN2142	0.233	0.545	0.382
	EN3022	0.003	0.294	0.230	EN3022	0.132	0.448	0.314
	EN2082	0.647	0.910	0.712	EN2082	0.753	0.919	0.733
Variance extracted	49.68				43.3			
Redundancy	30.44				24.74			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.190	0.609	0.477	MA1013	-0.237	0.203	0.142
	MA1023	0.088	0.616	0.482	MA1023	0.282	0.773	0.542
	MA2013	0.286	0.750	0.587	MA2013	0.039	0.666	0.466
	MA2023	0.275	0.817	0.639	MA2023	0.494	0.865	0.605
	MA2033	0.372	0.799	0.626	MA2033	0.445	0.846	0.592
	MA2042	0.154	0.607	0.475				
Variance extracted	49.77				50.90			
Redundancy	30.49				24.95			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 5.17: Important statistics related to the first pair of canonical variate – ME student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.688				0.769				0.748				0.758			
Squared canonical correlation	0.473				0.591				0.560				0.575			
Wilks' Lambda	0.421				0.306				0.390				0.319			
P-value	<.0001				<.0001				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	0.200	0.595	0.409	EE2803	0.294	0.714	0.549	ME2032	0.370	0.710	0.532	ME2032	0.182	0.724	0.549
	EN2852	0.071	0.435	0.299	EN2852	0.032	0.383	0.295	ME3072	0.201	0.626	0.468	ME3073	0.101	0.632	0.479
	ME2012	0.167	0.592	0.407	ME2012	0.413	0.764	0.587	ME3032	0.616	0.865	0.647	ME3032	0.320	0.729	0.553
	ME2022	-0.052	0.509	0.350	ME2023	0.095	0.475	0.365	ME3062	-0.308	0.226	0.169	ME3062	0.184	0.635	0.481
	ME2092	0.674	0.902	0.621	ME2092	0.098	0.480	0.369	ME2142	0.247	0.596	0.446	ME2153	0.514	0.884	0.670
	ME2112	0.286	0.596	0.410	ME2112	0.592	0.856	0.658								
					ME2602	-0.329	0.412	0.317								
Variance extracted	38.68				37.10				41.02				52.80			
Redundancy	18.31				21.92				22.96				30.34			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.190	0.524	0.360	MA1013	-0.035	0.338	0.260	MA1013	0.363	0.490	0.367	MA1013	0.020	0.329	0.249
	MA1023	0.498	0.799	0.550	MA1023	0.188	0.641	0.492	MA1023	0.164	0.469	0.351	MA1023	0.332	0.773	0.586
	MA2013	0.221	0.695	0.478	MA2013	0.437	0.860	0.661	MA2013	-0.106	0.356	0.266	MA2013	-0.109	0.562	0.426
	MA2023	0.466	0.750	0.516	MA2023	0.564	0.915	0.703	MA2023	0.203	0.562	0.421	MA2023	0.615	0.791	0.600
									MA2033	0.320	0.646	0.483	MA2033	0.056	0.546	0.414
									MA2042	0.579	0.799	0.598	MA2053	0.451	0.624	0.473
Variance extracted	48.96				52.54				32.65				38.92			
Redundancy	23.18				31.04				18.28				22.36			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 5.18: Important statistics related to the first pair of canonical variate – MT student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.807				0.739				0.881				0.738			
Squared canonical correlation	0.651				0.545				0.777				0.544			
Wilks' Lambda	0.198				0.266				0.073				0.119			
P-value	0.0003				0.0088				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	-0.042	0.616	0.497	EE2803	0.185	0.652	0.482	ME2142	0.072	0.752	0.663	ME2850	0.175	0.551	0.407
	EN2852	-0.328	0.462	0.373	EN2852	0.267	0.433	0.320	ME2832	0.530	0.871	0.767	ME2832	0.160	0.539	0.398
	ME1822	0.059	0.305	0.246	ME1822	-0.105	0.240	0.177	ME3062	0.413	0.772	0.680	ME3062	0.574	0.714	0.527
	ME2012	0.273	0.668	0.539	ME2012	0.733	0.871	0.643	MT2032	-0.210	0.734	0.647	MT2032	-0.562	0.138	0.102
	MT2042	1.316	0.935	0.754	MT2042	-0.732	0.098	0.072	MT2072	-0.060	0.679	0.599	MT2072	-0.543	0.091	0.067
	MT2122	-0.325	0.781	0.630	MT2122	-0.084	0.165	0.122	MT2142	0.020	0.712	0.628	MT2142	0.883	0.604	0.446
					MT2152	0.525	0.449	0.331	MT2152	0.442	0.782	0.689				
Variance extracted	43.6				23.81				57.69				24.95			
Redundancy	28.37				12.99				44.81				13.57			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.501	0.042	0.034	MA1013	-0.276	0.383	0.283	MA1013	-0.038	0.298	0.262	MA1013	-0.323	0.183	0.135
	MA1023	0.740	0.847	0.683	MA1023	0.335	0.748	0.553	MA1023	0.353	0.771	0.680	MA1023	0.073	0.570	0.420
	MA2013	0.506	0.706	0.570	MA2013	0.315	0.783	0.578	MA2013	-0.006	0.530	0.468	MA2013	-0.161	0.485	0.358
	MA2023	0.060	0.623	0.503	MA2023	0.645	0.944	0.697	MA2023	0.088	0.709	0.625	MA2023	0.631	0.849	0.626
									MA2033	0.442	0.827	0.729	MA2033	0.645	0.880	0.649
									MA3013	0.391	0.806	0.710	MA3013	-0.030	0.244	0.180
Variance extracted	40.13				55.24				46.67				35.79			
Redundancy	26.11				30.13				36.25				19.47			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

5.4. Relationship between GPA and First Canonical Variate

In this study, the first canonical variate was considered as a proxy indicator to judge the students' performance instead of real GPA based on number of credits and grade point as practiced in universities. Therefore, the strength of linearity between those two indicators were evaluated using Pearson correlation between GPA and first canonical variate of engineering modules in Level 2. The results for each case by disciplines are shown in Table 5.19.

Table 5.19: Pearson correlation between GPA and first canonical variate of engineering modules in Level 2

Discipline	2010		2011	
	S3	S4	S3	S4
CE	0.825	0.920	0.809	0.963
CH	0.881	0.974	0.895	0.972
CS	0.957	0.897	0.947	0.932
EE	0.895	0.954	0.898	0.817
EN	0.946	0.885	0.903	0.958
ME	0.911	0.707	0.791	0.948
MT	0.826	0.930	0.504	0.578

The coefficients of correlation reveal that there is a strong positive significant correlation (> 0.7) between GPA and first canonical variate derived from the marks in engineering modules in S3 and S4 in Level 2, for all engineering disciplines with exceptional in MT discipline for both academic years. This confirms that the first canonical variate of engineering modules in Level 2 can be considered as a good proxy estimator for the student actual engineering performance.

5.5. Chapter Summary

The combined impact of mathematics in Level 1 and Level 2 on students' engineering performance in two semesters in Level 2 is significant irrespective of the engineering disciplines and irrespective of two academic years considered in this study. The impact varied between disciplines. The impact of mathematics module in S1 in Level 1 is considerably lower compared with the impact of mathematics in S2 in Level 1 in all disciplines. Furthermore, impact of overall mathematics on the engineering performance in S4 is higher than the impact of overall mathematics on the engineering performance in S3 in all seven engineering disciplines. This can be occurred as there is a direct impact of mathematics in Level 1 (MA1013 and MA1023 modules) on mathematics performance in Level 2. Thus, the next chapter examines the individual impact of mathematics in Level 1 and Level 2 separately on the engineering performance in Level 2.

CHAPTER 6

SEPARATE IMPACT OF MATHEMATICS IN LEVEL 1 AND LEVEL 2

6.1. Introduction

In Chapter 5 the combined impact of mathematics in Level 1 and Level 2 was analyzed. However, in Section 5.5 it was highlighted the necessity of studying the impact of mathematics in Level 1 and in Level 2 separately as there can be a carry-over effect in Level 2 as Level 1 mathematics has already been taken by the students in Level 2. The two unexplored multivariate techniques (Mukuta and Harada, 2014) namely: (i) Part Canonical Correlation Analysis (Part CCA) and (ii) Partial Canonical Correlation Analysis (Partial CCA) are used to examine the separate individual impact of mathematics in Level 1 and Level 2.

The Part Canonical Correlation Analysis (Part CCA) is a statistical tool which used to determine a pair of linear projections on to a low dimensional space, where correlation between two multi-dimensional variables is maximized after eliminating influence of a third set of variables from one of the other two multi-dimensional variables. That is, Part CCA estimates the relationship between the two sets of variables, partialing out the linear effect of the third set of variables from one of the other two variable sets. Therefore, Part CCA is used to determine the relationship between students' mathematics performance in Level 1 and their engineering performance in Level 2 when the influence of mathematics in Level 2 is eliminated from engineering performance in Level 2.

The Partial Canonical Correlation Analysis (Partial CCA) approach allows to assess the partial independence of two sets of variables given a third set of variables. Therefore, Partial CCA was applied to identify the relationship between students' mathematics performance in Level 2 and their engineering performance in Level 2, after eliminating the effect of mathematics in Level 1 from both groups, as the students have already completed mathematics in Level 1 at Level 2.

As in chapter 5, the result of CH discipline is extensively discussed while the results of remaining engineering disciplines are briefly described. The analysis is done for two semesters: S3 and S4 in Level 2 separately in two academic years: 2010/2011 and 2011/2012.

6.2. Individual Impact of Mathematics in Level 1

The engineering modules in each semester in Level 2 are considered as the dependent set. The mathematics modules in Level 1 are the predictor set while mathematics modules in Level 2 are the control set, which eliminates its influence from the dependent set.

6.2.1. Impact on CH Student Performance

6.2.1.1. Academic Year 2010/2011 – S3

The undergraduates of CH discipline followed seven engineering modules and two mathematics modules in S3. Therefore, the dependent set contains seven engineering variables and the control set has two mathematics variables. The two mathematics modules in Level 1 are considered as the predictor set. The results of Part CCA for 2010 batch in S3 are presented in Table 6.1.

Table 6.1: Results of Part CCA – performance of CH in S3 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.328535	0.150947	0.102327	0.107935
2	0.260947	.	0.106897	0.068093

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.1210	0.0479	0.6235	0.6235	0.83132088	0.94	14	136	0.5181
2	0.0731		0.3765	1.0000	0.93190659	0.84	6	69	0.5432

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.83132088	0.94	14	136	0.5181
Pillai's Trace	0.17602881	0.95	14	138	0.5064
Hotelling-Lawley Trace	0.19406398	0.93	14	105.49	0.5270
Roy's Greatest Root	0.12099506	1.19	7	69	0.3186

By referring Wilks' lambda test statistic in Table 6.1, it can be seen that the first canonical variate pair of Part CCA is not statistically significant (p=0.518). That is, the first canonical variate pair is not sufficient to explain a significant amount of variability of the predictor set and dependent set. Furthermore, the first part canonical correlation found to be equal to 0.328 and squared canonical correlation indicates that only 10.8% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics in Level 1 when the effect of mathematics in Level 2 is eliminated from engineering performance.

Table 6.2 presents the standardized canonical coefficients, canonical loadings and canonical cross loadings for CH performance in S3.

Table 6.2: Standardized canonical coefficients and canonical structure - performance of CH in S3 (2010)

Measurements	Variable	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2042	0.4870	0.6755	0.2219
	CH2052	0.2591	0.6581	0.2162
	EE2802	0.1591	0.5730	0.1882
	EN2852	0.0124	0.3548	0.1166
	ME1822	-0.2488	0.0464	0.0152
	ME2012	0.6250	0.7061	0.2320
	ME2122	-0.3196	0.0778	0.0255
Mathematics	MA1013	-0.2689	0.2666	0.0876
	MA1023	1.1026	0.9720	0.3193

With reference to Table 6.2, the results of canonical loadings and canonical cross loadings for CH performance in S3 exhibit that the mathematics module in S1 (MA1013) and is weakly correlated with both first canonical variate of mathematics and first canonical variate of engineering. The canonical cross loading of 0.3193 suggests that MA1023 variable is also weakly correlated with first canonical variate of engineering after removing the effect of mathematics in Level 2 from engineering performance as the corresponding value has reduced from 0.5623 (Table 5.2) to 0.3193. Similar trend can be seen for MA1013. However, positive values of canonical cross loadings in both MA1013 and MA1023 suggest that there is impact of mathematics in Level 1 on engineering performance in S3 and S4 (in Level 2) evenafter the effect of mathematics in Level 2 is removed.

Table 6.3: Canonical Redundancy Analysis – performance of CH in S3 (2010)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.2643	0.2643	0.0285	0.0285
2	0.0936	0.3579	0.0064	0.0349

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.5079	0.5079	0.0548	0.0548
2	0.4921	1.0000	0.0335	0.0883

Based on the results of the part canonical redundancy analysis in Table 6.3, it can be concluded that amount of variability in engineering performance in S3 explained by the first canonical variate of mathematics is not sufficient (2.85%) when the effect of mathematics in Level 2 is removed from engineering performance. Apart from that the explainable variability of mathematics and engineering performance by its first canonical variate are 50.8% and 26.4% respectively.

6.2.1.2. Academic Year 2010/2011 – S4

As in the Section 6.2.1.1, the two mathematics modules in Level 1 is the predictor set. The dependent set contains five engineering variables (i.e. five engineering modules in S4) and the control set contains three mathematics variables (i.e. two mathematics modules in S3 and one mathematics module in S4).

The results of part canonical correlation and multivariate statistics for student performance in S4 are summarized in Table 6.4. The Wilks' lambda test statistic reflects that at least first canonical variate pair does not explain a significant amount of variability of the predictor and dependent sets. Moreover, part canonical correlation of 0.283 confirmed that the mathematics in Level 1 has a weak impact on engineering performance in S4 when the effect of mathematics in S3 and S4 is removed from engineering performance.

Table 6.4: Results of Part CCA – performance of CH in S4 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.283195	0.136568	0.105508	0.080199
2	0.202945	.	0.109983	0.041187

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.0872	0.0442	0.6699	0.6699	0.88191722	0.91	10	140	0.5279
2	0.0430		0.3301	1.0000	0.95881326	0.76	4	71	0.5532

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.88191722	0.91	10	140	0.5279
Pillai's Trace	0.12138592	0.92	10	142	0.5190
Hotelling-Lawley Trace	0.13014785	0.90	10	102.29	0.5337
Roy's Greatest Root	0.08719190	1.24	5	71	0.3005

Table 6.5 illustrates the standardized canonical coefficients, canonical loadings and canonical cross loadings for CH performance and it denotes that the mathematics module in S1 (MA1013) is weakly correlated with both first canonical variate of mathematics (0.204) and first canonical variate of engineering (0.058) as in Section 6.2.1.1. Besides that, MA1023 mathematics variable (in S2) is also weakly correlated with the first canonical variate of engineering (0.270). It is clear that the linear relationship between mathematics in Level 1 and engineering performance in S4 is significantly weak with the effect of mathematics in S3 and S4 partialed out of the dependent set of engineering performance.

Table 6.5: Standardized canonical coefficients and canonical structure – performance of CH in S4 (2010)

Measurements	Variables	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2062	0.6888	0.8996	0.2548
	CH2072	-0.0410	0.1188	0.0337
	CH2082	0.2879	0.6903	0.1955
	CH3092	-0.2250	0.4625	0.1310
	CH3102	0.4230	0.6868	0.1945
Mathematics	MA1013	-0.3402	0.2038	0.0577
	MA1023	1.1200	0.9548	0.2704

With respect to Table 6.6, the redundancy index of engineering found that the amount of variability in engineering performance in S4 explained by the first canonical variate of mathematics in Level 1 is 3.18%. It can be said that the real effect of mathematics in Level 1 is not sufficient to explain the engineering performance in S4.

Table 6.6: Canonical redundancy analysis – performance of CH in S4 (2010)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

	Their Own Canonical Variables		The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion
1	0.3971	0.3971	0.0318	0.0318
2	0.1268	0.5239	0.0052	0.0371

Standardized Variance of the Mathematics Measurements Explained by

	Their Own Canonical Variables		The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Proportion	Cumulative Proportion
1	0.4765	0.4765	0.0382	0.0382
2	0.5235	1.0000	0.0216	0.0598

6.2.1.3. Academic Year 2011/2012 – S3

The undergraduates of CH discipline followed four engineering modules and two mathematics modules in S3 in 2011/2012 academic year. The number of variables in each set of variables is four engineering variables in dependent set, two mathematics variables in Level 1 in predictor set and two mathematics variables in S3 in control set. Tables 6.7 to Table 6.9 provide the results of Part CCA for student academic performance in S3.

With reference to Wilks' lambda test statistic in Table 6.7, it is clear that the first canonical variate pair is not statistically significant (p=0.439). That is, the first part canonical variate pair is not sufficient to explain a significant amount of variability of the predictor set and dependent variable set.

Table 6.7: Results of Part CCA – performance of CH in S3 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.297521	0.194988	0.108943	0.088519
2	0.162431	0.111073	0.116369	0.026384

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.0971	0.0700	0.7818	0.7818	0.88743294	1.00	8	130	0.4394
2	0.0271		0.2182	1.0000	0.97361623	0.60	3	66	0.6197

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.88743294	1.00	8	130	0.4394
Pillai's Trace	0.11490252	1.01	8	132	0.4349
Hotelling-Lawley Trace	0.12421401	1.00	8	90.563	0.4415
Roy's Greatest Root	0.09711527	1.60	4	66	0.1841

The first part canonical correlation is found to be equal to 0.298 and it confirmed a weak relationship between mathematics in Level 1 and engineering performance when the effect of mathematics in Level 2 is eliminated from engineering performance. Moreover, the amount of variation in the canonical variate of engineering performance explained by the first canonical variate of the mathematics in Level 1 is 8.9%.

According to the values of standardized canonical coefficients and canonical loadings in Table 6.8, it can be said that CH2033 variable in engineering and MA1023 variable in mathematics are the most related variables. Moreover, canonical cross-loadings indicate that the observed variables in both predictor and dependent sets are weakly correlated with their opposite first canonical variate.

Table 6.8: Standardized canonical coefficients and canonical structure – performance of CH in S3 (2011)

Measurements	Variable	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2013	0.2586	0.4658	0.1386
	CH2023	0.0774	0.4061	0.1208
	CH2033	0.8854	0.9344	0.278
	ME2122	-0.3956	-0.0525	-0.0156
Mathematics	MA1013	-0.3025	0.3489	0.1038
	MA1023	1.1413	0.9687	0.2882

The results of the part canonical redundancy analysis for S3 are presented in Table 6.9 and it indicates that amount of variability in mathematics set (4.69%) and engineering set (2.78%) explained by their opposite canonical variate are not sufficient. Furthermore, the explainable variability of mathematics and engineering performance by its first canonical variate are 53% and 31.4% respectively.

Table 6.9: Canonical Redundancy Analysis – performance of CH in S3 (2011)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.3144	0.3144	0.0278	0.0278
2	0.2384	0.5529	0.0063	0.0341

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.5300	0.5300	0.0469	0.0469
2	0.4700	1.0000	0.0124	0.0593

6.2.1.4. Academic Year 2011/2012 – S4

In this analysis, five engineering variables are in dependent set and three mathematics variables in both S3 and S4 are in control set while the predictor set is two mathematics variables in Level 1.

Table 6.10: Results of Part CCA – performance of CH in S4 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.293193	0.168814	0.109248	0.085962
2	0.151964	0.046104	0.116763	0.023093

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.0940	0.0704	0.7991	0.7991	0.89292999	0.75	10	128	0.6803
2	0.0236		0.2009	1.0000	0.97690690	0.38	4	65	0.8192

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.89292999	0.75	10	128	0.6803
Pillai's Trace	0.10905514	0.75	10	130	0.6765
Hotelling-Lawley Trace	0.11768546	0.75	10	93.291	0.6799
Roy's Greatest Root	0.09404646	1.22	5	65	0.3087

The results of part canonical correlation and multivariate statistics are summarized in Table 6.10. By referring the Wilks' lambda test statistic, it can be seen that the first pair of canonical variate is not statistically significant (p=0.680). This implies that at least the first canonical variate pair does not explain a statistically significant amount of variability of the predictor and dependent sets.

Table 6.11: Standardized canonical coefficients and canonical structure – performance of CH in S4 (2011)

Measurements	Variable	Standardized Canonical Coefficients	Canonical Loadings	Canonical Cross Loadings
ENGINEERING	CH2043	0.7068	0.661	0.1938
	CH2053	0.5356	0.4831	0.1416
	CH2063	0.5287	0.3944	0.1156
	CH2073	-0.2661	0.0348	0.0102
	CH2083	-0.8819	-0.0848	-0.0249
MATHEMATICS	MA1013	0.0305	0.5911	0.1733
	MA1023	0.9823	0.9997	0.2931

The part canonical correlation (0.293) in Table 6.10 shows a weak linear relationship between mathematics in Level 1 and engineering performance in S4 with the effect of mathematics in Level 2 partialed out of the dependent set of engineering variables. In addition, first canonical variate of mathematics in Level 1 accounted for 8.6% of the variance of the first canonical variate of engineering.

Based on the results in Table 6.11, it is clear that, observed variables in both predictor and dependent sets are weakly correlated with their first canonical variate as well as with their opposite first canonical variate, when the effect of mathematics in Level 2 is eliminated from the dependent set of engineering variables.

Table 6.12: Canonical redundancy analysis – performance of CH in S4 (2011)

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.1668	0.1668	0.0143	0.0143
2	0.2969	0.4637	0.0069	0.0212

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.6744	0.6744	0.0580	0.0580
2	0.3256	1.0000	0.0075	0.0655

Table 6.12 illustrates the part canonical redundancy analysis of student performance in S4. The redundancy index of engineering found that the amount of variability in engineering performance in S4 explained by the first canonical variate of mathematics in Level 1 is 1.4%.

6.2.2. Impact on CE Student Performance

A similar procedure was carried out to find the individual impact of mathematics in Level 1 on students' engineering performance of the remaining engineering disciplines for two semesters in Level 2 separately. As in Section 5.2, the results of Part CCA are also summarized mainly focusing on the first pair of canonical variate. Table 6.13 depicts the summary of Part CCA results for each semester (S3 and S4) in two academic years.

6.2.2.1. Academic Year 2010/2011 – S3

With reference to Wilks' lambda test statistics of S3 in 2010/2011 academic year (in Table 6.13), it can be said that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent set. The part canonical correlation reflects that mathematics in Level 1 has a slightly weak impact on engineering performance in S3 (0.438) with the effect of mathematics in S3 partialed out of engineering variables. It can be seen that the mathematics module in S1 (MA1013) is weakly correlated with both first canonical variate of mathematics (0.352) and first canonical variate of engineering (0.154). The canonical redundancy index of engineering suggests that 7.18% of the total variance of engineering performance in S3 can be explained by the first canonical variate of mathematics.

6.2.2.2. Academic Year 2010/2011 – S4

The Wilks' lambda test statistics of S4 in academic year 2010/2011 implies that the first part canonical variate pair is not sufficient to explain a significant amount of variability of the predictor set and dependent variable set (p=0.212). The part canonical correlation confirmed that the mathematics in Level 1 is weakly correlated with the engineering performance in S4 (0.259) when the effect of mathematics in S3 and S4 is eliminated from engineering performance. The MA1013 mathematics variable denotes a negative relationship with engineering performance in S4 which cannot be acceptable. The proportion of variance explained by the first canonical variate of mathematics is 2.28% of engineering performance in S4.

6.2.2.3. Academic Year 2011/2012 – S3

By referring the Wilks' lambda test statistic of S3 in academic year 2011/2012, it is clear that the first pair of canonical variate is not statistically significant (p=0.217). Furthermore, part canonical correlation indicates that the linear relationship between students' mathematics performance and their engineering performance in S3 is significantly weak (0.292) when the effect of mathematics in S3 is eliminated from engineering performance. The first canonical variate of mathematics (in Level 1) can be explained only 2.35% of the total variance of engineering performance in S3 after adjusted for mathematics in S3 from engineering performance.

Table 6.13: Results of first pair of part canonical variate – CE student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.438				0.292				0.259				0.146			
Squared canonical correlation	0.192				0.085				0.067				0.021			
Wilks' Lambda	0.761				0.879				0.889				0.97			
P-value	0.002				0.217				0.212				0.962			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE2012	0.212	0.495	0.217	CE2012	0.389	0.579	0.169	CE2112	-0.536	0.055	0.014	CE2112	0.461	0.724	0.106
	CE2022	-0.288	0.383	0.168	CE2022	0.263	0.214	0.063	CE2122	0.563	0.754	0.195	CE2122	0.392	0.518	0.076
	CE2032	0.773	0.922	0.404	CE2032	-0.167	0.007	0.002	CE2132	0.182	0.537	0.139	CE2132	0.632	0.717	0.105
	CE2042	0.287	0.696	0.305	CE2042	0.433	0.745	0.218	CE2142	0.458	0.686	0.178	CE2142	-0.382	-0.038	-0.006
	CE2052	0.115	0.518	0.227	CE2052	0.035	0.365	0.107	CE3012	0.32	0.603	0.156	CE3012	-0.13	0.032	0.005
	CE2062	0.068	0.499	0.219	CE2062	0.505	0.76	0.222								
Variance extracted	37.37				27.48				33.91				26.18			
Redundancy	7.18				2.35				2.28				0.56			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.156	0.352	0.154	MA1013	-0.272	0.045	0.013	MA1013	-0.835	-0.32	-0.083	MA1013	-0.566	-0.26	-0.038
	MA1023	1.065	0.991	0.434	MA1023	1.048	0.966	0.282	MA1023	1.078	0.68	0.176	MA1023	1.013	0.842	0.123
Variance extracted	55.27				46.74				28.22				38.82			
Redundancy	10.61				3.99				1.89				0.83			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

6.2.2.4. Academic Year 2011/2012 – S4

According to the results Part CCA for S3 student performance in academic year 2011/2012 in Table 6.13, Wilks' lambda test statistics confirmed that at least first canonical variate pair is not sufficient to explain a significant amount of variability of both predictor and dependent sets. The part canonical correlation implies that the impact of mathematics in Level 1 on engineering performance in S4 is significantly weak when the effect of mathematics in S3 and S4 is removed from engineering performance (0.146).

6.2.3. Impact on Student Performance in Other Disciplines

As in Section 5.3, the results of Part CCA for student academic performance in other five disciplines are summarized mainly focusing on the first pair of canonical variate in each semester for two academic years. The summary results for the five disciplines: CS, EE, EN, ME and MT are shown in Tables 6.14 to 6.18 respectively.

6.2.3.1. Impact on CS Student Performance

With reference to Table 6.14, the first pair of canonical variate of the four cases are not statistically significant ($p>0.05$) which reflect at least the first pair of canonical variate is inadequate to explain a significant amount of variance in both predictor and dependent sets. The part canonical correlation exhibits that there is a weak linear relationship between students' mathematics performance and their engineering performance in Level 2, after adjusted for mathematics in Level 2 from engineering performance for both academic years in S3 and S4 in Level 2 as the first part canonical correlation between mathematics measurements and engineering measurements for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) are 0.363, 0.388, 0.350 and 0.377. Moreover, the amount of variance in engineering performance in Level 2 (S3 and S4) explained by the first part canonical variate of mathematics is less than 5% for both academic years.

6.2.3.2. Impact on EE Student Performance

The results of Part CCA for EE student academic performance in each semester for two academic years are provided in Table 6.15. Based on the Wilks' lambda test statistics, it can be said that at least the first canonical variate pair is not sufficient to explain a significant amount of variability of both predictor and dependent sets for all four cases. The results of part canonical correlation in all four cases: S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) the students' mathematics performance is weakly correlated with their corresponding engineering performance when the effect of mathematics in Level 2 is removed from engineering performance for both academic years in S3 and S4 in Level 2. The squared canonical correlation varied from 15% in S4 (2010/2011) to 8% in S3 (2011/2012).

6.2.3.3. Impact on EN Student Performance

According to the results in Table 6.16 it can be seen that at least the first pair of canonical variate is inadequate to explain a significant amount of variance in both predictor and dependent sets for all cases except S4 in 2011/2012 academic year. The first part canonical correlation between mathematics performance and engineering performance after adjusted for mathematics in Level 2 from engineering performance for both academic years in S3 and S4 in Level 2 are 0.300, 0.339, 0.290 and 0.315 respectively for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) and therefore corresponding squared canonical correlation are 9.0%, 11.5%, 8.4% and 9.9%. It can be said that mathematics in Level 1 has a weak impact on engineering performance in Level 2, when the effect of mathematics in Level 2 is removed from engineering performance.

6.2.3.4. Impact on ME Student Performance

With respect to Table 6.17, the Wilks' lambda test statistics confirmed that the first pair of canonical variates are not statistically significant ($p>0.05$) for all cases except the S3 student performance in 2010/2011 academic year. The first part canonical correlation between mathematics performance and their engineering performance, when the effect of mathematics in Level 2 is removed from engineering performance in Level 2 are 0.424 ($p=0.026$), 0.415 ($p=0.167$), 0.401 ($p=0.067$) and 0.284

(p=0.416) for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) respectively. It can be concluded that the actual individual effect of mathematics in Level 1 on engineering performance in Level 2 is slightly weak for all cases except the S4 student performance in 2011/2012 academic year.

6.2.3.5. Impact on MT Student Performance

The results in Table 6.18 showed that the first pair of canonical variates are not statistically significant (p>0.05) which reflects first canonical variate is inadequate to explain a significant amount of variance in both predictor and dependent sets for all cases except the S3 student performance in 2010/2011 academic year. It can be seen that student mathematics performance has moderately strong impact on engineering performance in Level 2, after adjusted for mathematics in Level 2 from engineering performance. The first part canonical correlation between mathematics performance and their engineering performance, when the effect of mathematics in Level 2 is removed from engineering performance in Level 2 are 0.649 (p=0.019), 0.551 (p=0.304), 0.536 (p=0.313) and 0.472 (p=0.483) for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) respectively.

Table 6.14: Results of first pair of part canonical variate – CS student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.363				0.388				0.350				0.377			
Squared canonical correlation	0.132				0.150				0.123				0.142			
Wilks' Lambda	0.860				0.841				0.836				0.845			
P-value	0.327				0.217				0.182				0.238			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE1822	0.198	0.443	0.161	CE1822	-0.150	0.137	0.053	CS3022	0.792	0.880	0.308	CS3022	0.019	0.403	0.152
	CS2032	0.115	0.480	0.174	CS2032	0.022	0.547	0.212	CS3032	0.236	0.576	0.202	CS3032	0.186	0.575	0.217
	CS2042	0.096	0.456	0.166	CS2042	0.376	0.734	0.285	CS3042	0.394	0.654	0.229	CS3042	0.169	0.521	0.196
	CS2062	0.456	0.717	0.261	CS2062	0.306	0.544	0.211	CS3242	-0.130	0.269	0.094	CS3242	0.275	0.453	0.171
	EN2022	0.185	0.449	0.163	EN2022	0.657	0.822	0.319	EN2062	-0.260	0.153	0.054	EN2062	0.763	0.881	0.332
	ME1822	0.531	0.760	0.276	ME1822	0.073	0.352	0.136	ME1802	-0.045	0.338	0.119	ME1802	0.003	0.305	0.115
Variance extracted	32.12				32.55				29.05				30.62			
Redundancy	4.24				4.9				3.57				4.35			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.204	0.219	0.079	MA1013	-0.061	0.299	0.116	MA1013	-0.792	-0.394	-0.138	MA1013	-0.150	0.217	0.082
	MA1032	1.063	0.982	0.357	MA1032	1.020	0.998	0.387	MA1032	1.001	0.687	0.241	MA1032	1.043	0.990	0.373
Variance extracted	50.64				54.31				31.36				51.37			
Redundancy	6.69				8.17				3.85				7.3			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.15: Results of first pair of part canonical variate – EE student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.342				0.284				0.383				0.359			
Squared canonical correlation	0.117				0.081				0.147				0.129			
Wilks' Lambda	0.819				0.897				0.816				0.837			
P-value	0.576				0.757				0.560				0.162			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2012	0.261	0.481	0.165	CE1822	0.479	0.722	0.205	EE2042	-0.106	0.087	0.033	EE2043	-0.774	-0.373	-0.134
	EE2022	0.190	0.580	0.199	EE2013	0.353	0.653	0.185	EE2052	0.216	0.322	0.123	EE2053	0.012	-0.002	-0.001
	EE2033	-0.196	-0.067	-0.023	EE2023	-0.029	0.158	0.045	EE2072	0.255	0.352	0.135	EE2063	-0.295	-0.150	-0.054
	EN2012	0.010	0.509	0.174	EE2033	0.137	0.558	0.158	EE2083	0.112	0.198	0.076	EE2073	0.545	0.547	0.196
	EN2022	0.599	0.863	0.295	EN2012	0.222	0.515	0.146	EE2132	0.429	0.267	0.102	EE2083	0.396	0.270	0.097
	ME2012	0.217	0.516	0.177	EN2022	0.061	0.426	0.121	EE3072	0.832	0.787	0.301	ME2842	0.576	0.456	0.164
	CE1822	0.221	0.529	0.181	ME2012	0.339	0.624	0.177	ME2842	-0.700	-0.083	-0.032				
Variance extracted	30.33				30.27				13.88				12.35			
Redundancy	3.55				2.44				2.03				1.59			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.349	0.031	0.010	MA1013	0.111	0.407	0.116	MA1013	-0.208	0.167	0.064	MA1013	-0.851	-0.589	-0.212
	MA1023	1.069	0.945	0.324	MA1023	0.960	0.994	0.282	MA1023	1.055	0.981	0.376	MA1023	0.850	0.587	0.211
Variance extracted	44.73				57.72				49.51				34.59			
Redundancy	5.24				4.65				7.25				4.46			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.16: Results of first pair of part canonical variate – EN student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.300				0.339				0.290				0.315			
Squared canonical correlation	0.090				0.115				0.084				0.099			
Wilks' Lambda	0.865				0.880				0.912				0.842			
P-value	0.200				0.312				0.374				0.146			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2092	-0.036	0.476	0.143	EE2092	-0.306	0.098	0.033	EN2072	0.517	0.424	0.123	EN2072	0.436	0.567	0.179
	EN2012	0.596	0.709	0.212	EN2012	-0.632	-0.139	-0.047	EN2082	0.753	0.606	0.176	EN2082	0.569	0.696	0.262
	EN2022	0.398	0.573	0.172	EN2022	-0.066	0.115	0.039	EN2142	-0.793	-0.409	-0.119	EN2142	0.772	0.841	0.265
	EN2052	-0.188	0.265	0.080	EN2052	0.664	0.565	0.191	EN3022	-0.006	-0.064	-0.019	EN3022	-0.348	-0.203	-0.064
	EN2062	0.571	0.730	0.219	EN2062	0.755	0.761	0.258								
Variance extracted	33.2				18.8				17.96				27.73			
Redundancy	2.98				2.16				1.51				3.86			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.817	0.939	0.281	MA1013	-0.307	0.055	0.019	MA1013	0.933	0.988	0.286	MA1013	0.864	0.941	0.297
	MA1023	0.365	0.638	0.191	MA1023	1.062	0.958	0.325	MA1023	0.163	0.476	0.138	MA1023	0.360	0.403	0.101
Variance extracted	64.47				45.99				60.14				44.29			
Redundancy	5.79				5.29				5.05				4.40			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.17: Results of first pair of part canonical variate – ME student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.424				0.415				0.401				0.284			
Squared canonical correlation	0.180				0.173				0.161				0.081			
Wilks' Lambda	0.778				0.810				0.830				0.893			
P-value	0.026				0.167				0.067				0.416			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	0.042	0.327	0.139	EE2803	-0.270	0.302	0.126	ME2032	0.742	0.807	0.324	ME2032	0.646	0.745	0.211
	EN2852	0.166	0.387	0.164	EN2852	0.791	0.916	0.381	ME3072	-0.008	0.285	0.114	ME2153	0.331	0.567	0.161
	ME2012	-0.168	0.186	0.079	ME2012	0.059	0.319	0.132	ME3032	0.522	0.630	0.253	ME3032	0.425	0.613	0.174
	ME2022	0.030	0.405	0.172	ME2023	0.030	0.530	0.220	ME3062	-0.409	0.119	0.048	ME3062	-0.396	-0.019	-0.006
	ME2092	0.968	0.954	0.404	ME2092	0.077	0.360	0.150	ME2142	0.293	0.421	0.169	ME3073	0.145	0.434	0.123
	ME2112	0.070	0.252	0.107	ME2112	0.158	0.421	0.175								
					ME2602	0.339	0.674	0.280								
Variance extracted	23.81				29.61				26.42				28.82			
Redundancy	4.28				5.11				4.26				2.32			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	0.342	0.619	0.263	MA1013	-0.474	-0.189	-0.079	MA1013	0.929	0.987	0.396	MA1013	-0.421	-0.134	-0.038
	MA1023	0.833	0.947	0.401	MA1023	1.023	0.891	0.370	MA1023	0.173	0.482	0.194	MA1023	1.032	0.914	0.260
Variance extracted	63.97				41.43				60.29				42.7			
Redundancy	11.5				7.15				9.71				3.44			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.18: Results of first pair of part canonical variate – MT student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.649				0.551				0.536				0.472			
Squared canonical correlation	0.421				0.303				0.287				0.223			
Wilks' Lambda	0.506				0.653				0.632				0.741			
P-value	0.019				0.304				0.313				0.483			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	-0.075	0.315	0.204	EE2803	0.248	0.382	0.210	ME2142	0.259	0.290	0.156	ME2832	-0.125	0.223	0.105
	EN2852	-0.548	0.214	0.139	EN2852	-0.164	0.344	0.189	ME2832	-0.182	0.477	0.256	ME2850	-0.717	0.184	0.087
	ME1822	0.146	0.005	0.003	ME1822	-0.739	-0.387	-0.213	ME3062	-0.424	-0.186	-0.100	ME3062	0.097	0.295	0.139
	ME2012	-0.009	0.163	0.106	ME2012	0.650	0.636	0.350	MT2032	0.895	0.912	0.489	MT2032	0.254	0.554	0.262
	MT2042	1.844	0.822	0.533	MT2042	0.688	0.437	0.240	MT2072	0.266	0.789	0.423	MT2072	-0.186	0.601	0.284
	MT2122	-0.766	0.488	0.317	MT2122	-0.372	0.005	0.003	MT2142	0.015	0.521	0.280	MT2142	1.290	0.854	0.403
					MT2152	-0.136	0.266	0.146	MT2152	-0.149	0.683	0.366				
Variance extracted	18.09				15.42				36.27				26.15			
Redundancy	7.62				4.68				10.42				5.83			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA1013	-0.954	-0.605	-0.393	MA1013	-0.882	-0.409	-0.225	MA1013	-1.004	-0.686	-0.368	MA1013	-1.075	-0.709	-0.335
	MA1023	0.869	0.487	0.316	MA1023	1.028	0.622	0.343	MA1023	0.794	0.392	0.210	MA1023	0.795	0.300	0.142
Variance extracted	30.15				27.7				31.19				29.62			
Redundancy	12.7				8.41				8.96				6.6			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

6.3. Individual Impact of Mathematics in Level 2

The Partial Canonical Correlation Analysis (Partial CCA) approach allows to assess the partial independence of two sets of variables given a third set of variables. Therefore, Partial CCA was applied to identify the relationship between students' mathematics performance in Level 2 and their engineering performance in Level 2, after eliminating the effect of mathematics in Level 1 from both groups, as the students have already completed mathematics in Level 1 at Level 2. The dependent set is the engineering modules in each semester in Level 2. The mathematics modules in Level 2 are the predictor set while mathematics modules in Level 1 are considered as the control set.

6.3.1. Impact on CH Student Performance

6.3.1.1. Academic Year 2010/2011 – S3

As in Section 6.2.1.1, the dependent variable set contains seven engineering variables. The predictor set has two mathematics variables (MA2013 and MA2023) while the control set also contains two mathematics variables (MA1013 and MA1023). The results of Partial CCA and multivariate statistics for 2010 batch in S3 are presented in Table 6.19.

Table 6.19: Results of Partial CCA – performance of CH in S3 (2010)

Canonical Correlation Analysis Based on Partial Correlations

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.671732	0.633658	0.063794	0.451224
2	0.329880	0.246965	0.103597	0.108821

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.8222	0.7001	0.8707	0.8707	0.48905776	4.05	14	132	<.0001
2	0.1221		0.1293	1.0000	0.89117937	1.36	6	67	0.2422

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.48905776	4.05	14	132	<.0001
Pillai's Trace	0.56004473	3.72	14	134	<.0001
Hotelling-Lawley Trace	0.94434602	4.40	14	102.29	<.0001
Roy's Greatest Root	0.82223746	7.87	7	67	<.0001

The results in Table 6.19 denotes that out of two canonical variate pairs only the first canonical variate pair is statistically significant ($p < 0.001$) according to Wilks' lambda test statistic. It implies that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set when the effect of mathematics in Level 1 is eliminated from both mathematics and engineering performance in Level 2.

The first partial canonical correlation found to be equal to 0.671 and squared canonical correlation indicates that only 45.1% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics in Level 2 after removing the effect of mathematics in Level 1 from both mathematics and engineering performance in Level 2.

Table 6.20: Standardized canonical coefficients and canonical structure – performance of CH in S3 (2010)

Measurements	Variable	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2042	0.2602	0.7514	0.5048
	CH2052	0.2582	0.7852	0.5274
	EE2802	0.5670	0.8173	0.5490
	EN2852	-0.3581	0.2644	0.1776
	ME1822	-0.0713	0.3154	0.2119
	ME2012	0.3044	0.7143	0.4798
	ME2122	0.0705	0.5390	0.3621
Mathematics	MA2013	0.5473	0.6875	0.4618
	MA2023	0.7396	0.8433	0.5665

Based on the results of standardized canonical coefficients, canonical loadings and canonical cross loadings for CH performance in S3 in Table 6.20, it can be seen that both mathematics modules, MA2013 and MA2023 are significantly correlated with its first canonical variate of mathematics. Moreover, both mathematics modules are moderately correlated with first canonical variate of engineering.

Table 6.21: Canonical Redundancy Analysis – performance of CH in S3 (2010)

Canonical Redundancy Analysis Based on Partial Correlations

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	0.4027	0.4027	0.1817	0.1817
2	0.1055	0.5082	0.0115	0.1932

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite anonical Variables Proportion	The Opposite anonical Variables Cumulative Proportion
1	0.5919	0.5919	0.2671	0.2671
2	0.4081	1.0000	0.0444	0.3115

With reference to Table 6.21, the results of the part canonical redundancy analysis exhibits that amount of variability in engineering performance in S4 explained by the first canonical variate of mathematics is not sufficient (18.17%). Apart from that the explainable variability of mathematics and engineering performance by its first canonical variate are 59.2% and 40.3% respectively.

6.3.1.2. Academic Year 2010/2011 – S4

The dependent set comprises five engineering variables (i.e. five engineering modules in S4) while the predictor set and the control set contain three mathematics modules in Level 2 (i.e. MA2013 and MA2023 in S3 and MA2033 in S4) and two mathematics modules in Level 1.

The results of partial canonical correlation and multivariate statistics for student performance in S4 are summarized in Table 6.22. The Wilks' lambda test statistic reflects that only the first canonical variate pair explains a significant amount of variability of the predictor and dependent sets.

Table 6.22: Results of Partial CCA – performance of CH in S4 (2010)

Canonical Correlation Analysis Based on Partial Correlations

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.691400	0.659168	0.063298	0.478034
2	0.277193	0.146514	0.111950	0.076836
3	0.189284	.	0.116923	0.035828

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.9158	0.8326	0.8838	0.8838	0.46459549	3.60	15	168.8	<.0001
2	0.0832	0.0461	0.0803	0.9641	0.89008848	0.93	8	124	0.4950
3	0.0372		0.0359	1.0000	0.96417153	0.78	3	63	0.5093

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.46459549	3.60	15	168.8	<.0001
Pillai's Trace	0.59069892	3.09	15	189	0.0002
Hotelling-Lawley Trace	1.03622633	4.15	15	110.09	<.0001
Roy's Greatest Root	0.91583537	11.54	5	63	<.0001

Partial canonical correlation of 0.691 confirmed that the mathematics in S3 and S4 in Level 2 has a significant impact on engineering performance in S4 when the effect of mathematics in Level 1 is removed from both engineering performance in S4 as well as mathematics performance in S3 and S4. Moreover, the first canonical variate of mathematics accounted for 47.8% of the variance in the first canonical variate of engineering performance.

Table 6.23: Standardized canonical coefficients and canonical structure – performance of CH in S4 (2010)

Measurements	**Variable**	**Standardized Canonical Coefficients**	**Canonical loadings**	**Canonical Cross loadings**
Engineering	CH2043	0.2284	0.7381	0.5103
	CH2053	0.1040	0.8277	0.5723
	CH2063	-0.0324	0.8233	0.5692
	CH2073	0.3377	0.8957	0.6193
	CH2083	0.4946	0.9495	0.6565
Mathematics	MA2013	0.1737	0.7522	0.5201
	MA2023	0.2271	0.6725	0.4650
	MA2033	0.7474	0.9589	0.6630

By referring Table 6.23, the standardized canonical coefficients denote that out of coefficients related to engineering only one engineering variable (CH2063) are close to zero. Besides that, the mathematics module in S4 (MA2033) has a significantly strong correlation with first canonical variate of mathematics (0.959). Furthermore, all mathematics modules in Level 2 are moderately correlated with first canonical variate of engineering when the effect of mathematics in Level 1 partialed out of the both engineering performance in S4 and mathematics performance in Level 2 (S3 and S4).

Table 6.24: Canonical redundancy analysis – performance of CH in S4 (2010)

Standardized Variance of the Engineering Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.7223	0.7223	0.3453	0.3453
2	0.0642	0.7865	0.0049	0.3502
3	0.0586	0.8451	0.0021	0.3523

Standardized Variance of the Mathematics Measurements Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	0.6458	0.6458	0.3087	0.3087
2	0.1612	0.8070	0.0124	0.3211
3	0.1930	1.0000	0.0069	0.3280

According to the results of Table 6.24, the redundancy index of engineering found that the amount of variability in engineering performance in S4 explained by the first canonical variate of mathematics in Level 2 is 34.53%. It can be said that the mathematics in Level 2 has sufficient real effect to explain the engineering performance in S4.

6.3.1.3. Academic Year 2011/2012 – S3

The analysis comprises two mathematics variables in S3 as the predictor set, four engineering variables in S3 as the dependent set and two mathematics variables in both S1 and S2 (in Level 1) as the control set, which eliminates its influence from both predictor and dependent sets. Table 6.25 presents the results of partial canonical correlation and multivariate statistics for student academic performance in S3.

Table 6.25: Results of Partial CCA – performance of CH in S3 (2011)

Canonical Correlation Analysis Based on Partial Correlations

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.662320	0.639266	0.068072	0.438667
2	0.219113	0.161161	0.115446	0.048010

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.7815	0.7310	0.9394	0.9394	0.53438299	5.80	8	126	<.0001
2	0.0504		0.0606	1.0000	0.95198955	1.08	3	64	0.3657

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.53438299	5.80	8	126	<.0001
Pillai's Trace	0.48667762	5.15	8	128	<.0001
Hotelling-Lawley Trace	0.83190598	6.49	8	87.707	<.0001
Roy's Greatest Root	0.78147428	12.50	4	64	<.0001

It is clear that out of two canonical variate pairs only the first canonical variate pair is statistically significant ($p < 0.001$). It suggests that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. The four multivariate statistics confirmed that the canonical correlations are significantly different from zero ($p < 0.001$) which indicates that there is a linear relationship between the mathematics and engineering performance.

As the effect of mathematics in Level 1 is statistically controlled by partial canonical correlation, the results confirmed that the mathematics in S3 has a moderately strong relationship with the engineering performance in S3 (0.662). The squared canonical correlation indicates that 43.8% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics in S3. It can be said that even after adjusting for mathematics in Level 1, there is a significant effect of mathematics in S3 on engineering performance in S3.

The results of standardized canonical coefficients, canonical loadings and canonical cross loadings for CH performance in S3 are summarized in Table 6.26.

Table 6.26: Standardized canonical coefficients and canonical structure – performance of CH in S3 (2011)

Measurements	Variable	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2013	0.6019	0.9254	0.6129
	CH2023	0.1548	0.7346	0.4866
	CH2033	0.4219	0.8448	0.5595
	ME2122	-0.0510	0.5303	0.3512
Mathematics	MA2013	0.6801	0.9276	0.6143
	MA2023	0.4482	0.8237	0.5456

The results of canonical coefficients denote that ME2122 engineering variable (-0.051) is close to zero which implies ME2122 is weakly important to first canonical variate of engineering. Canonical loadings reflect that both MA2013 and MA2023 mathematics variables are significantly correlated with both first canonical variate of mathematics and engineering performance. Considering the canonical cross-loadings, ME2122 variable is weakly related with the first canonical variate of mathematics (0.351). Therefore, it is clear that ME2122 engineering variable has the least association with mathematics in S3 as revealed by the standardized canonical coefficients and canonical loadings.

Table 6.27 provides the results of partial canonical redundancy analysis for S3. The redundancy measure of engineering reflects that the first canonical variate of mathematics performance accounted for 26.2% of the total variance of student engineering performance in S3. The explainable variability of performance in mathematics by its first canonical variate is 76.9%, while the proportion of variance in student engineering performance explained by its first canonical variate is 59.7%. These redundancy coefficients denote that the variability of mathematics performance in S3 explained by its first canonical variate is higher compared with the variability of student engineering performance in S3 explained by its first canonical variate.

Table 6.27: Canonical redundancy analysis – performance of CH in S3 (2011)

Canonical Redundancy Analysis

Variance of the ENG Variables Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	59.7470	59.7470	26.1759	26.1759
2	13.9709	73.7179	.6677	26.8436

Variance of the MAT Variables Explained by

Canonical Variable Number	Their Own Canonical Variables Proportion	Their Own Canonical Variables Cumulative Proportion	The Opposite Canonical Variables Proportion	The Opposite Canonical Variables Cumulative Proportion
1	76.9339	76.9339	33.7057	33.7057
2	23.0661	100.0000	1.1023	34.8080

6.3.1.4. Academic Year 2011/2012 – S4

The set of dependent variables is the engineering modules in S4 and it consists of five engineering variables. The set of predictor variables is the three mathematics variables in both S3 and S4 (in Level 2) and the control set is the two mathematics variables in Level 1. The results of partial canonical correlation and multivariate statistics with the effect of mathematics in Level 1 partialed out of both predictor and dependent sets are shown in Table 6.28.

Table 6.28: Results of Partial CCA – performance of CH in S4 (2011)

Canonical Correlation Analysis Based on Partial Correlations

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.691400	0.659168	0.063298	0.478034
2	0.277193	0.146514	0.111950	0.076836
3	0.189284	.	0.116923	0.035828

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.9158	0.8326	0.8838	0.8838	0.46459549	3.60	15	168.8	<.0001
2	0.0832	0.0461	0.0803	0.9641	0.89008848	0.93	8	124	0.4950
3	0.0372		0.0359	1.0000	0.96417153	0.78	3	63	0.5093

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.46459549	3.60	15	168.8	<.0001
Pillai's Trace	0.59069892	3.09	15	189	0.0002
Hotelling-Lawley Trace	1.03622633	4.15	15	110.09	<.0001
Roy's Greatest Root	0.91583537	11.54	5	63	<.0001

These results show that only the first of three canonical variate pairs is statistically significant ($p<0.001$) which implies that a significant amount of variability of predictor and dependent sets can be explained by the first canonical variate pair. In other words, the second and third canonical variant pairs cannot be relied upon to describe the data. Furthermore, multivariate statistics revealed that the canonical correlation is not zero ($p<0.001$) which indicates that there is a linear relationship between the mathematics in both S3 and S4 with engineering performance in S4 after eliminating the influence of mathematics in Level 1 from both sets.

According to Table 6.28, the first partial canonical correlation of 0.691 denotes that the students' mathematics performance in both S3 and S4 has a moderately strong linear relationship with their engineering performance in S4. Moreover, the first canonical variate of mathematics accounted for 47.8% of the variance in the first canonical variate of engineering performance. It is clear that, there is a significant influence of mathematics in both S3 and S4 on students' engineering performance in S4 even after the effect of mathematics in Level 1 is removed from both sets.

Table 6.29: Standardized canonical coefficients and canonical structure – performance of CH in S4 (2011)

Measurements	Variable	Standardized Canonical Coefficients	Canonical loadings	Canonical Cross loadings
Engineering	CH2043	0.2284	0.7381	0.5103
	CH2053	0.1040	0.8277	0.5723
	CH2063	-0.0324	0.8233	0.5692
	CH2073	0.3377	0.8957	0.6193
	CH2083	0.4946	0.9495	0.6565
Mathematics	MA2013	0.1737	0.7522	0.5201
	MA2023	0.2271	0.6725	0.4650
	MA2033	0.7474	0.9589	0.6630

With reference to standardized canonical coefficients in Table 6.29, the CH2063 engineering variable is close to zero. Besides that, canonical coefficient of MA2033 mathematics variable implies that mathematics variable in S4 is the most important, influential predictor of engineering performance in S4. Based on the canonical loadings it can be said that both mathematics and engineering variables are equally and strongly related with their first canonical variate (>0.65), though the effect of mathematics in Level 1 is removed from both groups. The values of canonical cross-loadings vary from 0.46 to 0.66 and it denotes that all mathematics and engineering variables have a moderately strong linear relationship with the opposite first canonical variate.

Table 6.30: Canonical redundancy analysis – performance of CH in S4 (2011)

Canonical Redundancy Analysis

Variance of the ENG Variables Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	72.2146	72.2146	34.5008	34.5008
2	6.4289	78.6436	.4947	34.9955
3	5.8455	84.4891	.2107	35.2062

Variance of the MAT Variables Explained by

Canonical Variable Number	Their Own Canonical Variables: Proportion	Their Own Canonical Variables: Cumulative Proportion	The Opposite Canonical Variables: Proportion	The Opposite Canonical Variables: Cumulative Proportion
1	64.5792	64.5792	30.8529	30.8529
2	16.1275	80.7069	1.2410	32.0939
3	19.2933	100.0000	.6954	32.7894

According to the results of redundancy indices in Table 6.30, the proportion of variance in engineering performance in S4 explained by the first canonical variate of mathematics in both S3 and S4 is 34.5% and it can be concluded that a considerable amount of variability in student engineering performance in S4 can be explained by the mathematics performance in Level 2 (both S3 and S4) after adjusted for mathematics in Level 1 from both sets. Furthermore, the variability of engineering performance as well as the variability of mathematics performance explained by its first canonical variate is 72.2% and 64.6% respectively.

6.3.2. Impact on CE Student Performance

As in Section 6.3.2, the analysis was continued to find the individual impact of mathematics in Level 2 on students' engineering performance of the remaining engineering disciplines for two semesters, S3 and S4 in Level 2 separately. The results of Partial CCA are also summarized mainly focusing on the first pair of canonical variate.

Table 6.31 depicts the summary of Partial CCA results for each semester (S3 and S4) in two academic years. With reference to Wilks' lambda test statistics of S3 in 2010/2011 academic year (in Table 6.31), it can be seen that the first pair of canonical variate is sufficient to explain a significant amount of variance of both predictor and dependent sets for all cases except S3 in 2010/2011 academic year.

6.3.2.1. Academic Year 2010/2011 – S3

The partial canonical correlation reflects that mathematics in S3 has a weak impact on engineering performance in S3 (0.280) with the effect of mathematics in Level 1 partialed out of both engineering and mathematics variables. It can be seen that MA2023 mathematics module is close to zero. The canonical redundancy index of engineering suggests that 1.43% of the total variance of engineering performance in S3 can be explained by the first canonical variate of mathematics when the effect of mathematics in Level 1 is removed from both engineering and mathematics performance in S3.

6.3.2.2. Academic Year 2010/2011 – S4

The partial canonical correlation confirmed that the mathematics in S3 and S4 is moderately correlated with the engineering performance in S4 (0.686) when the effect of mathematics in Level 1 is eliminated from both engineering and mathematics performance. The MA2033 mathematics variable is the most important, influential predictor of engineering performance in S4. The proportion of variance explained by the first canonical variate of mathematics is 23.6% of engineering performance in S4.

6.3.2.3. Academic Year 2011/2012 – S3

The partial canonical correlation indicates that the linear relationship between students' mathematics performance and their engineering performance in S3 is slightly weak (0.448) when the effect of mathematics in Level 1 is eliminated from both engineering and mathematics performance in S3. The first canonical variate of mathematics in S3 can be explained only 5.26% of the total variance of engineering performance in S3 after adjusted for mathematics in Level 1 from both engineering and mathematics performance in S3.

6.3.2.4. Academic Year 2011/2012 – S4

The partial canonical correlation for S4 in academic year 2011/2012 in Table 6.31 shows that the impact of mathematics in Level S3 and S4 (in Level 2) on engineering performance in S4 is moderately strong when the effect of mathematics in Level 1 is removed from both engineering and mathematics performance (0.679). Furthermore, the proportion of variance explained by the first canonical variate of mathematics is 23.6% of engineering performance in S4.

Table 6.31: Results of first pair of partial canonical variate – CE student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.280				0.448				0.686				0.679			
Squared canonical correlation	0.079				0.200				0.471				0.461			
Wilks' Lambda	0.901				0.765				0.451				0.486			
P-value	0.494				0.0016				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE2012	0.236	0.369	0.104	CE2012	0.747	0.908	0.406	CE2112	0.635	0.912	0.626	CE2112	0.430	0.797	0.541
	CE2022	-0.340	0.140	0.039	CE2022	0.087	0.010	0.005	CE2122	-0.064	0.530	0.364	CE2122	0.213	0.706	0.480
	CE2032	1.054	0.859	0.241	CE2032	-0.091	-0.025	-0.011	CE2132	0.105	0.698	0.479	CE2132	0.212	0.707	0.480
	CE2042	0.229	0.399	0.112	CE2042	0.253	0.552	0.247	CE2142	-0.117	0.419	0.288	CE2142	0.147	0.611	0.415
	CE2052	-0.160	0.192	0.054	CE2052	0.305	0.577	0.258	CE3012	0.504	0.853	0.586	CE3012	0.361	0.742	0.504
	CE2062	-0.388	0.012	0.004	CE2062	0.009	0.335	0.150								
Variance extracted	18.16				26.23				50.08				51.13			
Redundancy	1.43				5.26				23.60				23.59			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	1.001	1.000	0.280	MA2013	0.418	0.762	0.341	MA2013	0.029	0.206	0.142	MA2013	0.155	0.516	0.350
	MA2023	-0.008	0.153	0.043	MA2023	0.734	0.929	0.416	MA2023	0.337	0.356	0.244	MA2023	0.300	0.579	0.393
									MA2033	0.739	0.862	0.592	MA2033	0.330	0.654	0.444
									MA3013	0.399	0.595	0.408	MA3013	0.643	0.825	0.560
Variance extracted	51.16				72.19				31.65				42.75			
Redundancy	4.02				14.46				14.91				19.72			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

6.3.3. Impact on Student Performance in Other Disciplines

6.3.3.1. Impact on CS Student Performance

The results of Partial CCA for CS student performance in each semester for two academic years are summarized in Table 6.32. It can be seen that the first pair of canonical variate of the four cases are statistically significant ($p<0.05$) which reflect the first pair of canonical variate is sufficient to explain a significant amount of variance in both predictor and dependent sets. The partial canonical correlation exhibits that there is a significant linear relationship between students' mathematics performance and their engineering performance in Level 2, after adjusted for mathematics in Level 1 from both engineering and mathematics performance in Level 2. The percentages of variability of engineering performance explained by the linear function of mathematics for the four cases are 35.7%, 39.6%, 36.6% and 56.1% respectively for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012). Based on standardized coefficients, it can be concluded that all the mathematics modules have positive impact on engineering performance in Level 2. The redundancy measure of engineering indicates that the first canonical variate of mathematics accounted for 13.8% of the total variance of engineering performance in S3 after adjusted for mathematics in Level 1. The corresponding percentages for other three cases are 16.3%, 16.7% and 25.9% respectively for S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012).

6.3.3.2. Impact on EE Student Performance

With reference to the results of Partial CCA for EE student performance in Table 6.33, it is clear that the first canonical variate pair is sufficient to explain a significant amount of variability of both predictor and dependent sets for all four cases. It is clear that mathematics in Level 2 has significant impact on engineering performance in Level 2, when the effect of mathematics in Level 1 is removed from both engineering and mathematics performance. The squared canonical correlation varied from 30% in S3 (2011/2012) to 60% in S4 (2010/2011). The canonical redundancy measure of engineering indicates that the first canonical variate of mathematics can be explained 12.7%, 9.4%, 26.2% and 12.7% respectively of the total variance of engineering performance in S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012).

6.3.3.3. Impact on EN Student Performance

Table 6.34 depicts the results of Partial CCA for EN student performance in each semester for two academic years. It can be seen that at least the first pair of canonical variate is sufficient to explain a significant amount of variance in both predictor and dependent sets for all cases. The partial canonical correlation indicates that even after adjusting for mathematics in Level 1, there is a significant effect of mathematics in Level 2 on engineering performance in Level 2. The first partial canonical correlations between mathematics performance and engineering performance are 0.657, 0.739, 0.654 and 0.559 respectively for S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) and the corresponding squared canonical correlation are 43.2%, 54.7%, 42.8% and 31.2%. The standardized coefficients showed that all mathematics modules have positive impact on engineering performance in Level 2. The canonical redundancy index of engineering suggests that almost 21% of the total variance of engineering performance in S3 irrespective of academic year (2010/2011 or 2011/2012) can be explained by the first canonical variate of mathematics. The corresponding percentage for S4 is 23% in 2010/2011 and 13% in 2011/2012.

6.3.3.4. Impact on ME Student Performance

The results of Partial CCA for ME student performance in each semester for two academic years are presented in Table 6.35. According to the Wilks' lambda test statistics, first pair of canonical variates are statistically significant ($p<0.05$) for all cases. The first partial canonical correlation showed that in all four cases: S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) the students' mathematics performance is significantly correlated with their corresponding engineering performance, when the effect of mathematics in Level 1 is removed from both engineering and mathematics performance. The squared canonical correlation varied from 24% in S3 (2010/2011) to 47% in S3 (2011/2012). In all cases the standardized coefficients of mathematics measurements are all positive with exceptional for MA2013 in S4 for both academic years. The canonical redundancy measure of engineering indicates that the first canonical variate of mathematics can be explained 7.5%, 11.5%, 16.8% and 15.3% respectively of the total variance of engineering performance in S3 (2010/2011), S3 (2011/2012), S4 (2010/2011) and S4 (2011/2012) after adjusted for mathematics in Level 1 from both engineering and mathematics performance.

6.3.3.5. Impact on MT Student Performance

According to the results in Table 6.36, it is clear that first pair of canonical variates are statistically significant ($p<0.05$) which reflects first canonical variate is sufficient to explain a significant amount of variance in both predictor and dependent sets for S4 student performance in both academic years only. The first partial canonical correlation indicates that mathematics in S3 and S4 has significantly strong impact on engineering performance in S4 even after adjusting for mathematics in Level 1. However, the corresponding values for S3 student performance in both academic years are 0.554 ($p=0.110$) and 0.626 ($p=0.095$) respectively for 2010/2011 and 2011/2012 academic years. The redundancy measure of engineering indicates that the first canonical variate of mathematics performance accounted for less than 7% of the total variance of engineering performance for all cases except S4 (2010/2011) when the effect of mathematics in Level 1 is eliminated from both engineering and mathematics performance.

Table 6.32: Results of first pair of partial canonical variate – CS student performance

	Semester 3								**Semester 4**							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.597				0.629				0.605				0.749			
Squared canonical correlation	0.357				0.396				0.366				0.561			
Wilks' Lambda	0.596				0.540				0.544				0.394			
P-value	<.0001				<.0001				0.0005				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	CE1822	0.249	0.583	0.348	CE1822	0.331	0.717	0.451	CS3022	0.324	0.791	0.478	CS3022	-0.0001	0.591	0.443
	CS2032	0.013	0.602	0.359	CS2032	0.519	0.843	0.530	CS3032	0.067	0.611	0.370	CS3032	0.440	0.847	0.634
	CS2042	0.474	0.781	0.466	CS2042	-0.141	0.339	0.213	CS3042	0.385	0.733	0.443	CS3042	0.072	0.589	0.441
	CS2062	0.227	0.582	0.347	CS2062	0.310	0.775	0.488	CS3242	-0.143	0.338	0.204	CS3242	0.034	0.418	0.313
	EN2022	0.441	0.728	0.435	EN2022	0.224	0.559	0.352	EN2062	0.362	0.760	0.460	EN2062	0.505	0.864	0.647
	ME1822	0.065	0.375	0.224	ME1822	0.016	0.464	0.292	ME1802	0.270	0.717	0.434	ME1802	0.204	0.660	0.494
Variance extracted	38.68				41.12				45.73				46.17			
Redundancy	13.80				16.29				16.72				25.91			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA2023	0.425	0.554	0.331	MA2053	0.592	0.874	0.550	MA2023	0.087	0.117	0.071	MA2053	0.3259	0.718	0.538
	MA2042	0.842	0.907	0.542	MA2073	0.562	0.859	0.541	MA2042	0.363	0.464	0.281	MA2073	0.0323	0.544	0.407
									MA2013	0.566	0.787	0.476	MA2033	0.4122	0.826	0.619
									MA2033	0.537	0.738	0.446	MA2063	0.4717	0.865	0.648
Variance extracted	56.53				75.07				34.83				56.03			
Redundancy	20.17				29.73				12.73				31.44			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.33: Results of first pair of partial canonical variate – EE student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.607				0.544				0.774				0.646			
Squared canonical correlation	0.369				0.296				0.599				0.418			
Wilks' Lambda	0.542				0.659				0.305				0.462			
P-value	0.0008				0.0005				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2012	0.512	0.784	0.476	CE1822	-0.046	0.175	0.095	EE2042	0.410	0.727	0.563	EE2043	-0.319	0.212	0.137
	EE2022	0.195	0.670	0.407	EE2013	0.065	0.526	0.286	EE2052	0.232	0.525	0.406	EE2053	0.158	0.214	0.138
	EE2033	0.311	0.561	0.341	EE2023	0.468	0.727	0.396	EE2072	0.062	0.669	0.518	EE2063	0.202	0.507	0.328
	EN2012	0.120	0.682	0.414	EE2033	0.370	0.631	0.344	EE2083	0.345	0.762	0.590	EE2073	0.424	0.722	0.467
	EN2022	0.079	0.424	0.258	EN2012	0.030	0.388	0.211	EE2132	0.165	0.688	0.532	EE2083	0.585	0.804	0.519
	ME2012	0.310	0.618	0.375	EN2022	0.096	0.535	0.291	EE3072	0.060	0.483	0.374	ME2842	0.280	0.557	0.360
	CE1822	-0.153	0.092	0.056	ME2012	0.449	0.750	0.408	ME2842	0.184	0.726	0.562				
Variance extracted	34.49				31.91				43.78				30.4			
Redundancy	12.71				9.45				26.23				12.7			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	0.762	0.914	0.555	MA2013	0.224	0.532	0.290	MA2013	0.253	0.501	0.388	MA2013	0.061	0.383	0.247
	MA2023	0.433	0.700	0.425	MA2023	0.901	0.978	0.532	MA2023	-0.064	0.373	0.289	MA2023	0.454	0.656	0.424
									MA2033	0.803	0.936	0.725	MA2033	0.443	0.712	0.460
									MA2042	0.228	0.639	0.494	MA2053	0.528	0.688	0.445
Variance extracted	66.26				61.93				41.87				38.94			
Redundancy	24.43				18.34				25.09				16.26			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.34: Results of first pair of partial canonical variate – EN student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				**Academic Year 2011/2012**				**Academic Year 2010/2011**				**Academic Year 2011/2012**			
Canonical Correlation	0.657				0.739				0.654				0.559			
Squared canonical correlation	0.432				0.547				0.428				0.312			
Wilks' Lambda	0.544				0.424				0.483				0.660			
P-value	<.0001				<.0001				<.0001				0.0002			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2092	0.362	0.843	0.554	EE2092	0.582	0.830	0.614	EN2072	0.459	0.793	0.519	EN2072	0.714	0.805	0.429
	EN2012	0.526	0.865	0.568	EN2012	0.378	0.627	0.464	EN2082	0.493	0.809	0.529	EN2082	0.725	0.875	0.488
	EN2022	0.165	0.606	0.398	EN2022	0.290	0.638	0.472	EN2142	0.287	0.778	0.509	EN2142	0.245	0.457	0.255
	EN2052	-0.071	0.496	0.326	EN2052	-0.360	0.342	0.253	EN3022	0.039	0.367	0.240	EN3022	-0.214	-0.025	-0.014
	EN2062	0.277	0.633	0.416	EN2062	0.296	0.736	0.544								
Variance extracted	49.44				42.96				50.55				33.55			
Redundancy	21.35				23.49				21.65				12.67			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	0.636	0.849	0.558	MA2013	0.468	0.783	0.579	MA2013	0.287	0.587	0.384	MA2013	0.116	0.518	0.289
	MA2023	0.570	0.807	0.531	MA2023	0.697	0.909	0.672	MA2023	0.351	0.745	0.488	MA2023	0.623	0.866	0.484
									MA2033	0.553	0.787	0.515	MA2033	0.518	0.773	0.432
									MA2042	0.220	0.613	0.401				
Variance extracted	68.62				71.94				47.39				53.85			
Redundancy	29.64				39.34				20.30				16.81			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.35: Results of first pair of partial canonical variate – ME student performance

	Semester 3								Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012				Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.491				0.684				0.675				0.592			
Squared canonical correlation	0.242				0.467				0.455				0.350			
Wilks' Lambda	0.693				0.503				0.500				0.533			
P-value	0.0009				<.0001				<.0001				<.0001			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	0.306	0.571	0.281	EE2803	0.473	0.680	0.465	ME2032	0.345	0.636	0.429	ME2032	0.130	0.611	0.362
	EN2852	0.006	0.297	0.146	EN2852	-0.113	0.091	0.062	ME3072	0.207	0.582	0.393	ME2153	0.590	0.870	0.515
	ME2012	0.477	0.696	0.342	ME2012	0.404	0.664	0.454	ME3032	0.668	0.862	0.582	ME3032	0.240	0.529	0.313
	ME2022	-0.149	0.369	0.181	ME2023	0.053	0.246	0.168	ME3062	-0.330	0.215	0.145	ME3062	0.275	0.613	0.363
	ME2092	0.297	0.605	0.297	ME2092	0.071	0.331	0.226	ME2142	0.276	0.564	0.381	ME3073	0.179	0.628	0.372
	ME2112	0.535	0.686	0.337	ME2112	0.598	0.776	0.531								
					ME2602	-0.436	0.185	0.126								
Variance extracted	31.19				24.55				37.02				43.62			
Redundancy	7.53				11.47				16.84				15.29			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	0.500	0.732	0.360	MA2013	0.512	0.835	0.571	MA2013	-0.112	0.136	0.092	MA2013	-0.163	0.369	0.218
	MA2023	0.720	0.881	0.433	MA2023	0.638	0.897	0.613	MA2023	0.237	0.490	0.331	MA2023	0.833	0.728	0.431
									MA2033	0.396	0.735	0.496	MA2033	0.048	0.330	0.195
									MA2042	0.680	0.895	0.604	MA2053	0.692	0.633	0.375
Variance extracted	65.55				75.11				40.01				29.38			
Redundancy	15.83				35.11				18.2				10.3			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

Table 6.36: Results of first pair of partial canonical variate – MT student performance

	Semester 3							
	Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.554				0.626			
Squared canonical correlation	0.307				0.392			
Wilks' Lambda	0.580				0.552			
P-value	0.110				0.095			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)
	EE2802	0.250	0.448	0.248	EE2803	0.169	0.410	0.257
	EN2852	-0.844	-0.036	-0.020	EN2852	0.294	0.107	0.067
	ME1822	0.343	0.328	0.182	ME1822	0.075	0.249	0.156
	ME2012	0.435	0.667	0.370	ME2012	0.458	0.631	0.395
	MT2042	1.177	0.610	0.338	MT2042	-1.190	-0.232	-0.145
	MT2122	-0.555	0.474	0.263	MT2122	-0.199	-0.087	-0.055
					MT2152	0.924	0.324	0.203
Variance extracted	22.5				11.51			
Redundancy	6.92				4.52			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	0.884	0.967	0.536	MA2013	0.327	0.780	0.488
	MA2023	0.268	0.543	0.301	MA2023	0.773	0.964	0.604
Variance extracted	61.51				76.9			
Redundancy	18.91				30.18			

	Semester 4							
	Academic Year 2010/2011				Academic Year 2011/2012			
Canonical Correlation	0.775				0.706			
Squared canonical correlation	0.601				0.498			
Wilks' Lambda	0.210				0.198			
P-value	0.007				0.0002			
Engineering performance		(1)	(2)	(3)		(1)	(2)	(3)
	ME2142	0.127	0.687	0.533	ME2832	-0.237	-0.067	-0.047
	ME2832	0.560	0.719	0.557	ME2850	0.035	0.123	0.087
	ME3062	0.538	0.717	0.556	ME3062	-0.275	-0.096	-0.068
	MT2032	-0.370	0.450	0.349	MT2032	0.712	0.599	0.423
	MT2072	-0.188	0.381	0.296	MT2072	0.888	0.666	0.470
	MT2142	-0.046	0.427	0.331	MT2142	-0.827	0.078	0.055
	MT2152	0.621	0.615	0.477				
Variance extracted	34.46				13.94			
Redundancy	20.72				6.94			
Mathematics performance		(1)	(2)	(3)		(1)	(2)	(3)
	MA2013	-0.085	0.168	0.131	MA2013	0.099	-0.178	-0.126
	MA2023	0.192	0.573	0.444	MA2023	-0.378	-0.539	-0.380
	MA2033	0.634	0.894	0.693	MA2033	-0.631	-0.705	-0.498
	MA3013	0.477	0.708	0.549	MA3013	0.674	0.547	0.386
Variance extracted	41.41				27.96			
Redundancy	24.9				13.92			

(1) – Standardized canonical coefficients, (2) – Canonical loadings and (3) Canonical cross-loadings

6.4. Comparison of Joint Impact and Individual Impact of Mathematics

In order to identify the level of joint impact as well as individual impact of mathematics, a comparison is done between the results of unadjusted CCA in chapter 5 and adjusted CCA; Part CCA (in Section 6.1) and Partial CCA (in Section 6.2) for engineering academic performance in Level 2 (S3 and S4) by engineering disciplines.

It can be seen that the level of adjusted canonical correlations; partial canonical correlations and part canonical correlations are reduced due to the relevant adjustments compared to unadjusted canonical correlations. This implies that the joint effect of mathematics in Level 1 and Level 2 on engineering performance in Level 2 is significantly higher compared to the individual effects of mathematics in Level 1 and Level 2 irrespective of the engineering disciplines.

By comparing the individual effect of mathematics in Level 1 (in Section 6.1) and Level 2 (in Section 6.2), it is clear that the individual effect of mathematics in Level 2 is significantly higher than the individual effect of mathematics in Level 1 on the students' engineering performance in Level 2. Although, redundancy indices of Partial CCA are reduced compared to redundancy indices of unadjusted CCA (in chapter 5), the individual effect of mathematics in Level 2 on engineering performance is significant, even after adjusting for mathematics in Level 1. However, the individual effect of mathematics in Level 1 on engineering performance in Level 2 is not sufficient after eliminating the effect of mathematics in Level 2. Though the individual effect of mathematics in Level 1 is not significant, it can be a sufficient indirect effect of mathematics in Level 1 on engineering performance in Level 2.

6.5. Chapter Summary

As there is a significant difference in level of impact of mathematics on engineering performance among engineering disciplines, individual impact of mathematics in both Level 1 and Level 2 on the engineering performance in Level 2 is explored separately by using adjusted canonical correlation analyses, Part CCA and Partial

CCA in this chapter. It is found the individual effect of mathematics in Level 2 is considerably higher compared with the individual effect of mathematics in Level 1 on the students' engineering performance. Besides that, the individual effect of mathematics in Level 1 on engineering performance in Level 2 can be negligible. It can be concluded that, there exists a notable indirect effect of mathematics in Level 1 on engineering performance in Level 2. Hence, the next chapter discovers the underlying relationships between mathematics in Level 1 and Level 2 with engineering performance in Level 2.

CHAPTER 7
MODELING THE RELATIONSHIP OF MATHEMATICS AND STUDENTS' ENGINEERING PERFORMANCE

The analysis in this chapter examines whether or not the student performance in mathematics that are followed in Level 1 and Level 2 are sufficiently precise for the purpose of explaining their engineering performance. As mentioned in Chapter 2, the explanation or the prediction of a phenomenon (engineering academic performance) is represented by the general model described in Figure 3.2 (Section 3.4).

These models consist of two unobserved latent variables: (i) students' mathematics performance (MAT) as the 'exogenous reflectively' measured construct and (ii) students' engineering performance (ENG) as the 'endogenous formatively' measured construct. Observed variables related to MAT are marks of mathematics modules in Level 1 and Level 2 (S3 and S4). The marks of engineering modules in Level 2 (S3 and S4) are the observed variables to construct ENG with respect to the curriculum of each engineering discipline.

The Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis is done for academic performance in Level 2 in two academic years, 2010/2011 and 2011/2012 separately by engineering disciplines. In addition, an index is proposed to measure the mathematical influence on students' engineering performance. Bootstrap analysis was done with 5000 subsamples and bias-corrected and accelerated bootstrap method was utilized.

7.1. Modeling CH Student Performance

7.1.1. Student Performance in Academic Year 2010/2011

As mention in Section 3.1, by the end of Level 2, CH students have followed five mathematics modules: two modules in Level 1 (MA1013 and MA1023), two modules in S3 (MA2013 and MA2023) and one module in S4 (MA2033) as well as seven and five engineering modules in S3 and S4 respectively. Therefore, structural model comprises three MAT constructs and two ENG constructs. The MAT constructs are: Level 1 mathematics modules (L1_MAT), S3 mathematics modules (S3_MAT) and S4 mathematics modules (S4_MAT). Similarly, ENG constructs are: seven engineering modules in S3 (S3_ENG) and five engineering modules in S4 (S4_ENG). The PLS structural model for CH student performance in academic year 2010/2011 is shown in Figure 7.1.

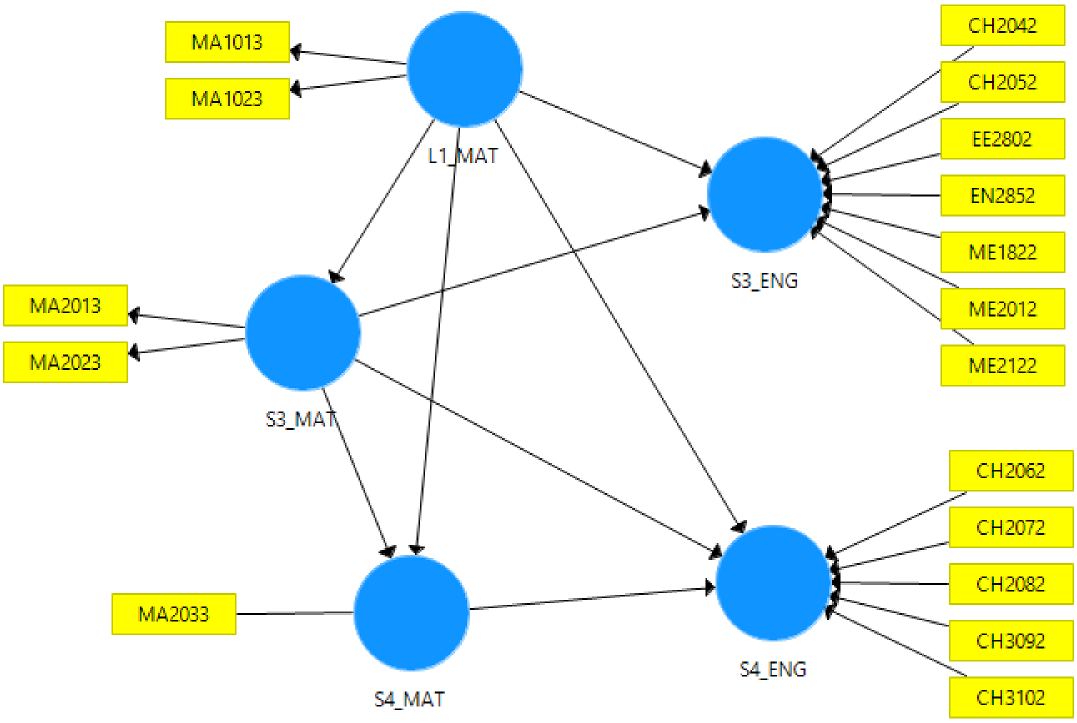

Figure 7.1: PLS structural model for CH student performance – 2010

As explained in Section 3.5.3, model evaluation is carried out in two separate processes for the measurement model and the structural model.

7.1.1.1. Evaluation of the Formative Measurement Model

Table 7.1 summarizes the results of indicator statistics for the formatively measured constructs: S3_ENG and S4_ENG including the outer weights, outer loadings and their corresponding p-values.

Table 7.1: Indicator statistics of formative constructs – CH performance (2010)

Formative Constructs	Indicators	Outer Weights	P-value	Outer Loadings	P-value
S3_ENG	CH2042	0.213	0.130	0.806	0.000
	CH2052	0.223	0.113	0.830	0.000
	EE2802	0.614	0.003	0.874	0.000
	EN2852	-0.269	0.057	0.370	0.011
	ME1822	-0.095	0.393	0.294	0.035
	ME2012	0.341	0.012	0.781	0.000
	ME2122	-0.074	0.611	0.439	0.004
S4_ENG	CH2062	0.192	0.331	0.797	0.000
	CH2072	0.123	0.370	0.556	0.000
	CH2082	0.437	0.029	0.891	0.000
	CH3092	0.229	0.298	0.864	0.000
	CH3102	0.224	0.240	0.855	0.000

The weights of EE2802 and ME2012 indicators of S3_ENG construct and CH2082 indicator of S4_ENG construct are significant at the 5% significance level whereas all the remaining indicators of both constructs are not significant. Since most of the indicators of S3_ENG and S4_ENG are insignificant, corresponding outer loadings were considered. According to the outer loadings of S3_ENG and S4_ENG indicators, it is clear that all indicators are significantly correlated with their construct. It implies that these indicators are supporting for capturing the engineering academic performance. Thus, the indicators in the S3_ENG and S4_ENG formative constructs can be retained in the model, even though their outer weights are not significant.

7.1.1.2. Evaluation of the Reflective Measurement Model

The reflective construct, S4_MAT is a single item construct. The results for the reflectively measured constructs: L1_MAT, S3_MAT and S4_MAT are shown in Table 7.2.

Table 7.2: Reliability and validity statistics of reflective constructs – CH performance (2010)

Reflective Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
L1_MAT	MA1013	0.810	0.656	0.653	0.849	0.738
	MA1023	0.906	0.820			
S3_MAT	MA2013	0.835	0.698	0.507	0.802	0.669
	MA2023	0.800	0.641			
S4_MAT	MA2033	Single Item Construct				

By referring Table 7.2, the outer loadings of the indicators in L1_MAT and S3_MAT constructs denote that all mathematics variables are highly correlated (>0.80) with their respective construct. Furthermore, MA1023 is the most important mathematics variable of L1_MAT construct while two mathematics variables: MA2013 and MA2023 are equally important to their S3_MAT construct. The squared outer loadings suggest that the amount of variation of the indicators in L1_MAT and S3_MAT constructs explained by their respective construct are considerably higher (>60%) with an exceptional 82% by MA1023.

With reference to the values of cronbach's alpha in Table 7.2, it can be seen that cronbach's alpha for both L1_MAT and S3_MAT constructs are less than minimum requirement of 0.7 (Hair et al., 2016). This may occurred due to the less number of indicators. However, the values of composite reliability (CR) for both L1_MAT and S3_MAT constructs are above the cut-off value of 0.7 (Hair et al., 2016). It implies that high levels of internal consistency reliability among both constructs. Further, the values of average variance extracted (AVE) which measures the convergent validity are higher than the required minimum level of 0.50 (Hair et al., 2016) for both L1_MAT and S3_MAT constructs confirmed that both constructs have high levels of convergent validity.

As mentioned in Section 3.5.3.1, two measures were examined for the discriminant validity: cross-loadings and Fornell-Larcker criterion. The corresponding results of these two measures are given in Table 7.3 and Table 7.4 respectively.

Table 7.3: Cross loadings matrix – CH performance (2010)

Constructs	**Indicators**	**L1_MAT**	**S3_MAT**	**S4_MAT**	**S3_ENG**	**S4_ENG**
L1_MAT	MA1013	0.810	0.418	0.312	0.376	0.363
	MA1023	0.906	0.498	0.417	0.561	0.552
S3_MAT	MA2013	0.497	0.835	0.407	0.608	0.537
	MA2023	0.375	0.800	0.279	0.635	0.529
S4_MAT	MA2033	0.431	0.422	1.000	0.410	0.534
S3_ENG	CH2042	0.453	0.611	0.317	0.806	0.700
	CH2052	0.435	0.639	0.325	0.830	0.728
	EE2802	0.488	0.663	0.293	0.874	0.711
	EN2852	0.227	0.274	0.074	0.370	0.477
	ME1822	0.148	0.229	0.144	0.294	0.286
	ME2012	0.438	0.592	0.366	0.781	0.574
	ME2122	0.122	0.374	0.020	0.439	0.235
S4_ENG	CH2062	0.517	0.474	0.438	0.599	0.797
	CH2072	0.293	0.387	0.266	0.454	0.556
	CH2082	0.455	0.599	0.469	0.633	0.891
	CH3092	0.480	0.535	0.499	0.682	0.864
	CH3102	0.455	0.574	0.437	0.748	0.855

According to the results of cross loadings in Table 7.3, it is clear that outer loadings of the indicators with their associated construct are considerably higher than all of their loadings with all the remaining constructs except EN2852, ME1822, ME2122 indicators in S3_ENG and CH2072 indicator in S4_ENG. Thus, it can be concluded that the requirement of the first assessment of discriminant validity is satisfied.

Table 7.4: Fornell-Larcker criterion – CH performance (2010)

Constructs	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.859**				
S3_MAT	0.536	**0.818**			
S4_MAT	0.431	0.422	**single item construct**		
S3_ENG	0.559	0.759	0.410	**formative construct**	
S4_ENG	0.546	0.651	0.534	0.771	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

Table 7.4 compares the square root of AVE of all constructs with their cross correlations between all constructs. It can be seen that the square roots of AVE values of L1_MAT and S3_MAT constructs are greater than their respective correlations with any other constructs. It suggests that L1_MAT and S3_MAT constructs share more variance with their associated indicators than with any other construct. It is confirmed that requirements of second assessment of discriminant validity are also satisfied. Therefore, it can be concluded that there was sufficient evidence for construct validity based on the evidence for both convergent validity and discriminant validity.

Considering the assessment of formative measurement models as well as assessment of reflective measurement models jointly, all formative and reflective constructs exhibit sufficient evidence of quality for the evaluation of the structural model to be proceeded.

7.1.1.3. Evaluation of the Structural Model

The structural model is evaluated based on path coefficients, coefficient of determination (R^2), effect size (f^2) and total effects including direct and indirect effects. The results are presented in Table 7.5 and Table 7.6.

Table 7.5: Results of structural model– CH performance (2010)

Dependent constructs	Independent constructs	Path coefficients	t-statistics	P-value	f^2	R^2
S3_MAT	L1_MAT	0.536	6.389	0.000	0.404	0.288
S4_MAT	L1_MAT	0.287	2.608	0.009	0.077	0.237
	S3_MAT	0.268	2.304	0.022	0.067	
S3_ENG	L1_MAT	0.213	1.817	0.070	0.082	0.608
	S3_MAT	0.645	6.639	0.000	0.755	
S4_ENG	L1_MAT	0.200	1.951	0.050	0.057	0.532
	S3_MAT	0.432	3.378	0.001	0.266	
	S4_MAT	0.265	2.539	0.011	0.115	

Table 7.6: Direct, Indirect and Total effects assessment– CH performance (2010)

Links	Direct	Indirect	Total
L1_MAT -> S3_MAT	0.536	-	0.536
L1_MAT -> S3_ENG	0.213	0.346	0.559
L1_MAT -> S4_MAT	0.287	0.144	0.431
L1_MAT -> S4_ENG	0.200	0.346	0.546
S3_MAT -> S3_ENG	0.645	-	0.645
S3_MAT -> S4_MAT	0.268	-	0.268
S3_MAT -> S4_ENG	0.432	0.071	0.503
S4_MAT -> S4_ENG	0.265	-	0.265

With respect to Table 7.5, the path coefficients related to S3_MAT and S4_MAT constructs are statistically significant ($p < 0.05$). Thus, it can be concluded that the exogenous construct; L1_MAT significantly contributes to explain the variation in S3_MAT construct and L1_MAT and S3_MAT constructs significantly contribute to explain the variation in S4_MAT construct.

According to the path coefficients of L1_MAT construct related to endogenous constructs, it is clear that L1_MAT construct is not significant in endogenous model; S3_ENG ($p=0.07$) at 5% level, but it is significant at 10% level. Nevertheless, the remaining constructs related to S3_ENG and S4_ENG endogenous models are statistically significant at 5% level. It concluded that L1_MAT and S3_MAT constructs significantly contribute to explain the variation in S3_ENG construct and all constructs significantly contribute to explain the variation in S4_ENG construct. It can be concluded that mathematics in Level 2 (S3 and S4) is significantly more influences on the engineering academic performance of CH students in Level 2 than that of mathematics in Level 1.

By referring the R^2 values of endogenous constructs in Table 7.5, it can be concluded that 60.8% of variance in engineering performance in S3 explained by mathematics in Level 1 and S3. Also, mathematics in Level 1 and Level 2 (S3 and S4) explains 53.2% of the variance in engineering performance in S4.

The values of effect size (f^2) in Table 7.5 reveal that L1_MAT construct has small relative effect on S3_ENG (0.082) and S4_ENG (0.057) endogenous constructs whereas S3_MAT construct has significant effects on S3_ENG (0.755) and S4_ENG (0.266) endogenous constructs. This reflects that relative impact of mathematics in S3 on engineering performance is higher than that of mathematics in Level 1.

Examining the direct effects as well as indirect effects is particularly useful when exploring the differential impact of mathematics on engineering performance. The results of total effects, direct effects and indirect effects of the L1_MAT, S3_MAT and S4_MAT constructs on endogenous constructs S3_ENG and S4_ENG are shown in Table 7.6.

It is clear that indirect effect of L1_MAT construct on both endogenous constructs S3-ENG and S4_ENG is significantly higher than the direct effect of L1_MAT construct on S3-ENG and S4_ENG endogenous constructs. This reveals that even though mathematics in Level 1 has no significant direct effect on both engineering performance in S3 and S4, it has significant indirect effect which suggests that mathematics in Level 1 is still important for both engineering performance in S3 and S4.

7.1.2. Student Performance in Academic Year 2011/2012

Accoding to Section 3.1, the engineering modules during 2011/2012 academic year has chaged in the path diagram. The structural model for CH student performance in academic year 2011/2012 is depicted in Figure 7.2.

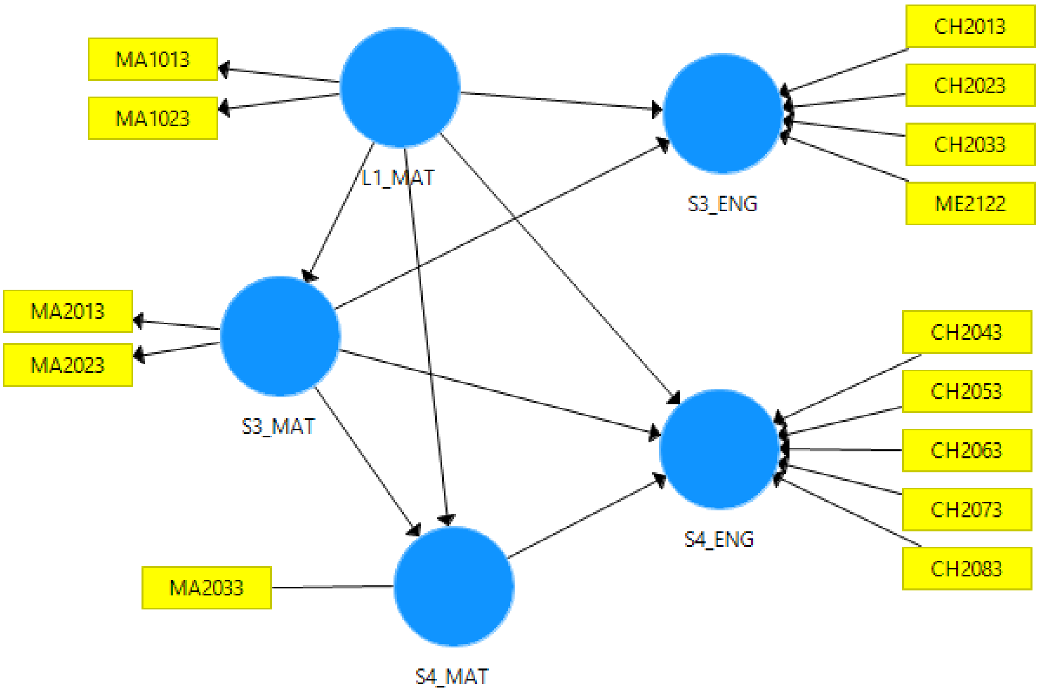

Figure 7.2: Path diagram of structural model for CH student performance – 2011

The corresponding tables for Table 7.1 – Table 7.4 are shown in Table 7.7 – Table 7.10 respectively. As explained in details in Section 7.1.1.1 and Section 7.1.1.2, it is found that all formative and reflective constructs provide sufficient evidence for the evaluation of the structural model in student performance in 2011/2012 academic year. Therefore, only the results of structural model are discussed.

Table 7.7: Indicator statistics in formative constructs – CH performance (2011)

Formative Constructs	Indicators	Outer Weights	P-value	Outer Loadings	P-value
S3_ENG	CH2013	0.361	0.033	0.882	0.000
	CH2023	0.216	0.089	0.818	0.000
	CH2033	0.582	0.000	0.946	0.000
	ME2122	-0.094	0.506	0.476	0.003
S4_ENG	CH2043	0.381	0.022	0.883	0.000
	CH2053	0.270	0.224	0.916	0.000
	CH2063	0.095	0.706	0.895	0.000
	CH2073	0.165	0.322	0.878	0.000
	CH2083	0.205	0.348	0.911	0.000

Table 7.8: Reliability and validity statistics of reflective constructs – CH performance (2011)

Reflective Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
L1_MAT	MA1013	0.857	0.735	0.727	0.879	0.784
	MA1023	0.913	0.833			
S3_MAT	MA2013	0.930	0.864	0.833	0.923	0.857
	MA2023	0.922	0.850			
S4_MAT	MA2033	Single Item Construct				

Table 7.9: Cross loadings matrix – CH performance (2011)

Constructs	Indicators	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	MA1013	0.857	0.549	0.489	0.460	0.436
	MA1023	0.913	0.611	0.602	0.635	0.596
S3_MAT	MA2013	0.595	0.930	0.754	0.752	0.665
	MA2023	0.622	0.922	0.670	0.709	0.645
S4_MAT	MA2033	0.622	0.770	1.000	0.742	0.785
S3_ENG	CH2013	0.484	0.717	0.669	0.882	0.732
	CH2023	0.496	0.652	0.623	0.818	0.699
	CH2033	0.630	0.736	0.696	0.946	0.744
	ME2122	0.211	0.402	0.418	0.476	0.448
S4_ENG	CH2043	0.583	0.623	0.683	0.671	0.883
	CH2053	0.562	0.640	0.718	0.743	0.916
	CH2063	0.528	0.597	0.717	0.736	0.895
	CH2073	0.453	0.650	0.692	0.748	0.878
	CH2083	0.456	0.654	0.728	0.761	0.911

Table 7.10: Fornell-Larcker criterion – CH performance (2011)

Construct	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.885**				
S3_MAT	0.657	**0.926**			
S4_MAT	0.622	0.770	**Single item construct**		
S3_ENG	0.628	0.790	0.742	**formative construct**	
S4_ENG	0.592	0.708	0.785	0.805	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

7.1.2.1. Evaluation of the Structural Model

Table 7.11 provides the results of structural model for CH academic performance in academic year 2011/2012.

Table 7.11: Results of structural model – CH performance (2011)

Dependent constructs	Independent constructs	Path coefficients	T-statistics	P-value	f^2	R^2
S3_MAT	L1_MAT	0.657	10.793	0.000	0.759	0.431
S4_MAT	L1_MAT	0.205	1.765	0.078	0.062	0.616
	S3_MAT	0.635	6.696	0.000	0.598	
S3_ENG	L1_MAT	0.193	1.840	0.066	0.060	0.645
	S3_MAT	0.663	7.165	0.000	0.704	
S4_ENG	L1_MAT	0.109	0.917	0.359	0.018	0.649
	S3_MAT	0.205	1.220	0.223	0.043	
	S4_MAT	0.560	4.058	0.000	0.342	

The path coefficients of MAT constructs show that the path coefficient of L1_MAT construct related to S3_MAT construct and S3_MAT construct related to S4_MAT construct are statistically significant. This reveals that L1_MAT construct significantly contribute to explaining the variation in S3_MAT construct and S3_MAT construct significantly contribute to explaining the variation in S4_MAT construct. Moreover, path coefficients of L1_MAT construct are not significant in both endogenous models; S3_ENG (p=0.066) and S4_ENG (p=0.359). The path coefficients related to endogenous constructs reflect that S3_MAT construct significantly contribute to explaining the variation in S3_ENG construct while S4_MAT constructs significantly contribute to explaining the variation in S4_ENG construct.

With reference to R^2 values of endogenous constructs, 64.5% of variance in engineering performance in S3 explained by mathematics in Level 1 and S3 and the explainable variability in engineering performance in S4 by mathematics in Level 1 and Level 2 (S3 and S4) is 64.9%. The f^2 values indicate that L1_MAT construct has small relative effect on S3_ENG (0.060) and S4_ENG (0.018) endogenous constructs whereas S3_MAT construct has significant effect on S3_ENG (0.704) and S4_MAT construct has significant effect on S4_ENG (0.342). It reveals that the impact of mathematics in S3 and S4 on engineering performance is higher than that of mathematics in Level 1.

Table 7.12 shows the results of total effects, direct effects and indirect effects of the L1_MAT, S3_MAT and S4_MAT constructs on endogenous constructs.

Table 7.12: Direct, Indirect and Total effects assessment– CH performance (2011)

Links	Direct	Indirect	Total
L1_MAT -> S3_MAT	0.657	-	0.657
L1_MAT -> S3_ENG	0.192	0.436	0.628
L1_MAT -> S4_MAT	0.205	0.417	0.622
L1_MAT -> S4_ENG	0.109	0.483	0.592
S3_MAT -> S3_ENG	0.663	-	0.663
S3_MAT -> S4_MAT	0.635	-	0.635
S3_MAT -> S4_ENG	0.206	0.355	0.561
S4_MAT -> S4_ENG	0.560	-	0.560

It can be seen that indirect effects of L1_MAT construct on both endogenous constructs S3-ENG and S4_ENG are significantly higher than the direct effect of L1_MAT construct on S3-ENG and S4_ENG endogenous constructs. This suggests that mathematics in Level 1 has significant indirect effect on both engineering performance in S3 and S4, even though it has no significant direct effect. It can be concluded that mathematics in Level 1 is still important for both engineering performance in S3 and S4.

7.2. Modeling CE Student Performance

As in Section 7.1, the analysis was continued to examine the theoretical model underlying relationship between students' mathematics performance in Level 1 and

Level 2 with their engineering performance for CE discipline. The results of PLS-SEM for two academic years are summarized in Table 7.13 to Table 7.16.

7.2.1. Evaluation of the Measurement Model

Table 7.13 presents the results for formatively measured constructs S3_ENG and S4_ENG for two academic years.

Table 7.13: Indicator statistics of formative constructs – CE performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	CE2012	0.004	0.354	CE2012	0.705*	0.901
	CE2022	-0.256	0.405	CE2022	0.194	**0.188**
	CE2032	0.787*	0.948	CE2032	-0.076	**0.058**
	CE2042	0.195	0.685	CE2042	0.366*	0.722
	CE2052	0.166	0.534	CE2052	0.104	0.467
	CE2062	0.215	0.626	CE2062	0.046	0.435
S4_ENG	CE2112	0.548*	0.907	CE2112	0.402*	0.831
	CE2122	0.087	0.681	CE2122	0.191	0.747
	CE2132	0.139	0.761	CE2132	0.243*	0.778
	CE2142	-0.114	0.484	CE2142	0.100	0.625
	CE3012	0.452*	0.870	CE3012	0.350*	0.781

*. Outer weight is significant at the 0.05 level

Outer loading in bold is not significant at the 0.05 level

Based on the results of outer weights, it can be seen that only three indicators, one in S3_ENG construct and two in S4_ENG construct in 2010 batch as well as five indicators, two in S3_ENG construct and three in S4_ENG construct in 2011 batch are statistically significant. Therefore, the outer loadings were considered as there are number of insignificant indicators in both batches. With respect to outer loadings, all indicators are significantly correlated ($p < 0.05$) with their construct except two indicators in S3_ENG construct in 2011 batch. It implies that the indicators in the S3_ENG and S4_ENG construct can be retained in the model.

The results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years are presented in Table 7.14 and Table 7.15.

Table 7.14: Reliability and validity statistics of reflective constructs – CE performance

Academic Year	Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	CR	AVE
2010	L1_MAT	MA1013	0.806	0.649	0.646	0.846	0.734
		MA1023	0.905	0.819			
	S3_MAT	MA2013	0.745	0.555	0.432	0.777	0.636
		MA2023	0.846	0.716			
	S4_MAT	MA2033	0.876	0.768	0.501	0.796	0.663
		MA3013	0.747	0.558			
2011	L1_MAT	MA1013	0.731	0.535	0.464	0.784	0.647
		MA1023	0.871	0.759			
	S3_MAT	MA2013	0.875	0.766	0.726	0.879	0.785
		MA2023	0.897	0.804			
	S4_MAT	MA2033	0.846	0.715	0.626	0.842	0.728
		MA3013	0.860	0.740			

Table 7.15: Fornell-Larcker criterion – CE performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.857**				
S3_MAT	0.483	**0.797**			
S4_MAT	0.359	0.230	**0.814**		
S3_ENG	0.539	0.387	0.309	**formative construct**	
S4_ENG	0.293	0.344	0.680	0.455	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.804**				
S3_MAT	0.518	**0.886**			
S4_MAT	0.551	0.527	**0.853**		
S3_ENG	0.481	0.571	0.571	**formative construct**	
S4_ENG	0.475	0.570	0.719	0.642	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

The outer loadings of indicators in all reflective constructs for both academic years are significantly correlated with their respective construct. The squared outer loadings exhibit that the amount of variation in L1_MAT, S3_MAT and S4_MAT indicators explained by their respective construct are considerably higher for both academic years. The values of cronbach's alpha are less than minimum requirement of 0.7. But, the values of CR, which suggest high levels of internal consistency reliability among the MAT constructs in both academic years. The values of AVE confirmed the convergent validity of reflective constructs for two academic years. Moreover, cross loadings of all indicators and Fornell-Larcker criterion confirmed that requirements of assessment of discriminant validity are satisfied for two academic years. Based on the evidence for both convergent validity and discriminant validity, it is clear that there was sufficient evidence for construct validity.

7.2.2. Evaluation of the Structural Model

Table 7.16 provides the results of structural model for CE academic performance in academic year 2010/2011 and 2011/2012. The path coefficients of MAT constructs implies that L1_MAT construct significantly contribute to explaining the variation in S3_ENG construct in 2010 batch while both L1_MAT and S3_MAT constructs significantly contribute to explaining the variation in S3_ENG construct in 2011 batch. Furthermore, L1_MAT construct has a weak relationship with S4_ENG construct in both academic years. With reference to R^2 values of endogenous constructs, the proportion of variability in S3_ENG construct explained by the MAT constructs are 31% in 2010 and 37% in 2011. Similarly, the amount of variance in S4_ENG construct explained by the MAT constructs are 65% in 2010 and 57% in 2011. According to the effect size, it is clear that the effect of mathematics in S3 and S4 on engineering performance is higher than that of mathematics in Level 1. The indirect effects of L1_MAT construct on both endogenous constructs S3-ENG and S4_ENG are significantly higher than its direct effect on S3-ENG and S4_ENG constructs in both academic years.

Table 7.16: Results of structural model– CE performance

Academic Year	Dependent constructs	Independent constructs	Path coefficient	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.483*	0.304	0.233	-	0.483
	S4_MAT	L1_MAT	0.323*	0.093	0.133	0.036	0.359
		S3_MAT	0.074	0.005		-	0.074
	S3_ENG	L1_MAT	0.459*	0.234	0.311	0.080	0.539
		S3_MAT	0.166	0.031		-	0.166
	S4_ENG	L1_MAT	-0.043	0.003	0.501	0.336	0.293
		S3_MAT	0.216*	0.071		0.048	0.264
		S4_MAT	0.646*	0.726		-	0.646
2011	S3_MAT	L1_MAT	0.518*	0.366	0.268	-	0.518
	S4_MAT	L1_MAT	0.379*	0.171	0.383	0.171	0.481
		S3_MAT	0.330*	0.130		-	0.439
	S3_ENG	L1_MAT	0.254*	0.075	0.373	0.227	0.551
		S3_MAT	0.439*	0.225		-	0.33
	S4_ENG	L1_MAT	0.031	0.001	0.568	0.445	0.475
		S3_MAT	0.254*	0.097		0.188	0.442
		S4_MAT	0.568*	0.462		-	0.568

*. Path coefficient is significant at the 0.05 level

7.3. Modeling CS Student Performance

7.3.1. Evaluation of the Measurement Model

The results for formatively measured constructs S3_ENG and S4_ENG for two academic years are shown in Table 7.17. By referring outer weights and outer loadings, it is evident that with the exception of one indicator of S4_ENG construct in 2010, all other indicators of S3_ENG and S4_ENG constructs in both academic years are supporting for capturing the engineering academic performance.

Table 7.17: Indicator statistics of formative constructs – CS performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	CE1822	0.214*	0.648	CE1822	0.205	0.678
	CS2032	-0.046	0.645	CS2032	0.499*	0.906
	CS2042	0.416*	0.806	CS2042	-0.019	0.579
	CS2062	0.169	0.666	CS2062	0.261	0.817
	EN2022	0.387*	0.780	EN2022	0.281*	0.724
	ME1822	0.218	0.647	ME1822	0.007	0.536
S4_ENG	CS3022	0.279*	0.811	CS3022	0.041	0.694
	CS3032	0.010	0.622	CS3032	0.352*	0.879
	CS3042	0.335*	0.728	CS3042	0.082	0.710
	CS3242	-0.186	**0.268**	CS3242	0.009	0.481
	EN2062	0.522*	0.884	EN2062	0.566*	0.932
	ME1802	0.160	0.697	ME1802	0.109	0.670

*. Outer weight is significant at the 0.05 level

Outer loading in bold is not significant at the 0.05 level

Table 7.18 and Table 7.19 provides the results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years.

Table 7.18: Reliability and validity statistics of reflective constructs – CS performance

Academic Year	**Constructs**	**Indicators**	**Outer Loadings**	**Squared Outer Loadings**	**Cronbach's alpha**	**CR**	**AVE**
2010	L1_MAT	MA1013	0.773	0.598	0.568	0.819	0.694
		MA1023	0.889	0.790			
	S3_MAT	MA2023	0.787	0.619	0.493	0.797	0.663
		MA2042	0.841	0.707			
	S4_MAT	MA2033	0.872	0.760	0.628	0.843	0.728
		MA2013	0.834	0.696			
2011	L1_MAT	MA1013	0.831	0.690	0.521	0.807	0.676
		MA1023	0.814	0.663			
	S3_MAT	MA2073	0.897	0.805	0.766	0.895	0.81
		MA2053	0.903	0.815			
	S4_MAT	MA2033	0.914	0.836	0.806	0.911	0.837
		MA2063	0.916	0.839			

Table 7.19: Fornell-Larcker criterion – CS performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.833**				
S3_MAT	0.554	**0.814**			
S4_MAT	0.514	0.420	**0.853**		
S3_ENG	0.561	0.708	0.482	**formative construct**	
S4_ENG	0.563	0.483	0.675	0.667	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.822**				
S3_MAT	0.564	**0.900**			
S4_MAT	0.532	0.673	**0.915**		
S3_ENG	0.545	0.729	0.730	**formative construct**	
S4_ENG	0.622	0.686	0.795	0.820	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

The outer loadings reveals that all indicators of MAT constructs are significantly important to their respective construct. Furthermore, CR values confirmed the internal consistency reliability of three MAT constructs in both academic years. The convergent validity of MAT constructs is confirmed by AVE values. The Fornell-Larcker criterion and cross loadings suggest that discriminant validity is satisfied. Hence, it is clear that there was sufficient evidence for construct validity based on the evidence for both convergent validity and discriminant validity.

7.3.2. Evaluation of the Structural Model

The results of structural model for CS performance in academic year 2010/2011 and 2011/2012 are shown in Table 7.20.

Table 7.20: Results of structural model– CS performance

Academic Year	Dependent constructs	Independent constructs	Path coefficients	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.554*	0.444	0.307	-	0.554
	S4_MAT	L1_MAT	0.406*	0.161	0.291	0.108	0.514
		S3_MAT	0.195*	0.037		-	0.195
	S3_ENG	L1_MAT	0.244*	0.090	0.542	0.317	0.561
		S3_MAT	0.573*	0.496		-	0.573
	S4_ENG	L1_MAT	0.225*	0.065	0.534	0.338	0.563
		S3_MAT	0.149	0.032		0.097	0.246
		S4_MAT	0.497*	0.375		-	0.497
2011	S3_MAT	L1_MAT	0.545*	0.422	0.297	-	0.545
	S4_MAT	L1_MAT	0.235*	0.076	0.707	0.297	0.532
		S3_MAT	0.545*	0.410		-	0.545
	S3_ENG	L1_MAT	0.237*	0.092	0.571	0.327	0.564
		S3_MAT	0.600*	0.589		-	0.6
	S4_ENG	L1_MAT	0.225*	0.113	0.491	0.396	0.622
		S3_MAT	0.199*	0.068		0.295	0.494
		S4_MAT	0.542*	0.510		-	0.542

*. Path coefficient is significant at the 0.05 level

According to the results in Table 7.20, it is clear that all MAT constructs are significantly contribute to explaining the variation in both S3_ENG and S4_ENG constructs in both academic years except S3_MAT related to S4_ENG in 2010. Based on the R^2 values of ENG constructs, the amount of variance in S3_ENG construct explained by the MAT constructs are 54% in 2010 and 57% in 2011. Also, the amount of variance in S4_ENG construct explained by the MAT constructs are 53% in 2010 and 49% in 2011. The effect size indicates that the effect of mathematics in S3 and S4 on engineering performance is higher than that of mathematics in Level 1. Furthermore, L1_MAT construct has significant indirect effect on both S3_ENG and S4_ENG constructs, even though it has no significant direct effect.

7.4. Modeling EE Student Performance

7.4.1. Evaluation of the Measurement Model

Table 7.21 exhibits the results for formatively measured constructs S3_ENG and S4_ENG for two academic years.

Table 7.21: Indicator statistics of formative constructs – EE performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	CE1822	-0.140	**0.191**	CE1822	0.067	0.427
	EE2012	0.537*	0.837	EE2013	0.282*	0.781
	EE2022	0.143	0.698	EE2023	0.275*	0.696
	EE2033	0.190	0.485	EE2033	0.150	0.638
	EN2012	-0.009	0.667	EN2012	0.138	0.595
	EN2022	0.254	0.643	EN2022	0.039	0.581
	ME2012	0.324*	0.706	ME2012	0.421*	0.853
S4_ENG	EE2042	0.377*	0.768	EE2043	-0.106	0.430
	EE2052	0.233*	0.618	EE2053	0.224*	0.436
	EE2072	0.083	0.741	EE2063	0.222*	0.624
	EE2083	0.344*	0.817	EE2073	0.462*	0.837
	EE2132	0.138	0.721	EE2083	0.338*	0.797
	EE3072	0.069	0.592	ME2842	0.227*	0.674
	ME2842	0.118	0.715			

*. Outer weight is significant at the 0.05 level

Outer loading in bold is not significant at the 0.05 level

With reference to outer weights and outer loadings, it is clear that all inidcators of S3_ENG and S4_ENG constructs in both academic years are supporting for capturing the engineering academic performance except one indicator of S3_ENG construct in 2010.

Table 7.22 and Table 7.23 present the results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years.

Table 7.22: Reliability and validity statistics of reflective constructs – EE performance

Academic Year	Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	CR	AVE
2010	L1_MAT	MA1013	0.772	0.596	0.524	0.805	0.675
		MA1023	0.868	0.753			
	S3_MAT	MA2013	0.855	0.731	0.628	0.843	0.729
		MA2023	0.852	0.726			
	S4_MAT	MA2033	0.911	0.830	0.700	0.868	0.766
		MA2053	0.839	0.703			
2011	L1_MAT	MA1013	0.736	0.542	0.472	0.787	0.65
		MA1023	0.871	0.759			
	S3_MAT	MA2013	0.866	0.750	0.718	0.876	0.779
		MA2023	0.899	0.809			
	S4_MAT	MA2033	0.926	0.858	0.462	0.769	0.632
		MA2053	0.638	0.407			

Table 7.23: Fornell-Larcker criterion – EE performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.822**				
S3_MAT	0.485	**0.854**			
S4_MAT	0.518	0.536	**0.875**		
S3_ENG	0.514	0.694	0.654	**formative construct**	
S4_ENG	0.522	0.561	0.805	0.705	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.806**				
S3_MAT	0.655	**0.883**			
S4_MAT	0.597	0.573	**0.795**		
S3_ENG	0.615	0.698	0.671	**formative construct**	
S4_ENG	0.604	0.633	0.721	0.740	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

According to the outer loadings in Table 7.22, it can be said that all indicators of MAT constructs are significantly important to their respective construct. The results of Table 7.22 confirmed the internal consistency reliability (based on CR) and convergent validity (based on AVE) of three MAT constructs in both academic years. The Fornell-Larcker criterion in Table 7.23 and cross loadings suggest that discriminant validity is also satisfied. Hence, there was sufficient evidence for construct validity based on the evidence for both convergent validity and discriminant validity.

7.4.2. Evaluation of the Structural Model

The results of structural model for EE performance in academic year 2010/2011 and 2011/2012 are provided in Table 7.24.

Table 7.24: Results of structural model– EE performance

Academic Year	Dependent constructs	Independent constructs	Path coefficients	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.485*	0.307	0.235	-	0.485
	S4_MAT	L1_MAT	0.337*	0.139	0.374	0.18	0.518
		S3_MAT	0.372*	0.169		-	0.372
	S3_ENG	L1_MAT	0.232*	0.087	0.523	0.282	0.514
		S3_MAT	0.581*	0.541		-	0.581
	S4_ENG	L1_MAT	0.100	0.021	0.678	0.422	0.522
		S3_MAT	0.153	0.048		0.25	0.403
		S4_MAT	0.671*	0.876		-	0.671
2011	S3_MAT	L1_MAT	0.655*	0.752	0.429	-	0.655
	S4_MAT	L1_MAT	0.388*	0.147	0.415	0.209	0.597
		S3_MAT	0.319*	0.099		-	0.319
	S3_ENG	L1_MAT	0.276*	0.092	0.531	0.339	0.615
		S3_MAT	0.517*	0.326		-	0.517
	S4_ENG	L1_MAT	0.142	0.025	0.601	0.461	0.604
		S3_MAT	0.261*	0.089		0.155	0.416
		S4_MAT	0.486*	0.347		-	0.486

*. Path coefficient is significant at the 0.05 level

By referring path coefficients of MAT constructs, it can be seen that L1_MAT and S3_MAT constructs significantly contribute to explaining the variation in S3_ENG construct in both academic years. However, the contribution of L1_MAT construct in explaining the variation in S4_ENG construct is not significant in both academic years. According to the R^2 values of ENG constructs, the amount of variance in S3_ENG construct explained by the MAT constructs are 52% in 2010 and 53% in 2011. Also, the amount of variance in S4_ENG construct explained by the MAT constructs are 68% in 2010 and 60% in 2011. The f^2 values in both academic years illustrate that L1_MAT construct has small relative effect on S3_ENG and S4_ENG constructs as well as S3_MAT construct also has small relative effect on S4_ENG construct. The indirect effects of L1_MAT construct on both endogenous constructs S3-ENG and S4_ENG are significantly higher than its direct effect on S3-ENG and S4_ENG constructs in both academic years.

7.5. Modeling EN Student Performance

7.5.1. Evaluation of the Measurement Model

The results for formatively measured constructs S3_ENG and S4_ENG for two academic years are shown in Table 7.25.

Table 7.25: Indicator statistics of formative constructs – EN performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	EE2092	0.295*	0.881	EE2092	0.484*	0.880
	EN2012	0.434*	0.880	EN2012	0.197	0.651
	EN2022	0.215	0.759	EN2022	0.230*	0.711
	EN2052	-0.062	0.579	EN2052	-0.198	0.581
	EN2062	0.296*	0.776	EN2062	0.449*	0.885
S4_ENG	EN2072	0.456*	0.816	EN2072	0.694*	0.913
	EN2082	0.672*	0.920	EN2082	0.308*	0.662
	EN2142	0.023	0.616	EN2142	0.184	0.504
	EN3022	-0.017	0.373	EN3022	0.148	0.471

*. Outer weight is significant at the 0.05 level

With respect to outer weights and outer loadings, it is clear that all inidcators of S3_ENG and S4_ENG constructs in both academic years are supporting for capturing the engineering academic performance.

The results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years are presented in Table 7.26 and Table 7.27.

Table 7.26: Reliability and validity statistics of reflective constructs – EN performance

Academic Year	Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	CR	AVE
2010	L1_MAT	MA1013	0.790	0.625	0.502	0.8	0.667
		MA1023	0.842	0.709			
	S3_MAT	MA2013	0.868	0.753	0.701	0.87	0.77
		MA2023	0.887	0.786			
	S4_MAT	MA2033	0.865	0.747	0.539	0.811	0.683
		MA2042	0.786	0.618			
2011	L1_MAT	MA1013	0.666	0.443	0.508	0.785	0.652
		MA1023	0.928	0.861			
	S3_MAT	MA2013	0.883	0.779	0.768	0.895	0.811
		MA2023	0.918	0.842			
	S4_MAT	MA2033	1.000	1.000	Single Item Construct		

Table 7.27: Fornell-Larcker criterion – EN performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.817**				
S3_MAT	0.594	**0.877**			
S4_MAT	0.490	0.625	**0.826**		
S3_ENG	0.641	0.785	0.640	**formative construct**	
S4_ENG	0.587	0.703	0.669	0.763	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.808**				
S3_MAT	0.624	**0.900**			
S4_MAT	0.615	0.609	**single item construct**		
S3_ENG	0.582	0.828	0.718	**formative construct**	
S4_ENG	0.490	0.600	0.595	0.706	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

The outer loadings reflect that all indicators of MAT constructs are significantly important to their respective construct. The results of CR and AVE of three MAT constructs in both academic years confirmed the internal consistency reliability and convergent validity respectively. Also, the Fornell-Larcker criterion in Table 7.27 and cross loadings confirmed discriminant validity of reflective constructs in both academic years. Based on the evidence for both convergent validity and discriminant validity, it is clear that there was sufficient evidence for construct validity.

7.5.2. Evaluation of the Structural Model

The results of structural model for EN performance in academic year 2010/2011 and 2011/2012 are provided in Table 7.28.

Table 7.28: Results of structural model– EN performance

Academic Year	Dependent constructs	Independent constructs	Path coefficient	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.594*	0.546	0.353	-	0.594
	S4_MAT	L1_MAT S3_MAT	0.183 0.516*	0.037 0.294	0.413	0.307 -	0.49 0.516
	S3_ENG	L1_MAT S3_MAT	0.270* 0.625*	0.140 0.750	0.663	0.371 -	0.641 0.625
	S4_ENG	L1_MAT S3_MAT S4_MAT	0.200* 0.373* 0.338*	0.064 0.176 0.170	0.606	0.387 0.174 -	0.587 0.547 0.338
2011	S3_MAT	L1_MAT	0.624*	0.638	0.389	-	0.624
	S4_MAT	L1_MAT S3_MAT	0.386* 0.368*	0.169 0.153	0.461	0.229 -	0.615 0.368
	S3_ENG	L1_MAT S3_MAT	0.108 0.761*	0.023 1.148	0.692	0.475 -	0.582 0.761
	S4_ENG	L1_MAT S3_MAT S4_MAT	0.057 0.356* 0.343*	0.003 0.121 0.114	0.446	0.433 0.126 -	0.49 0.482 0.343

*. Path coefficient is significant at the 0.05 level

All MAT constructs are significantly contribute to explaining the variation in both S3_ENG and S4_ENG constructs in both academic years except L1_MAT construct related to S3_ENG and S4_ENG constructs in 2011. By referring the R^2 values of ENG constructs, the amount of variance in S3_ENG construct explained by the MAT constructs are 66% in 2010 and 69% in 2011. Also, the amount of variance in S4_ENG construct explained by the MAT constructs are 61% in 2010 and 45% in 2011. The f^2 values in both academic years reflect that the effect of S3_MAT and S4_MAT constructs on S3_ENG and S4_ENG constructs are higher than that of L1_MAT construct. Furthermore, L1_MAT construct has significant indirect effect on both S3_ENG and S4_ENG constructs, even though it has no significant direct effect.

7.6. Modeling ME Student Performance

7.6.1. Evaluation of the Measurement Model

Table 7.29 show the results for formatively measured constructs S3_ENG and S4_ENG for two academic years. All inidcators of S3_ENG and S4_ENG constructs in both academic years are supporting for capturing the engineering academic performance except one indicator of S4_ENG construct in 2011.

Table 7.29: Indicator statistics of formative constructs – ME performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	EE2802	0.239	0.625	EE2803	0.309*	0.706
	EN2852	0.091	0.452	EN2852	-0.009	0.344
	ME2012	0.207	0.613	ME2012	0.416*	0.757
	ME2022	-0.052	0.513	ME2023	0.100	0.459
	ME2092	0.627*	0.886	ME2092	0.106	0.476
	ME2112	0.260*	0.590	ME2112	0.599*	0.853
				ME2602	-0.356*	0.385
S4_ENG	ME2032	0.320*	0.683	ME2032	0.210	0.722
	ME3072	0.228	0.643	ME2153	0.447*	0.819
	ME3032	0.624*	0.871	ME3032	0.368*	0.771
	ME3062	-0.310*	**0.229**	ME3062	0.322	0.713
	ME2142	0.267	0.609	ME3073	-0.062	0.513

*. Outer weight is significant at the 0.05 level

Outer loading in bold is not significant at the 0.05 level

Table 7.30 and Table 7.31 present the results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years.

Table 7.30: Reliability and validity statistics of reflective constructs – ME performance

Academic Year	Constructs	Indicators	Outer Loadings	Squared Outer Loadings	Cronbach's alpha	CR	AVE
2010	L1_MAT	MA1013	0.749	0.561	0.499	0.796	0.662
		MA1023	0.874	0.764			
	S3_MAT	MA2013	0.830	0.689	0.592	0.831	0.71
		MA2023	0.855	0.731			
	S4_MAT	MA2033	0.785	0.617	0.575	0.822	0.699
		MA2042	0.884	0.781			
2011	L1_MAT	MA1013	0.639	0.408	0.436	0.763	0.624
		MA1023	0.917	0.841			
	S3_MAT	MA2013	0.890	0.791	0.768	0.896	0.811
		MA2023	0.912	0.832			
	S4_MAT	MA2033	0.863	0.745	0.413	0.768	0.626
		MA2053	0.712	0.507			

Table 7.31: Fornell-Larcker criterion – ME performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	0.814				
S3_MAT	0.465	0.843			
S4_MAT	0.187	0.361	0.836		
S3_ENG	0.569	0.595	0.318	**formative construct**	
S4_ENG	0.434	0.417	0.653	0.520	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	0.790				
S3_MAT	0.555	0.901			
S4_MAT	0.468	0.468	0.791		
S3_ENG	0.494	0.760	0.444	**formative construct**	
S4_ENG	0.574	0.610	0.535	0.668	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

Based on the outer loadings of MAT indicators, it is clear that all indicators of MAT constructs are significantly important to their respective construct. The CR and AVE values in both academic years, reveals that the requirments of internal consistency reliability and convergent validity are satisfied respectively. Also, the Fornell-Larcker criterion in Table 7.31 and cross loadings suggest that discriminant validity is satisfied. Hence, there was sufficient evidence for construct validity based on the evidence for both convergent validity and discriminant validity.

7.6.2. Evaluation of the Structural Model

Table 7.32 displays the results of structural model for ME academic performance in academic year 2010/2011 and 2011/2012.

Table 7.32: Results of structural model– ME performance

Academic Year	Dependent constructs	Independent constructs	Path coefficient	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.465*	0.275	0.216	-	0.465
	S4_MAT	L1_MAT	0.025	0.001	0.131	0.162	0.187
		S3_MAT	0.349*	0.110		-	0.349
	S3_ENG	L1_MAT	0.372*	0.202	0.463	0.196	0.569
		S3_MAT	0.422*	0.260		-	0.422
	S4_ENG	L1_MAT	0.292*	0.143	0.531	0.142	0.434
		S3_MAT	0.074	0.008		0.2	0.274
		S4_MAT	0.572*	0.606		-	0.572
2011	S3_MAT	L1_MAT	0.555*	0.446	0.308	-	0.555
	S4_MAT	L1_MAT	0.301*	0.087	0.282	0.167	0.468
		S3_MAT	0.301*	0.087		-	0.301
	S3_ENG	L1_MAT	0.104	0.018	0.585	0.39	0.494
		S3_MAT	0.702*	0.822		-	0.702
	S4_ENG	L1_MAT	0.266*	0.090	0.496	0.308	0.574
		S3_MAT	0.346*	0.151		0.075	0.42
		S4_MAT	0.248*	0.088		-	0.248

*. Path coefficient is significant at the 0.05 level

The path coefficients of MAT constructs implies that all MAT constructs are significantly contribute to explaining the variation in both S3_ENG and S4_ENG constructs in both academic years except S3_MAT related to S4_ENG construct in 2010 and L1_MAT related to S3_ENG construct in 2011. With reference to R^2 values of endogenous constructs, the proportion of variability in S3_ENG construct explained by the MAT constructs are 46% in 2010 and 59% in 2011. Similarly, the amount of variance in S4_ENG construct explained by the MAT constructs are 53% in 2010 and 50% in 2011. According to the f^2 values, it is clear that the effect of mathematics in S3 and S4 on engineering performance is higher than that of mathematics in Level 1. The indirect effects of L1_MAT construct on both endogenous constructs S3-ENG and S4_ENG are significantly higher than its direct effect on S3-ENG and S4_ENG constructs in both academic years.

7.7. Modeling MT Student Performance

7.7.1. Evaluation of the Measurement Model

Table 7.33 shows the results for formatively measured constructs S3_ENG and S4_ENG for two academic years.

Table 7.33: Indicator statistics of formative constructs – MT performance

Academic Year	**2010**			**2011**		
Constructs	**Indicators**	**Outer Weights**	**Outer Loadings**	**Indicators**	**Outer Weights**	**Outer Loadings**
S3_ENG	EE2802	-0.017	0.688	EE2803	0.099	0.581
	EN2852	-0.034	0.568	EN2852	0.396	0.383
	ME1822	-0.049	0.423	ME1822	0.086	0.335
	ME2012	0.574*	0.872	ME2012	0.603*	0.787
	MT2042	0.406	0.862	MT2042	-0.034	**-0.025**
	MT2122	0.241	0.836	MT2122	-0.038	**0.139**
				MT2152	0.660	0.404
S4_ENG	ME2142	0.016	0.736	ME2832	-0.070	0.540
	ME2832	0.540*	0.840	ME2850	0.262	0.679
	ME3062	0.513*	0.810	ME3062	0.834	0.904
	MT2032	-0.338	0.681	MT2032	-0.030	**0.400**
	MT2072	-0.022	0.655	MT2072	-0.521	**0.251**
	MT2142	0.036*	0.688	MT2142	0.410	0.606
	MT2152	0.453*	0.748			

*. Outer weight is significant at the 0.05 level

Outer loading in bold is not significant at the 0.05 level

By referring outer weights and outer loadings, it is clear that all inidcators of S3_ENG and S4_ENG constructs in both academic years are supporting for capturing the engineering academic performance except two indicators of S3_ENG construct and two indicators of S4_ENG construt in 2011.

The results for the reflective constructs, L1_MAT, S3_MAT and S4_MAT for two academic years are presented in Table 7.34 and Table 7.35.

Table 7.34: Reliability and validity statistics of reflective constructs – MT performance

Academic Year	**Constructs**	**Indicators**	**Outer Loadings**	**Squared Outer Loadings**	**Cronbach's alpha**	**CR**	**AVE**
2010	L1_MAT	MA1013	0.685	0.470	0.574	0.805	0.679
		MA1023	0.942	0.888			
	S3_MAT	MA2013	0.857	0.734	0.678	0.861	0.756
		MA2023	0.882	0.778			
	S4_MAT	MA2033	0.877	0.769	0.65	0.851	0.74
		MA3013	0.844	0.712			
2011	L1_MAT	MA1013	0.825	0.680	0.631	0.843	0.729
		MA1023	0.882	0.778			
	S3_MAT	MA2013	0.923	0.852	0.847	0.929	0.867
		MA2023	0.939	0.881			
	S4_MAT	MA2033	0.904	0.817	0.483	0.784	0.649
		MA3013	0.694	0.482			

Table 7.35: Fornell-Larcker criterion – MT performance

2010					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.824**				
S3_MAT	0.650	**0.870**			
S4_MAT	0.519	0.606	**0.860**		
S3_ENG	0.628	0.661	0.626	**formative construct**	
S4_ENG	0.642	0.640	0.838	0.675	**formative construct**
2011					
	L1_MAT	S3_MAT	S4_MAT	S3_ENG	S4_ENG
L1_MAT	**0.854**				
S3_MAT	0.696	**0.931**			
S4_MAT	0.629	0.695	**0.806**		
S3_ENG	0.488	0.708	0.564	**formative construct**	
S4_ENG	0.407	0.621	0.624	0.721	**formative construct**

Note: The diagonal elements in bold, are the square root of AVE

The outer loadings reflect that all indicators of MAT constructs are significantly important to their respective construct. The results of CR and AVE of three MAT constructs in both academic years confirmed the internal consistency reliability and convergent validity respectively. Also, the Fornell-Larcker criterion in Table 7.35 and cross loadings confirmed discriminant validity of reflective constructs in both academic years. Based on the evidence for both convergent validity and discriminant validity, it is clear that there was sufficient evidence for construct validity.

7.7.2. Evaluation of the Structural Model

The results of structural model for MT performance in academic year 2010/2011 and 2011/2012 are provided in Table 7.36.

Table 7.36: Results of structural model– MT performance

Academic Year	Dependent constructs	Independent constructs	Path coefficients	f^2	R^2	Indirect effect	Total effect
2010	S3_MAT	L1_MAT	0.650*	0.732	0.423	-	0.650
	S4_MAT	L1_MAT	0.216	0.045	0.394	0.302	0.519
		S3_MAT	0.465*	0.206		-	0.465
	S3_ENG	L1_MAT	0.344	0.138	0.505	0.284	0.628
		S3_MAT	0.437	0.223		-	0.437
	S4_ENG	L1_MAT	0.248	0.144	0.764	0.394	0.642
		S3_MAT	0.077	0.012		0.309	0.385
		S4_MAT	0.664*	.1.131		-	0.664
2011	S3_MAT	L1_MAT	0.696*	0.937	0.484	-	0.696
	S4_MAT	L1_MAT	0.281	0.086	0.524	0.347	0.629
		S3_MAT	0.500*	0.271		-	0.5
	S3_ENG	L1_MAT	-0.009	0.000	0.502	0.497	0.488
		S3_MAT	0.715*	0.530		-	0.715
	S4_ENG	L1_MAT	-0.166	0.025	0.470	0.573	0.407
		S3_MAT	0.446	0.152		0.209	0.655
		S4_MAT	0.418	0.157		-	0.418

*. Path coefficient is significant at the 0.05 level

The path coefficients of MAT constructs related to endogenous constructs indicate that only S4_MAT related to S4_ENG construct in 2010 and S3_MAT related to S3_ENG construct in 2011 are significantly contribute to explaining the variation in endogenous constructs in both academic years. By referring the R^2 values of ENG constructs, the amount of variance in S3_ENG construct explained by the MAT constructs are 51% in 2010 and 50% in 2011. Also, the amount of variance in S4_ENG construct explained by the MAT constructs are 76% in 2010 and 47% in 2011. The f^2 values in both academic years reflect that the effect of S3_MAT and S4_MAT constructs on S3_ENG and S4_ENG constructs are higher than that of L1_MAT construct. Furthermore, L1_MAT construct has significant indirect effect on both S3_ENG and S4_ENG constructs, even though it has no significant direct effect.

7.8. Proposed Index to Quantify the Influence of Mathematics

The mathematical influence index proposed (Section 3.6) to determine the level of influence of mathematics modules in Level 1 and Level 2 on student engineering performance in Level 2 (S3 and S4) based on PLS-SEM approach. The proposed index is a compromise between communality and redundancy which takes the both predictive performance of mathematics constructs (MAT) and predictive performance of structural model into account. The results of mathematical influence index for two semesters: S3 and S4 by engineering disciplines for two academic years are computed using the equation 11 in Section 3.6.

Table 7.37: Results of mathematical influenc index

Discipline	2010		2011		Mean
	S3 (%)	S4 (%)	S3 (%)	S4 (%)	
CH	65.4	65.3	72.7	75.6	69.8
CE	50.7	64.1	56.1	64.3	58.8
CS	66.8	66.7	70.1	65.7	67.3
EE	66.2	75.9	66.9	70.3	69.8
EN	74.9	71.3	76.6	68.3	72.8
ME	61.9	66.4	70.1	63.9	65.6
MT	65.2	80.5	66.9	65.6	69.6

Results in Table 7.37 indicate that the influence of mathematics modules in Level 1 and Level 2 on engineering performance in S3 and S4 are greater than 50% for all disciplines in both academic years. Considering the two academic years in CH discipline, the impact of mathematics on engineering performance is significantly increased from 2010 to 2011 compared with other engineering disciplines.

7.9. Chapter Summary

The two facts of the conceptual validity of the theoritical model: measurement validity and statistical conclusion validity (based on structural model) with respect to the engineering disciplines are tested using PLS-SEM approach. The measurement validity of all models is assessed for reflective and formative constructs separately and it is found that all models possessed the basic requirments for measurement relaiability and measurement validity. Furthermore, the assessment of structural model found that all models also possessed the statistical conclusion validity. It is observed that all models are statisfied with the level of conceptual validity and the proposition defined in Section 3.1 is accepted. The proposed mathematical influence index reveals that the impact of mathematics in Level 1 and Level 2 is significantly high on engineering performance in Level 2 for all seven engineering disciplines.

CHAPTER 8
CONCLUSIONS AND RECOMMENDATIONS

The conclusions, recommendations and suggestions based on the results of this study are given below.

8.1. Conclusions

- The effect of mathematics in Level 1 and Level 2 on engineering performance in Level 2 for a given discipline was statistically proved in this study.
- The first canonical variate of engineering which is a linear combination of the raw marks of engineering modules in Level 2 ($V_1 = \sum_{i=1} b_{1i} Y_i$) was found as a proxy estimator for the student engineering performance in Level 2 as it did not significantly deviate from the normal GPA.
- As CCA technique does not consider in removing any effect due to covariate, Partial CCA and Part CCA can be used as efficient statistical techniques to eliminate the effect of mathematics in Level 1 and in Level 2 respectively.
- PLS-SEM technique can be used to model the underlying relationship between mathematics and engineering performance based on the results obtained from Partial CCA and Part CCA.
- The proposed index to determine the impact of mathematics on engineering performance for a given discipline and to compare the impact of mathematics among the engineering disciplines was $\sqrt{\left[\frac{1}{I}\sum_i \left(\frac{1}{n_i}\sum_{j=1}^{n_i} corr^2(X_{ij}, MAT_i)\right)\right]} * R_k$.
- The student overall performance in Level 2 was significantly correlated with the performance in mathematics modules in both S1 (MA1013) and S2 (MA1023) for all engineering disciplines except MT discipline.
- The association between student overall performance in Level 2 and mathematics performance in S2 was higher compared with the association between student overall performance in Level 2 and mathematics performance in S1.

- The level of impact of mathematics varies among engineering disciplines.
- In all disciplines only the first canonical pair was found to be sufficient to explain significant amount of variability of engineering and mathematics performance.
- The overall impact of mathematics modules in S1 and S2 in Level 1 and mathematics modules in S3 and S4 in Level 2 was significant on engineering performance in S3 and S4 for all disciplines irrespective of two academic years.
- When both mathematics modules in Level 1 and Level 2 were considered simultaneously, the impact from mathematics in S1 (MA1013) was found lower compared with the impact from mathematics in S2 (MA1023).
- The individual effect of mathematics in Level 2 was considerably higher compared with the individual effect of mathematics in Level 1 on the student engineering performance in Level 2.
- By comparing the joint effect of mathematics in Level 1 and Level 2 with their individual effects, it was found that the joint effect of mathematics in Level 1 and Level 2 on students' engineering performance in Level 2 was significantly higher compared with both individual effects of mathematics in Level 1 and Level 2.
- Based on the results of the testing of hypotheses formulated in Chapter 7, the influence of mathematics in S3 and S4 were identified as having significant effects on engineering academic performance in S3 and S4 (in Level 2) irrespective of the engineering disciplines.
- The analysis of direct and indirect effects reveals that although direct effect of mathematics in Level 1 on engineering performance in S3 and S4 was not significant, there was a significant effect indirectly, which implied that mathematics in Level 1 was still important in affecting students' engineering performance in Level 2.
- The proposed mathematical influence index based on the results of PLS-SEM approach reflects that the level of impact of mathematics in Level 1 and Level 2 was significantly higher on engineering performance in Level 2 for all seven engineering disciplines.

- The impact of mathematics on engineering performance in Level 2 varies among disciplines. The highest impact of mathematics was found in engineering performance in EN discipline in S3 for both academic years. However, the least impact was found in engineering performance in CE discipline irrespective of academic year and the semester.

8.2. Recommendations

- Engineering students are encouraged to acquire mathematical concept and knowledge during their undergraduate level for better performance in engineering sciences.
- The results can be effectively used by both Mathematics and other departments to improve the students' performance in all engineering disciplines.
- The methodology developed in this study needs to apply for all the compulsory mathematics modules up to Semester 5 alone with the engineering performance in Level 3 and Level 4 as well.

8.3. Suggestions for Future Research

- Further investigation is required to find the impact of preceding engineering modules on the academic performance of engineering students.
- In this study except student performance based on marks other external variables were not considered. It is essential to validate the underlying relationships between students' engineering performance using other influential variables as well.
- This study can be extended for other engineering faculties in Sri Lankan universities and more academic years before implementing various decisions.

CHAPTER 9
PUBLICATIONS BASED ON THIS STUDY

It is compulsory to publish papers in referred journals or international conferences by the research students. The publications based on this study are given below.

9.1. List of Publications

1. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2016). Influence of mathematics on academic performance of engineering students: PLS-SEM approach. *Communications in Statistics: Case Studies, Data Analysis and Applications,* 2(3-4), 106-111, doi: 10.1080/23737484.2017.1391724.

2. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2016). Impact of Mathematics in Level 1 on the Academic Performance of Engineering Students: A Case Study. *International Journal of Applied Mathematics & Statistical Sciences*, 5(4), 1-8.

3. Peiris, T. S. G., & Nanayakkara, K. A. D. S. A. (2017). Application of Adjusted Canonical Correlation Analysis (ACCA) to study the association between mathematics in Level 1 and Level 2 and performance of engineering disciplines in Level 2. *Journal of Physics: Conference Series* 890. doi:10.1088/1742-6596/890/1/012092.

4. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2017). *Identifying the Influence of Mathematics on Academic Performance of Engineering Students*. Paper presented at the Engineering Research Conference (MERCon) 2017 Moratuwa, Sri Lanka. doi:10.1109/MERCon.2017.7980490.

5. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2016). *Application of Canonical Correlation Analysis to study the influence of mathematics on engineering programs: A case study*. Paper presented at the Engineering Research Conference (MERCon) 2016 Moratuwa, Sri Lanka. doi:10.1109/MERCon.2016.7480129.

6. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2016). Impact of mathematics on academic performance of engineering students: A canonical correlation analysis. In *Proceedings of the International Research Symposium on Pure and Applied Sciences (IRSPAS)*, Sri Lanka. p.40.

7. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2015). Influence of Mathematics in Level 1 on Students' Performance in Engineering Programs: A Case Study. In *Proceedings of the International Postgraduate Research Conference (IPRC) 2015*, Sri Lanka. p.259.

COMMUNICATIONS IN STATISTICS: CASE STUDIES, DATA ANALYSIS AND APPLICATIONS
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CASE REPORT

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Influence of mathematics on academic performance of engineering students: PLS-SEM approach

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ABSTRACT
Discovering information from existing academic-related data is a crucial aspect of the educational research. The objective of this study is to propose a relationship model between students' mathematics performance and their overall academic performance in engineering programs. The study was conducted with engineering undergraduates from Chemical and Process Engineering at the Faculty of Engineering, University of Moratuwa, Sri Lanka. The partial least-square structural equation modeling is used to examine the relationship of academic performance of engineering students. The results revealed that mathematics performance significantly influences on the student academic performance in chemical and process engineering programs.

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Engineering mathematics; structural equation modeling; student academic performance

1. Introduction

Higher education is an important tool for the socioeconomic and technological development of any country as it provides capable manpower to transform the resources into wealth. Many researchers have made extensive efforts to study various aspects of student academic performance in higher education. Improving student academic performance is crucial importance for the universities as their main objective is to provide quality education to their undergraduates with the changes in higher education. There is an urgency to look into the effectiveness of the academic programs. This will lead to discover the possible factors that assist to improve student academic performance.

Mathematics plays a major role in higher education as it assists to enhance students' knowledge in various disciplines, especially, in engineering fields. According to Sazhin (1998), mathematics is a language of expressing physical, chemical, and engineering laws in engineering sciences. Many researchers have revealed the importance of mathematical knowledge for engineering students to develop their logical and analytical thinking (Harris et al. 2015; Pyle 2001; Sazhin 1998). Goold (2012) stated that the mathematical knowledge gained prior and during engineering education is highly essential in engineering practice as they use a high level of curriculum mathematics and mathematical thinking in their work. Therefore, developing students' understanding and improving their mathematical thinking is a major task in engineering education.

In many countries including Sri Lanka, the pre-university requirement for engineering degrees is based mostly on mathematics for all higher education institutions. As a result, most of the students in the Faculty of Engineering, University of Moratuwa, Sri Lanka have acquired higher grades for mathematics in the General Certificate of Examination (G.C.E.) Advanced Level. However, in a recent study Nanayakkara and Peiris (2015) have shown that mathematics performance of engineering students in their undergraduate degree programs at the Faculty of Engineering, University of Moratuwa varies significantly between and within different engineering disciplines. Consequently, to understand the influence of mathematical knowledge that engineering student gained from their undergraduate degree program is desired.

In recent decades, when a research problem contains both exogenous and endogenous measured variables as well as latent variables, Structural Equation Modeling (SEM) is considered as one of the most useful advanced methods among the multivariate statistical techniques to discover the underlying relationships between them

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(Hair Jr et al. 2016). Several educational researchers focused on examining the relationships of student academic performance and its influential variables using SEM techniques (Fenollar, Román, and Cuestas 2007; Kusurkar et al. 2013; Rugutt and Chemosit 2005; Saenz et al. 1999). Recently, partial least-squares structural equation modeling (PLS-SEM) has been used in various applications to explain the variability of the dependent variables (Bass et al. 2003; Cenfetelli and Bassellier 2009; Henseler, Ringle, and Sinkovics 2009).

1.1. Theoretical framework for empirical testing

The impact of pre-university mathematical knowledge on student performance in engineering degree programs have widely studied in the literature. Several studies have confirmed that pre-mathematical knowledge significantly influence on engineering mathematics courses (Barry and Chapman 2007; Eng, Li, and Julaihi 2010; Ismail et al. 2012; Zarpelon, Resende, and Reis 2015). Hermon and Cole (2012) concluded that pre-university mathematical knowledge is an effective predictor of academic performance in aerospace engineering. A study conducted among undergraduates of three engineering programs by Imran, Nasor, and Hayati (2011) revealed that students' overall academic performance was significantly correlated with the performance in the mathematics and physical science courses taken in their respective programs and the impact was relatively stronger for the mathematics courses compared to the physical science courses.

Many authors have been reported on the use of university mathematics support with strong mathematical backgrounds. A study by Lee et al. (2008) concluded that first year engineering students' performance can be improved with the help obtained from the university mathematics learning support center. Similarly, the benefits of mathematics support in university engineering students are well documented in several studies (Parsons and Adams 2005; Patel and Little 2006; Pell and Croft 2008).

Recently, Nanayakkara and Peiris (2016) concluded that the mathematics in Level 1 is significantly correlated to student academic performance in Level 2 irrespective of the seven engineering disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka.

On the view of the past studies, it can be hypothesized that students' mathematics performance influences on their academic performance in engineering programs.

1.2. Purpose of the study

The present study is to find the influence of mathematics on students' engineering performance and proposes a relationship model between students' mathematics performance and their academic performance of engineering students in Chemical and Process Engineering. The PLS-SEM approach is employed in order to develop a theoretical model underlying the relationship between students' mathematics performance and their academic performance at the end of Level 2 in engineering programs.

2. Materials and methods

2.1. Variables and data description

The study was conducted with 71 engineering undergraduates who follow the B.Sc. engineering degree in Chemical and Process Engineering (CH) at the Faculty of Engineering, University of Moratuwa, Sri Lanka in academic year 2011/2012. Data were collected from Examination division, University of Moratuwa. Students' examination marks of mathematics courses in Level 1 (i.e., semester 1 (S1) and semester 2 (S2)) as well as Level 2 (i.e., semester 3 (S3) and semester 4 (S4)) and all compulsory engineering courses in Level 2 were used. Table 1 presents the mathematics and engineering courses in CH which are considered in this study.

2.2. Partial least squares structural equation modeling (PLS-SEM)

The SEM technique is a non-parametric method which allows to model simultaneously estimate and test

Table 1. Mathematics and engineering courses in CH discipline.

Subject area	Semester	Course code	Course
Mathematics	S1	MA1013	Mathematics
	S2	MA1023	Methods of Mathematics
	S3	MA2013	Differential Equation
		MA2023	Calculus
	S4	MA2033	Linear Algebra
Engineering	S3	CH 2013	Heat and Mass Transfer
		CH 2023	Unit Operations 1
		CH 2033	Thermodynamics
		ME 2122	Engineering Drawing & Computer Aided Modeling
	S4	CH 2043	Particle Technology
		CH 2053	Fuels and Lubricants
		CH 2063	Principles of Biological Engineering Fundamentals
		CH 2073	Polymer Science and Technology
		CH 2083	Environmental Science and Technology

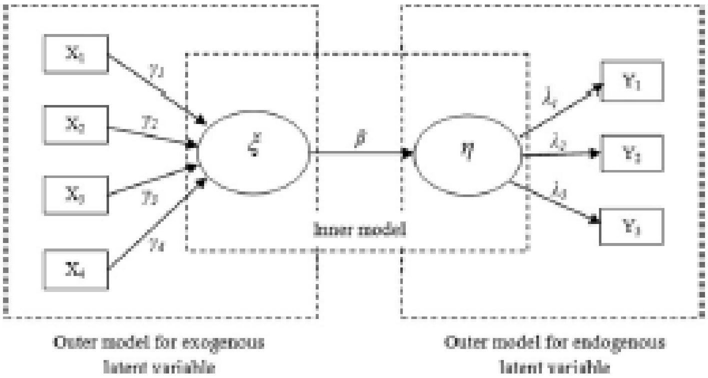

Figure 1. General PLS structural equation model.

complex theories with empirical data (Hair Jr et al. 2016). Structural equation models are developed based on systematically related hypotheses following the scientific method to explain the outcomes. An ordinary least-square (OLS)-based method is the estimation procedure for PLS-SEM. This will estimate the path relationship (coefficients) in the model that maximize the explained variance of the endogenous latent variables and minimize the unexplained variances.

A simple PLS structural equation model is depicted in Fig. 1. This contains two elements, inner model and outer model. The inner model, also known as the structural model, represents the relationship between constructs (i.e., variables that are not directly measured). The outer model which is also referred to as the measurement model represents the relationship between the constructs and observed variables (Hair Jr et al. 2016).

There are two different ways in measurement model; reflective and formative measurement. Reflective measurement indicates that the construct causes the measurement of the indicators. In contrast, formative measurement is based on the assumption that indicators cause the changes in the construct. According to Fig. 1, outer model for exogenous latent variable represents a formative model while outer model for endogenous latent variable is a reflective model.

The formative measurement model can be represented as follows:

$$\xi = \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \gamma_4 X_4 + \varepsilon, \qquad (1)$$

where, ξ is the exogenous latent variable, X_i is the ith exogenous observed variable, γ_i is the regression coefficient of X_i, ε is the error term of formative construct, and $i = 1,2,3,4$.

Equation (2) presents the relationship between reflective construct and its indicators mathematically:

$$Y_j = \lambda_j \eta + \delta_j, \qquad (2)$$

where, Y_j is the jth endogenous observed variable, η is the endogenous latent variable, λ_j is the coefficient representing effect of η on Y_j, δ_j is the measurement error for Y_j, and $j = 1,2,3$.

The structural model is defined as follows:

$$\eta = \beta \xi + \zeta, \qquad (3)$$

where β is the path coefficient and ζ is the error term of inner model.

The evaluation of estimates of PLS-SEM consists two separate processes for the measurement model and the structural model. With reference to assessment of the measurement model, specific criteria associated with formative and reflective model evaluate the reliability and validity of the construct measures.

2.3. Assessment of model validation

The evaluation of estimates of PLS-SEM consists two separate processes for the measurement model and the structural model. With reference to assessment of measurement model, specific criteria associated with reflective and formative models to evaluate the reliability and validity of the construct measures were different procedures and techniques (Fornell and Larcker 1981; Hair et al. 2016).

Reflective measurement models are assessed on their internal consistency reliability and validity. To establish indicator reliability, the squared standardized outer loadings of the indicators were considered. Internal consistency reliability is measured through

Cronbach's alpha, which provides an estimate of the reliability based on the intercorrelations of the observed indicator variables and composite reliability (CR), which takes into account the different outer loadings of the indicator variables. To evaluate convergent validity on the construct level, average variance extracted (AVE) criteria are considered and discriminant validity evaluates by using two measures, cross loadings of the indicators on indicator level and Fornell–Larcker criterion on construct level. Formative measurement models are assessed for their convergent validity, the weights and their significance as well as outer loadings of the indicators (Hair et al. 2016).

The structural model is assessed after the assessment of measurement models is established. The coefficients of determination (R^2), the magnitude, and significance of path coefficients are the evaluation criteria for structural model (Hair et al. 2016).

2.4. *Bootstrapping technique*

As PLS-SEM is a non-parametric method that does not require assumptions about the data distribution, the significance tests cannot be applied to test whether the coefficients are significant. Therefore, a non-parametric bootstrapping technique was used to test the significance of various results such as path coefficients, outer weights, outer loadings, and R^2 values. In bootstrapping, subsamples are randomly drawn using the resampling with replacement procedure. The subsample is then used to estimate the PLS path model and this process is repeated for all random subsamples. The estimations from the bootstrap subsamples are used to assess the significance of PLS-SEM results.

In this study, PLS-SEM approach was applied separately for both semesters; S3 and S4 in Level 2. These models consist of two unobserved latent variables; students' mathematics performance (MAT) as the exogenous formatively measured construct and their engineering performance (ENG) as the endogenous reflectively measured construct. Observed variables of MAT construct are prior and core mathematics courses while engineering courses are the observed variables of ENG construct with respect to the curriculum of each semester. That is, MAT construct as well as ENG construct have four and five observed variables in the PLS structural model for S3 and S4, respectively. Bootstrap analysis was done with 5000 subsamples and bias-corrected and accelerated bootstrap method was utilized.

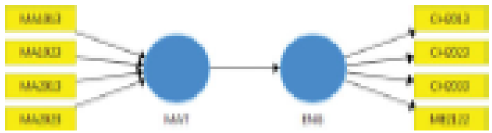

Figure 2. PLS structural model for student performance in S3.

3. Results and discussion

The PLS structural model for student academic performance in S3 and S4 were determined and shown in Fig. 2 and Fig. 3, respectively.

Table 2 presents the results summary of measurement models in S3 as well as S4 including outer weights, outer loadings, *p*-values, and evaluation criteria.

The weights of MAT indicators in S3 model are significant at the 5% level except MA1013 ($p = 0.458$). Also, this weight is negative and small, which is unacceptable. It can be said that mathematics courses in S3 (MA2013 and MA2023) are relatively important compared with mathematics courses in Level 1. By referring the weights of MAT indicators in S4 model, it is clear that the relatively most important MAT indicator is MA2033 (0.712). Moreover, the weights of other MAT indicators are not significant at the 5% level of significance. However, the weight of MA1013 is not acceptable as in S3 model. Thus, it is clear that Mathematics course (MA1013) in S1 has a weak relationship with engineering courses in Level 2.

Since most of the formative indicators (MAT) in both models are non-significant, their outer loadings were considered and it suggests that MAT indicators can be included in the PLS structural model as they are greater than 0.50.

The outer loadings of the reflective indicators in S3 as well as S4 models denote that all engineering courses are highly correlated (>0.80) with engineering performance except ME2122 course in S3. Moreover, the

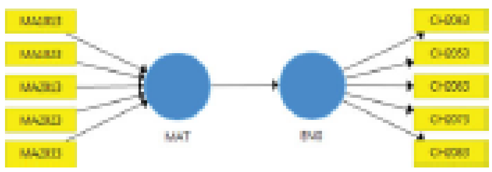

Figure 3. PLS structural model for student performance in S4.

Table 2. Results of measurement models.

	Formative measurement model				Reflective measurement model							
	MAT indicators	Outer weights (Outer loadings)	*T* value	*P* value	ENG indicators	Outer loadings	Squared loadings	Cross loadings	Cronbach's alpha	Composite reliability	AVE	Fornell–Larcker criterion
S3	MA1013	−0.088 (0.536)	0.743	0.458	CH2013	0.917	0.841	0.728	0.860	0.904	0.705	0.840
	MA1023	0.253 (0.738)	2.300	0.024	CH2023	0.870	0.757	0.658				
	MA2013	0.497 (0.937)	3.599	< 0.001	CH2033	0.872	0.760	0.785				
	MA2023	0.45 (0.898)	2.598	0.009	ME2122	0.681	0.464	0.392				
S4	MA1013	−0.068 (0.522)	0.771	0.435	CH 2043	0.823	0.677	0.718	0.944	0.957	0.818	0.905
	MA1023	0.171 (0.716)	1.310	0.183	CH 2053	0.926	0.857	0.790				
	MA2013	0.082 (0.823)	0.570	0.560	CH 2063	0.931	0.867	0.726				
	MA2023	0.193 (0.788)	1.115	0.263	CH 2073	0.908	0.824	0.716				
	MA2033	0.712 (0.973)	4.745	< 0.001	CH 2083	0.929	0.863	0.796				

results of squared outer loadings which reflect the indicator reliability show that the amount of variation in ENG indicators is explained by its construct is considerably higher (> 0.7) for all ENG indicators except ME2122 indicator with a value of 0.464 in S3 model and CH2043 indicator (0.677) in S4 model.

With reference to the values of Cronbach's alpha and composite reliability, it can be said that reflective construct in both PLS structural models have high levels of internal consistency reliability. The average variance extracted (AVE) values of 0.705 (in S3) and 0.818 (in S4) are higher than the required minimum level of 0.50. It suggests that ENG construct in both models have high levels of convergent validity. The values of Fornell–Larcker criterion and cross loadings of reflective indicators (engineering courses) provide evidence for discriminant validity of reflective construct in both models of S3 and S4. However, cross loading of ME2122 indicator is considerably lower compared to other cross loadings.

Hence, all model evaluation criteria provide support for the reliability and validity of the ENG constructs in both reflective models (S3 and S4).

With respect to Table 3, the coefficient of determination (R^2) of both structural models in S3 and S4 are 0.613 and 0.647, respectively. That is, 61.3% of the variance in students' engineering performance in S3 explained by mathematics in Level 1 and S3. Considering the S4 performance, the students' mathematics performance explains 64.7% of the variance in their engineering performance in S4. The path coefficients of structural models of S3 (0.783) and S4 (0.804) reveal that the mathematics performance significantly influences the engineering academic performance of CH students.

Table 3. Results of structural model.

Semester	Path coefficient	*p* value	*R* square	*R* sq adjusted
S3	0.783	< 0.001	0.613	0.607
S4	0.804	< 0.001	0.647	0.642

4. Conclusions and recommendations

This study adopted partial least-square structural equation modeling (PLS-SEM) to investigate the impact of engineering students' mathematics performance on their academic performance in chemical and process engineering courses. The results revealed that students' academic performance in engineering courses is influenced by their mathematics performance, explaining 61% and 64% of variance in semester 3 and semester 4, respectively. Furthermore, it was found that core mathematics courses are more important compared with prior mathematics courses. It is observed that both models are satisfied with the level of conceptual validity and the hypothesis defined is accepted.

The findings of this study can be useful for various stakeholders in particularly, the academic staff of both departments, Mathematics and Chemical and Process Engineering to improve the students' academic performance. The students are encouraged to acquire mathematical concept and knowledge during their undergraduate level for better performance in engineering sciences.

This study can be extended for more engineering disciplines and more academic years before implement various decisions. Furthermore, this study has considered only the effect of mathematics courses which are taught in the university. Therefore, future research can identify other components that constitute the remaining unexplained variance.

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IMPACT OF MATHEMATICS IN LEVEL 1 ON THE ACADEMIC PERFORMANCE OF ENGINEERING STUDENTS: A CASE STUDY

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ABSTRACT

In engineering sciences, mathematical knowledge is highly essential to improve the analytical thinking of engineering undergraduates. Therefore, a significant component of advanced mathematics has been included in the engineering degree programs. The objective of this study is to explore the impact of mathematics in Level 1 on the academic performance of undergraduate engineering students in Level 2. The study was conducted with engineering students at the University of Moratuwa, Sri Lanka. Findings revealed that the mathematics performance in Level 1 was significantly correlated with students' overall performance in all engineering disciplines. The impact of mathematics in Semester 2 was significantly higher than the impact of mathematics in Semester 1 on the students' performance in Level 2. Furthermore, the impact of mathematics was significantly different among various engineering disciplines. The study concluded that the performance in mathematics in Level 1 could indicate the trend towards the student academic performance in all engineering programs.

KEYWORDS: Engineering Mathematics, Multivariate Multiple Linear Regression, Students' Academic Performance

INTRODUCTION

Mathematics is more than a tool for solving problems and it can develop intellectual maturity and logical thinking of students. The skills in mathematics would certainly assist to enhance students' knowledge in other subjects such as engineering, physics, accounting, etc. (Imran, Nasor and Hayati 2011; Aina 2013; Alfan and Othman 2005). Especially, in engineering sciences, mathematical knowledge is crucial importance to improve the analytical thinking of engineering undergraduates. Pyle (2001) and Sazhin (1998) stated the importance of mathematical knowledge for engineering students. A study by Goold and Devitt (2012), with the focus on professional engineers in Ireland, discovered that mathematical knowledge gained prior and during engineering education is highly essential in engineering practice as they use a high level of curriculum mathematics and mathematical thinking in their work. It is clear that mathematics is more important foundation for the education of engineers.

In many countries, the pre-university requirement for engineering degrees is based mostly on mathematics for all higher education institutions. Similarly, in Sri Lanka, for engineering undergraduate degree programs, higher mean Z score of the individual Z scores of Mathematics, Physics and Chemistry subjects in General Certificate of Education Advanced Level; G.C.E. (A/L) examination is the pre-requisite.

Pre-university qualification and admission criteria for university entrance, have been widely studied in the literature and are commonly accepted to have a beneficial effect on students' subsequent performance in a variety of academic fields: Engineering (Ali and Ali 2010; Hermon and Cole 2012), Chemistry (Seery 2009), Medicine (Ali 2008; Hailikari, Katajavuori and Lindblom-Ylanne 2008; Mufti and Qayum 2013), Equine and animal studies (Huws and Taylor

2008), Accounting (Alfan and Othman 2005) and Psychology (Huws, Reddy and Talcott 2006; Thompson and Zamboanga 2004).

Numerous studies have been investigated on the predictive validity of pre-university mathematical knowledge on student performance in engineering degree programs and revealed that pre-university mathematical knowledge effect on the performance of engineering students (Barry and Chapman 2007; Hermon and Cole 2012; Ismail, et al. 2012; Lee et al. 2008; Othman et al. 2009). Conversely, Adamson and Clifford (2002) and Todd (2001) found that engineering student performance in university cannot be reliably predicted from pre-university qualification. A study by Nopiah, Fuaad, Rosli, Arzilah, and Othman (2013) in Malaysia, was focused on predicting the performance of students in subsequent engineering mathematics courses using pre-test. They found a weak correlation between the pre-test and performance in engineering mathematics courses.

A study conducted among undergraduates of three engineering programs by Imran et al. (2011) revealed students' overall performance in engineering programs were significantly correlated with the performance in the mathematics and physical science courses taken in their respective programs. This correlation was relatively stronger for the mathematics courses compared to the physical science courses. However, there is a lack of studies related to examining the impact of mathematics in undergraduate engineering degree programs on student' academic performance.

According to Sri Lankan education system, students entering university with diverse prior knowledge and background. However, there is a high probability that the students who admitted to the Faculty of Engineering, University of Moratuwa, Sri Lanka have obtained higher grades for mathematics in G.C.E. (A/L) examination. Nevertheless, mathematics performance of engineering students in their undergraduate degree programs varies significantly between and within different engineering disciplines. Hence, it is crucial to understand the impact of mathematical knowledge that students acquired from their undergraduate degree programs. This knowledge would be useful for educational stakeholders at different level of decision making. The purpose of this study is therefore to explore the impact of mathematics in Level 1 on the academic performance of undergraduate engineering students in Level 2.

MATERIALS AND METHODS

The study was conducted with 626 engineering students from seven different disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka for the academic year 2011/2012. Data were collected from Examination division, University of Moratuwa after due permission was taken. Seven different engineering disciplines used for the study are namely; Chemical and Process Engineering (CH), Civil Engineering (CE), Computer Science and Engineering (CSE), Electrical Engineering (EE), Electronic and Telecommunications Engineering (ENTC), Materials Science and Engineering (MT) and Mechanical Engineering (ME).

Students' examination marks of mathematics courses in both semesters in Level 1: semester 1 (S1) and semester 2 (S2) and all compulsory courses other than mathematics courses in both semesters in Level 2: semester 3 (S3) and semester 4 (S4) were utilized. Average marks of these courses were considered as the students' academic performance for S3 and S4 separately. Furthermore, academic performance of these courses irrespective of S3 and S4 was considered as an average of S3 and S4.

Explanatory data analysis was carried out initially followed by ANOVA to examine the significant differences in mean marks of mathematics courses in Level 1 among various engineering disciplines. Regression models were developed using the stepwise method and furthermore, multivariate regression was applied to the academic performance of S3 and

S4.

RESULTS AND DISCUSSIONS

Explanatory Data Analysis

Table 1 presents descriptive statistics for each of the explanatory and response variables irrespective of engineering students' disciplines. It is clear that both mean and median marks in S1 are higher compared with corresponding values in S2 indicating student performance of mathematics in S1 is better than that in S2. However, such a difference in both mean and median was not observed in average marks in S3 and S4.

Table 1: Descriptive Statistics of Students' Marks

Variable	Mean	SE of Mean	Median
Math_S1	68.9	0.48	69.3
Math_S2	57.2	0.54	56.4
Mean_S3	66.3	0.33	66.6
Mean_S4	66.4	0.33	66.9
Mean_composite	66.4	0.31	66.8

The box plots in Figure 1 and Figure 2 exhibit the distribution of mathematics marks in S1 and S2 by engineering disciplines respectively. According to Figure 1, the highest average mark for the mathematics course in S1 is from ENTC discipline (79.7) followed by CSE discipline (77.1) while the lowest average mark is from MT discipline (48.7). Most of the mathematics marks (Math_S1) in all disciplines except MT discipline have lied between 50 and 90 region. However, few students in CE, CH and CSE disciplines have obtained higher marks than the highest mark obtained by ENTC discipline indicating high marks by individuals were obtained by students in CE, CH and CSE disciplines.

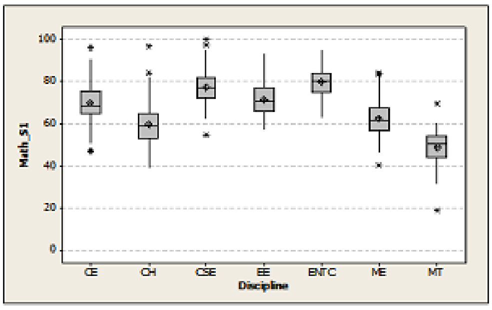

Figure 1: Distribution of Mathematics Marks in S1 by Engineering Discipline

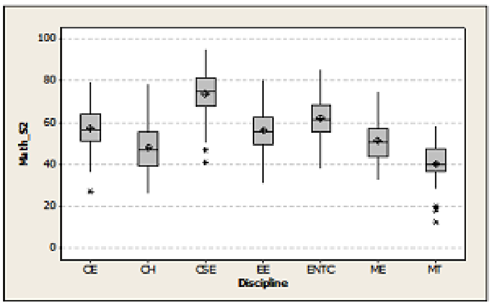

Figure 2: Distribution of Mathematics Marks in S2 by Engineering Discipline

Figure 2 shows that the variations of all distributions of mathematics marks in S2 are higher than that in S1. Most of the students in all disciplines except CSE discipline, obtained between 40 and 70 percent for mathematics course in S2. Students of CSE discipline have obtained the highest average mark (73.9) while students from MT discipline have obtained the lowest average mark (40.1) for mathematics in S2. Comparing both figures 1 and 2, it is clear that the performance of mathematics has decreased from S1 to S2 in all disciplines. The overall best performance in both mathematics courses are from students of ENTC and CSE disciplines while the least performance is from students of MT discipline.

Comparison Among Engineering Disciplines

ANOVA was conducted for students' mathematics marks in S1 and S2 separately for a randomly selected sample size of 100 students in order to compare mathematics marks among engineering disciplines. This was repeated five times with replacement sampling. The null hypothesis tested was there is no significant difference between mean marks of mathematics course among engineering disciplines. The summary of the ANOVAs carried out for each sample are shown in Table 2. Results concluded that both mean marks of mathematics courses in S1 and S2 among engineering disciplines are significantly different.

Table 2: ANOVA for Mathematics Courses

Sample		1	2	3	4	5
P - value	Math_S1	0.000	0.000	0.000	0.000	0.000
	Math_S2	0.000	0.000	0.000	0.001	0.000

Impact of Mathematics Marks on Students' Performance

Table 3 shows the correlation coefficient between marks of mathematics and response variables and found that correlation coefficients for all pairs are significantly greater than zero ($P < 0.01$). Furthermore, results indicate mathematics course in S2 is strongly correlated with students' overall performance than mathematics course in S1 indicating that more impact can be expected from marks of Math_S2 on the overall performance in Level 2 than that of marks of Math_S1.

Table 3: Correlation Coefficient Between Marks of Mathematics and Response Variables

	Mean_S3	Mean_S4	Mean_composite
Math_S1	.487**	.418**	.481**
Math_S2	.501**	.524**	.541**
**. Correlation is significant at the 0.01 level (1-tailed).			

Table 4: Correlation Coefficient Between Marks of Mathematics and Responses by Discipline

Criterion	Predictors	CE	ENTC	ME	EE	MT	CH	CSE
		(N=125)	(N=96)	(N=96)	(N=99)	(N=44)	(N=71)	(N=95)
Mean_S3	**Math_S1**	0.314**	0.332**	0.238*	0.461**	0.393**	0.483**	0.482**
	Math_S2	0.485**	0.631**	0.575**	0.606**	0.556**	0.603**	0.501**
Mean_S4	**Math_S1**	0.342**	0.224*	0.233*	0.372**	0.198	0.446**	0.492**
	Math_S2	0.490**	0.617**	0.613**	0.600**	0.482**	0.600**	0.507**
Mean_composite	**Math_S1**	0.360**	0.307**	0.253*	0.439**	0.308*	0.486**	0.507**
	Math_S2	0.534**	0.659**	0.634**	0.635**	0.541**	0.630**	0.524**
**. Correlation is significant at the 0.01 level (1-tailed)								
*. Correlation is significant at the 0.05 level (1-tailed)								

Furthermore, the correlation between marks of Math_S1 and Math_S2 and the average marks of the courses in S3 and S4 as well as Level 2 with respect to engineering discipline are shown in Table 4. Results show significant correlation between predictors and response variables for all disciplines at the 0.05 level except the correlation between mathematics course in S1 and average marks of S4 of MT discipline. Moreover, the correlation between mathematics course in S2 and students' overall performance are stronger compared with the correlation between mathematics course in S1 and students' overall performance.

Multiple Linear Regression (MLR)

Stepwise regression analysis was carried out on the three students' academic performance outcomes: average marks of S3, average marks of S4 and composite of S3 and S4, irrespectively to their discipline. Table 5 denotes model statistics, ANOVA F-statistics as well as coefficients.

Table 5: Summary of the Fitted Model Irrespective of the Disciplines

	Mean_S3	Mean_S4	Mean_Composite
Constant	41.185	44.226	42.501
Math_S1	0.198	0.105	0.155
Math_S2	0.200	0.261	0.231
ANOVA F statistic	135.69	127.13	152.52
P-value	0.000	0.000	0.000
Std. Error of the Estimate	6.91	6.88	6.41
R-sq	30.4	29.0	32.9
R-sq (adj)	30.1	28.8	32.7

Predictors: (Constant), Math_S1, Math_S2

Dependent Variable: Average marks

Models with average marks of S3 (Mean_S3) and average marks of S4 (Mean_S4) as the outcome measure, explained 30% and 29% of the variation in students' academic performance respectively. Similarly, model with the composite outcome explained 33% of variation in students' academic performance. Though the amount of variance explained by the fitted model is not sufficient, P-values for the F statistic denote that all three fitted models are significant at the 0.05 level. Moreover, both predictors: Math_S1 and Math_S2 are significant ($P < 0.01$) in all three models. However, residual analyses suggest that all fitted models are not adequate due to the violation of normality assumption.

Furthermore, regression analysis was carried out for engineering student discipline wise, to identify the impact of mathematics separately. Mean_composite was considered as the response variable and the model statistics, ANOVA F-statistics and coefficients are provided in Table 6.

Table 6: Summary of the Fitted Model by Discipline

	CE	ENTC	ME	EE	MT	CH	CSE
Constant	45.615	40.690	37.970	41.300	40.250	35.330	19.280
Math_S1	0.132			0.174			0.335
Math_S2	0.249	0.443	0.460	0.293	0.454	0.618	0.290
ANOVA F statistic	29.88	71.97	63.32	42.23	17.41	45.49	29.76
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std. Error of the Estimate	4.42	5.24	4.96	3.84	6.67	8.31	5.84
R-sq	32.9	43.4	40.3	46.8	29.4	39.7	39.3
R-sq (adj)	31.8	42.8	39.7	45.7	27.7	38.9	37.9

Dependent Variable: Mean_composite

R-square values for all seven models, illustrated that the fitted models explained 29% to 47% of the variation in students' academic performance. F statistics of ANOVA output imply that all seven fitted models are significant at the 0.05 level. However, mathematics course in S1 is significant at the 0.05 level in three fitted models only and that is for CE, EE and CSE disciplines. Mathematics course in S2 has the strongest influence on students' academic performance in all engineering disciplines. Moreover, observations on the t-value indicate that mathematics course in S2 is a high significant predictor in determining students' performance. Furthermore, residual analysis confirmed that all the fitted models are adequate.

Multivariate Multiple Linear Regression

In order to determine how mathematics courses in S1 and S2 effect on academic performance in S3 and S4, multivariate multiple linear regression analysis was utilized as it consider multiple responses and multivariate tests provide a way to understand the relationships of predictors across separate response measures.

Table 7 shows the Pearson correlation between Mean_S3 and Mean_S4 discipline wise. According to these results, it is clear that academic performance of S3 and S4 (Mean_S3 and Mean_S4) are highly correlated for all disciplines and this was suggested that multivariate MLR could be applied for Mean_S3 and Mean_S4 as the outcomes with respect to engineering disciplines separately.

Table 7: Pearson Correlation Between Mean_S3 and Mean_S4

Discipline	CE	ENTC	ME	EE	MT	CH	CSE
Correlation coefficient	0.665	0.793	0.738	0.813	0.834	0.817	0.851

Table 8 presents the multivariate MLR model summaries for each discipline separately. Results in Table 8 show that Math_S2 is significant at 0.05 level for all fitted models, while Math_S1 is significant only for three disciplines; CE, EE and CSE in both semesters S3 and S4. F statistics and residual analysis confirmed the adequacy of all fitted models in both semesters. R-squared values for all models, illustrated that the fitted models explained 23% to 45% of the variation in students' academic performance. Furthermore, these results indicate that in some disciplines, academic performance in S3 is more predictable than academic performance in S4 from mathematics courses in Level 1.

Table 8: Discipline Wise Multivariate MLR Model Summary

	CE	ENTC	ME	EE	MT	CH	CSE
Dependent Variable: Mean_S3							
Constant	48.31**	29.26**	34.97**	39.55**	34.43**	29.43**	19.98**
Math_S1	0.111**	0.15	0.071	0.212**	0.156	0.207*	0.319**
Math_S2	0.227**	0.449**	0.429**	0.297**	0.389**	0.466**	0.279**
ANOVA F statistic	22.11**	32.82**	23.78**	39.38**	10.27**	21.89**	25.65**
Std. Error of the Estimate	4.59	6.11	5.62	4.24	6.41	8.24	6.03
R-sq	26.61	41.38	33.84	45.07	33.38	39.17	35.8
R-sq (adj)	25.4	40.12	32.41	43.92	30.13	37.38	34.4
Dependent Variable: Mean_S4							
Constant	42.54**	41.91**	34.57**	43.06**	42.21**	28.49**	18.71**
Math_S1	0.156**	0.015	0.057	0.135**	-0.03	0.176	0.349**
Math_S2	0.274**	.383**	0.463**	0.29**	0.466**	0.561**	0.299**
ANOVA F statistic	23.91**	28.7**	28.5**	31.88**	6.24**	20.41**	26.79**
Std. Error of the Estimate	5.54	5.12	5.46	4.14	7.87	9.53	6.39
R-sq	28.16	38.16	38.00	39.91	23.33	37.51	36.8
R-sq (adj)	26.98	36.83	36.67	38.66	19.59	35.67	35.43
M1 test - F statistic	0.73	3.39*	0.05	3.05*	3.88*	0.10	0.26
M2 test - F statistic	1.07	1.79	0.31	0.03	0.75	1.06	0.19
* $p<0.1$; ** $p<0.05$							

The first multivariate test (M1 test) revealed that the parameter for Math_S1 is the same for the academic performance of S3 (Mean_S3) and S4 (Mean_S4) in four disciplines; CE, ME, CH and CSE. In other words, the parameter for Math_S1 is not the same for the academic performance of S3 and S4 in ENTC, EE and MT disciplines. The parameter for Math_S2 is the same for the academic performance of S3 (Mean_S3) and S4 (Mean_S4) in all seven disciplines is exposed from the second multivariate test (M2 test).

These results suggest that if a student who studied in any engineering discipline, was able to perform well in the mathematics courses in Level 1, it is likely that he/she would perform well in courses in Level 2 as well.

CONCLUSIONS

It can be inferred that students' performance of mathematics in Level 1 is significantly different among various engineering disciplines. The impact of mathematics in Semester 2 was significantly higher than the impact of mathematics in Semester 1 on the students' academic performance in Level 2 irrespective of the engineering disciplines. Moreover, the effects of mathematics courses in Level 1 are equally performed on students' academic performance in S3 and S4. The performance in mathematics in Level 1 is a good indicator to judge student academic performance in engineering programs in Level 2. This analysis is recommended to carry out for more years before implement various decisions.

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Application of Adjusted Canonical Correlation Analysis (ACCA) to study the association between mathematics in Level 1 and Level 2 and performance of engineering disciplines in Level 2

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Abstract. Mathematics plays a key role in engineering sciences as it assists to develop the intellectual maturity and analytical thinking of engineering students and exploring the student academic performance has received great attention recently. The lack of control over covariates motivates the need for their adjustment when measuring the degree of association between two sets of variables in Canonical Correlation Analysis (CCA). Thus to examine the individual effects of mathematics in Level 1 and Level 2 on engineering performance in Level 2, two adjusted analyses in CCA: Part CCA and Partial CCA were applied for the raw marks of engineering undergraduates for three different disciplines, at the Faculty of Engineering, University of Moratuwa, Sri Lanka. The joint influence of mathematics in Level 1 and Level 2 is significant on engineering performance in Level 2 irrespective of the engineering disciplines. The individual effect of mathematics in Level 2 is significantly higher compared to the individual effect of mathematics in Level 1 on engineering performance in Level 2. Furthermore, the individual effect of mathematics in Level 1 can be negligible. But, there would be a notable indirect effect of mathematics in Level 1 on engineering performance in Level 2. It can be concluded that the joint effect of mathematics in both Level 1 and Level 2 is immensely beneficial to improve the overall academic performance at the end of Level 2 of the engineering students. Furthermore, it was found that the impact mathematics varies among engineering disciplines. As partial CCA and partial CCA are not widely explored in applied work, it is recommended to use these techniques for various applications.

1. Introduction

The studies on the factors that influence students academic performance has received great attention among researchers. Several researchers have stated the importance of mathematical knowledge for engineering students to develop their analytical thinking [1-3]. A study by [4] revealed that mathematics in Level 1 is significantly influenced on students' overall academic performance in Level 2 irrespective of the seven engineering disciplines at the Faculty of Engineering and the impact of mathematics varies among engineering disciplines. This study is therefore to determine the individual effect of mathematics in both Level 1 and Level 2 separately on engineering performance in Level 2.

2. Materials and Methods

2.1. Data Description

The study was conducted with engineering undergraduates from three different disciplines namely: Civil Engineeering (CE), Mechanical Engineering (ME) and Electronic and Telecommunications Engineering (EN) at the Faculty of Engineering, University of Moratuwa, Sri Lanka for the academic year, 2011/2012. Students' examination marks of mathematics modules in Level 1 (i.e. semester 1 (S1) and semester 2 (S2)) as well as Level 2 (i.e. semester 3 (S3) and semester 4 (S4)) and all compulsory engineering modules in Level 2 were used. Table 1 presents the mathematics modules followed in each semester in Level 1 and Level 2.

Table 1. Mathematics modules in Level 1 and Level 2.

Academic Level	Semester	Module Code	Module Name
Level 1	S1	MA1013	Mathematics
	S2	MA1023	Methods of Mathematics
Level 2	S3	MA2013	Differential Equation
		MA2023	Calculus
	S4	MA2033	Linear Algebra
		MA2053	Graph Theory
		MA3013	Applied Statistics

2.2. Unadjusted and Adjusted Canonical Correlation Analysis (CCA)

In this study unadjusted CCA and adjusted CCA: partial CCA [5] and part CCA [6] were used. The CCA was used to examine the joint effects of mathematics in Level 1 and Level 2 on engineering performance in Level 2.The partial CCA was used to find the individual effect of mathematics in Level 2 on engineering performance in Level 2, when the effect of mathematics in Level 1 is removed from both groups, as the students have already completed mathematics in Level 1 at Level 2. The part CCA was used to determine the individual effect of mathematics in Level 1 on engineering performance in Level 2 when the effect of mathematics in Level 2 is eliminated from engineering performance in Level 2.

3. Results and Discussion

3.1. Correlation Analysis

Correlation analysis confirmed data are suitable for CCA as most of the mathematics and engineering variables are significantly correlated ($p<0.05$) within their sets as well as between the two sets for all disciplines. Thus, adjusted CCA (part CCA and partial CCA) for two semesters in Level 2 (S3 and S4) were done separately for each engineering disciplines.

The marks of all compulsory engineering modules in two semesters (S3 and S4) in Level 2 are the dependent set of variables, but the number of variables in both S3 and S4 varied based the engineering disciplines. The results of unadjusted and adjusted CCA were summarized mainly focusing on the mathematics variables.

3.2. Impact of mathematics in Level 1 and semester 3 on the engineering performance in semester 3
The results of unadjusted and adjusted CCA for student performance in S3 by their engineering disciplines are summarized in Table 2.

3.2.1. CCA. Mathematics modules in S1 and S2 in Level 1 and S3 are taken as the predictor set. The p-value of Wilk's lambda test statistics confirmed that only the first canonical variate pair is statistically significant ($p < 0.05$) for all engineering disciplines. It implies that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. According to the first canonical correlation (CC), it is clear that student mathematics performance is strongly correlated with engineering performance in S3 for all disciplines (CC >0.6). The proportion of the variance in the first canonical variate of engineering performance explained by the first canonical variate of the mathematics performance varied from 39% (in CE) to 70% (in EN). The canonical loadings of mathematics variables reflect that all mathematics variables are strongly associated with its first canonical variate except MA1013 in all disciplines. The redundancy index of engineering indicates that the explainable variability of engineering performance by the first canonical variate of mathematics varied from 12% (in CE) to 40% (in EN).

3.2.2. Part CCA. The two mathematics modules in Level 1 are the predictor set while mathematics modules in S3 are the control set, which eliminates its influence from the dependent set. By referring p-value of Wilk's lambda test statistics, it is clear that at least a first canonical variate pair of part CCA does not explain a statistically significant amount of variability of the predictor and dependent sets for all disciplines ($p>0.1$). It implies that the linear relationship between mathematics in Level 1 and engineering performance in S3 is not statistically significant with the effect of mathematics in S3 partialed out of the engineering performance in S3 for all disciplines. Furthermore, the first part canonical correlations are found to be less than 0.5 for all disciplines. It confirmed that mathematics in Level 1 is weakly correlated with engineering performance when the effect of mathematics in S3 is eliminated from engineering performance in S3. The results of squared canonical correlations indicate that the variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics in Level 1 is less than 18% for almost all disciplines. In addition to that, the redundancy measures in all disciplines imply that amount of variability in mathematics and engineering sets explained by their opposite first canonical variate are not sufficient.

3.2.3 Partial CCA. The two mathematics variables in S3 as the predictor set and two mathematics variables in both S1 and S2 (in Level 1) as the control set, which eliminates its influence from both predictor and dependent sets are comprised in partial CCA. With reference to p-value of Wilk's lambda test statistics, it is clear that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set for all disciplines. Based on the results of first partial canonical correlations, it can be seen that the mathematics in S3 has moderately strong linear relationship with the engineering performance in S3 (CC > 0.5) for all disciplines except CE discipline, when the effect of mathematics in Level 1 is removed. The squared canonical correlations illustrate that the first canonical variate of mathematics accounted for 20% (in CE) to 55% (in EN) of the variance in the first canonical variate of engineering and it reflects that mathematics in S3 is significantly influenced on engineering performance in S3, even after the effect of mathematics in Level 1 is removed. Moreover, the canonical loadings reveal that mathematics variables are strongly correlated (>0.75) with their first canonical variates for all disciplines. The redundancy index of engineering reflects that the proportion of variance in engineering performance in S3 explained by the first canonical variate of mathematics also varied from 5% (in CE) to 23% (in EN).

3.3. Impact of mathematics in Level 1 and Level 2 on the engineering performance in semester 4

The summary of results of CCA, Partial CCA and Part CCA for academic performance in S4 is presented in Table 2 for the same three engineering disciplines.

3.3.1. CCA. As in Section 3.2.1, mathematics in S1 and S2 in Level 1 as well as S3 and S4 in Level 2 are taken as the predictor set. By referring the p-value of Wilk's lambda test statistics, it can be said that a significant amount of variability of predictor and dependent sets can be explained by the first canonical variate pair. The first canonical correlations reveal that mathematics in both Level 1 and Level 2 has a significantly strong linear relationship ($CC > 0.7$) with the engineering performance in S4. According to the canonical loadings, mathematics in S1 (MA1013) is weakly correlated with its first canonical variate whereas the remaining mathematics variables are significantly correlated with their first canonical variate for all disciplines. The amount of variance in engineering performance in S4 explained by the first canonical variate of mathematics in both Level 1 and Level 2 varied from 25% (in EN) to 34% (in CE) and it can be concluded that a considerable amount of variability in engineering performance in S4 can be explained by the mathematics performance in both Level 1 and Level 2.

3.3.2. Part CCA. The two mathematics variables in Level 1 are considered as the predictor set and the control set which removes its effect from dependent set, contains mathematics variables in both S3 and S4 in Level 2. With respect to the p-value of Wilk's lambda test statistics, the first pair of canonical variate in Part CCA is not statistically significant ($p > 0.05$) for all disciplines. This implies that at least a first canonical variate pair of Part CCA does not explain a statistically significant amount of variability of the predictor and dependent sets. Based on the results of part canonical correlation, it is clear that mathematics in Level 1 has a weak association with engineering performance in S4, after eliminating the effect of mathematics in S3 and S4. It is confirmed by the redundancy indices of engineering performance, which found less than 5% of the total variance of engineering performance that can be explained by the first canonical variate of mathematics in Level 1.

3.3.3. Partial CCA. The mathematics modules in S3 and S4 in Level 2 are the predictor set while mathematics modules in Level 1 are considered as the control set. The first canonical variate pair of Partial CCA is statistically significant ($p < 0.05$) as revealed by the p-value of Wilk's lambda test statistics. That is, the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set when the effect of mathematics in Level 1 is eliminated from both mathematics and engineering performance in Level 2. As the effect of mathematics in Level 1 is statistically controlled by partial correlation, the results confirmed that the mathematics in S3 and S4 has a significant relationship with the engineering performance in S4 (>0.55). The squared canonical correlations show that the first canonical variate of mathematics accounted for 31% (in EN) to 46% (in CE) of the variance in the first canonical variate of engineering. Furthermore, the proportion of variance in engineering performance in S4 explained by the first canonical variate of mathematics in both S3 and S4 varied from 13% (in EN) to 24% (in CE) after adjusting for mathematics in Level 1.

Table 2. Results of unadjusted and adjusted CCA for S3 and S4 for the three selected disciplines.

Semester	Discipline		CC	Sq. CC	P-value	Mathematics performance								Engineering performance	
						Canonical Loadings						Variance extracted	Red.	Variance extracted	Red.
						MA1013	MA1023	MA2013	MA2023	MA2033	Extra module				
S3	CE	CCA	0.623	0.388	<.0001	0.428	0.765	0.758	0.862	-	-	52.12	20.26	30.39	11.81
		Part CCA	0.292	0.085	0.217	0.045	0.966	-	-	-	-	46.74	3.99	27.48	2.35
		Partial CCA	0.448	0.200	0.002	-	-	0.762	0.929	-	-	72.19	14.46	26.23	5.26
	EN	CCA	0.834	0.696	<.0001	0.373	0.698	0.838	0.941	-	-	55.38	38.53	56.90	39.59
		Part CCA	0.339	0.115	0.312	0.055	0.958	-	-	-	-	45.99	5.29	18.80	2.16
		Partial CCA	0.739	0.547	<.0001	-	-	0.783	0.909	-	-	71.94	39.34	42.96	23.49
	ME	CCA	0.769	0.591	<.0001	0.338	0.641	0.860	0.915	-	-	52.54	31.04	37.10	21.92
		Part CCA	0.415	0.173	0.167	-0.189	0.891	-	-	-	-	41.43	7.15	29.61	5.11
		Partial CCA	0.684	0.467	<.0001	-	-	0.835	0.897	-	-	75.11	35.11	24.55	11.47
S4	CE	CCA	0.766	0.587	<.0001	0.374	0.602	0.612	0.693	0.736	0.865	44.10	25.90	57.29	33.66
		Part CCA	0.146	0.021	0.962	-0.260	0.842	-	-	-	-	38.82	0.83	26.18	0.56
		Partial CCA	0.679	0.461	<.0001	-	-	0.516	0.579	0.654	0.825	42.75	19.72	51.13	23.59
	EN	CCA	0.700	0.490	<.0001	0.203	0.773	0.666	0.865	0.846	-	50.90	24.95	43.3	24.74
		Part CCA	0.315	0.099	0.146	0.941	0.403	-	-	-	-	44.29	4.40	27.73	3.86
		Partial CCA	0.559	0.312	0.000	-	-	0.518	0.866	0.773	-	53.85	16.81	33.55	12.67
	ME	CCA	0.758	0.575	<.0001	0.329	0.773	0.562	0.791	0.546	0.624	38.92	22.36	52.80	30.34
		Part CCA	0.284	0.081	0.416	-0.134	0.914	-	-	-	-	42.70	3.44	28.82	2.32
		Partial CCA	0.592	0.350	<.0001	-	-	0.369	0.728	0.330	0.633	29.38	10.30	43.62	15.29

3.4. Comparison

According to the results of unadjusted and adjusted CCA for both academic performance in S3 and S4, it can be seen that the level of adjusted canonical correlations; partial canonical correlations and part canonical correlations are reduced due to the relevant adjustments. This implies that the joint effect of mathematics in Level 1 and Level 2 on engineering performance in Level 2 is significantly higher compared to the individual effects of mathematics in Level 1 and Level 2. By comparing the results of partial CCA and part CCA, it is clear that the individual effect of mathematics in Level 2 is significantly higher than the individual effect of mathematics in Level 1 on the students' engineering performance in Level 2. Moreover, redundancy measures of partial CCA indicate that the individual effect of mathematics in Level 2 on engineering performance is significant, even after adjusting for mathematics in Level 1. Conversely, the individual effect of mathematics in Level 1 on engineering performance is not sufficient after eliminating the effect of mathematics in Level 2. Though the individual effect of mathematics in Level 1 is not significant, it can be a sufficient indirect effect of mathematics in Level 1 on engineering performance.

4. Conclusion

The joint effect of mathematics in Level 1 as well as Level 2 is significant on engineering performance in Level 2 irrespective of the engineering disciplines. As expected, the joint effect of mathematics in Level 1 and Level 2 on engineering performance in Level 2 is significantly higher compared with both individual effects of mathematics in Level 1 and Level 2. Moreover, the individual effect of mathematics in Level 1 is extensively lower compared with the individual effect of mathematics in Level 2 on the students' engineering performance. This reveals that it is not worth considering only the individual effect of mathematics in Level 1 on engineering performance. However, there exists a significant indirect effect of mathematics in Level 1 on engineering performance in Level 2.

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Identifying the Influence of Mathematics on Academic Performance of Engineering Students

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***Abstract*—Mathematics plays a major role in higher education as it is particularly essential to develop the analytical thinking of students. Investigating the student academic performance has been a crucial aspect of the educational research recently. The objective of this study is to explore the relationships between students' mathematics performance in Level 1 and Level 2 with their engineering performance in Level 2 separately. Firstly, Canonical Correlation Analysis was employed to study the joint impact of mathematics in Level 1 and Level 2 on engineering performance. The two adjusted analyses; Partial Canonical Correlation Analysis and Part Canonical Correlation Analysis were used to determine the unique effect of mathematics in Level 1 and Level 2 on students' engineering performance in Level 2. The study was conducted with engineering undergraduates from Chemical and Process Engineering discipline at the Faculty of Engineering, University of Moratuwa, Sri Lanka. Results revealed that the mathematics in Level 1 and Level 2 jointly influenced on students' engineering performance in Level 2. Adjusted analyses showed that unique effect of mathematics in Level 2 is significantly higher compared to the unique effect of mathematics in Level 1 on students' engineering performance in Level 2. But, there would be a notable indirect effect of mathematics in Level 1 on engineering performance in Level 2. It can be concluded that the combined effect of mathematics in both Level 1 and Level 2 is immensely beneficial to improve the overall academic performance at the end of Level 2 of the engineering students.**

Keywords*—engineering mathematics; part canonical correlation; partial canonical correlation; student academic performance

I. Introduction

Identification of various factors that influence on student academic performance has become crucially important in higher education recently. Mathematics plays a vital role in higher education as it is particularly essential to develop the analytical thinking of students. Mathematical skills would support to enhance students' knowledge in a wide range of disciplines, especially, in engineering sciences. Several researchers have stated the importance of mathematical knowledge for engineering students to develop their logical thinking [1-3].

In many countries including Sri Lanka, the pre-university requirement for engineering degrees is based mostly on mathematics for all higher education institutions. As a result, most of the students in the Faculty of Engineering, University of Moratuwa, Sri Lanka have acquired higher grades for mathematics in the General Certificate of Examination (G.C.E.) Advanced Level. Recently, a study by [4] revealed that mathematics in Level 1 is significantly influenced on students' overall academic performance in Level 2 irrespective of the seven engineering disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka. Further, it was found that the level of impact of mathematics varies among engineering disciplines. In that study, mathematics marks in Level 2 were also included in the overall academic performance in Level 2. Therefore, the objective of the present study is to determine the direct impact of mathematics in both Level 1 and Level 2 separately on engineering performance in Level 2.

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II. Materials and Methods

A. Data Description

The study was conducted with 71 engineering undergraduates who follow the B.Sc. engineering degree in Chemical and Process Engineering (CH) at the Faculty of Engineering, University of Moratuwa, Sri Lanka in academic year 2011/2012. Data were collected from Examination division, University of Moratuwa. Students' examination marks of mathematics courses in Level 1 (i.e. semester 1 (S1) and semester 2 (S2)) as well as Level 2 (i.e. semester 3 (S3) and semester 4 (S4)) and all compulsory engineering courses in Level 2 were used. Table I presents the mathematics and engineering courses in CH which are considered in this study.

B. Canonical Correlation Analysis (CCA)

CCA is a powerful multivariate statistical technique for measuring the linear relationship between two multidimensional systems [5]. Let two vectors $X = (X_1, X_2, \ldots, X_p)$ and $Y = (Y_1, Y_2, \ldots, Y_q)$ of random variables, and there are correlations among the variables, then CCA will find linear combinations of the X_i and Y_j which have maximum correlation with each other. The CCA computes two projection vectors, a and b such that the correlation coefficient:

$$R_c = \frac{cov(a^T X, b^T Y)}{\sqrt{var(a^T X).var(b^T Y)}} = \frac{a^T \sum_{XY} b}{\sqrt{a^T \sum_X a}\sqrt{b^T \sum_Y b}} \quad (1)$$

is maximized, where $\sum_{XY}$ is the covariance matrix between X and Y, and $\sum_X$ and $\sum_Y$ are the covariance matrices of X and Y

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TABLE I. MATHEMATICS AND ENGINEERING COURSES IN CH DISCIPLINE

Subject Area	Academic Level	Semester	Course Code	Course
Mathematics	Level 1	S1	MA1013	Mathematics
		S2	MA1023	Methods of Mathematics
	Level 2	S3	MA2013	Differential Equation
			MA2023	Calculus
		S4	MA2033	Linear Algebra
Engineering	Level 2	S3	CH 2013	Heat and Mass Transfer
			CH 2023	Unit Operations 1
			CH 2033	Thermodynamics
			ME 2122	Engineering Drawing & Computer Aided Modeling
		S4	CH 2043	Particle Technology
			CH 2053	Fuels and Lubricants
			CH 2063	Principles of Biological Engineering Fundamentals
			CH 2073	Polymer Science and Technology
			CH 2083	Environmental Science and Technology

respectively. Since R_c is invariant to the scaling of vectors a and b, CCA can be formulated equivalently as,

$$\max_{a,b} a^T \textstyle\sum_{XY} b \quad (2)$$

subject to, $a^T \sum_X a = 1$ and $b^T \sum_Y b = 1$.

The first pair of canonical variables or first canonical variate pair (U_1, V_1) is the pair of linear combinations of X and Y respectively, having the highest correlation between the two systems. If the optimum values of (a, b) are denoted as (a_1^T, b_1^T) and then, $U_1 = a_1^T X$ and $V_1 = b_1^T Y$ is the pair of first canonical variables.

The second pair of canonical variables is the pair of linear combinations U_2 and V_2 having unit variances, which has the highest correlation subject to U_2, being uncorrelated with U_1, and V_2, being uncorrelated with V_1 (the construction actually ensures that U_1 and V_2 are uncorrelated, as well as are U_2 and V_1). Therefore, at the k^{th} step, the canonical vectors are obtained as:

$$(a_k^T, b_k^T) = \arg\max_{a,b} a^T \textstyle\sum_{XY} b \quad (3)$$

subject to,

$$var(U_k) = var(V_k) = 1$$
$$corr(U_k, U_l) = 0 \quad \text{for} \quad k \neq l$$
$$corr(V_k, V_l) = 0 \quad \text{for} \quad k \neq l$$

for all $l = 1,2, \dots, k-1$ and $k \leq min\{p, q\}$.

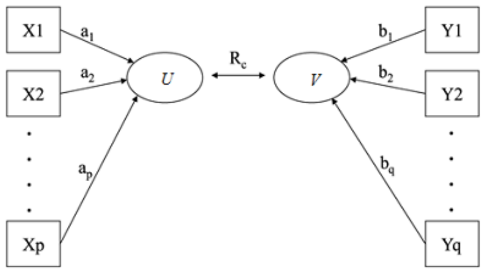

Fig. 1. Illustration of the conceptual framework in CCA

The process continues, until subsequent pairs of linear combinations no longer produce a significant correlation. The conceptual framework of the canonical correlation function is illustrated in Fig. 1.

C. *Partial Canonical Correlation Analysis (Partial CCA)*

The partial canonical correlation is a multivariate generalization of ordinary partial correlation, which used to assess the partial independence of two sets of variables given a third set of variables [6].

Suppose there is another vector, $Z = (Z_1, Z_2, \dots, Z_r)$ of random variables and it is interested to study the relation between the vectors *X* and *Y* partialing out the linear effect of vector *Z* from both *X* and *Y* vectors. Partial canonical correlation represents the maximal correlation between the partial canonical variates $U^* = a^{*T} e_X$ and $V^* = b^{*T} e_Y$, of unit variance where e_X and e_Y represent the residual vectors obtained after regressing *X* on *Z* and *Y* on *Z* respectively. Mathematically, this is equivalent to maximizing,

$$P_{XY.Z} = \max_{a^*,b^*} a^{*T} \textstyle\sum_{XY.Z} b^* \quad (4)$$

subject to, $a^{*T} \sum_{XX.Z} a^* = 1$ and $b^{*T} \sum_{YY.Z} b^* = 1$. The matrices $\sum_{ij.Z}$ are the covariance matrices of the residual vectors e_X and e_Y.

The Partial CCA focuses on the real impact of mathematics in Level 2 on engineering performance in Level 2, when the effect of mathematics in Level 1 is removed from both groups, as the students have already completed mathematics in Level 1 at Level 2.

D. *Part Canonical Correlation Analysis (Part CCA)*

The Part CCA is proposed by [7] as an alternative for Partial CCA, for the case where the third set of variables influences only one of the other two variable sets. In other words, the part canonical correlation estimates the relation between the vectors *X* and *Y* partialing out the linear effect of vector *Z* from vector *Y* but not vector *X*. That is, part canonical correlation computes linear combinations of the variates e_Y and *X*, $U' = a'^T X$ and $V' = b'^T e_Y$, of unit variance such that the correlation between U' and V' is maximal. This is equivalent to maximizing

$$P_{X(Y.Z)} = \max_{a',b'} a'^T \textstyle\sum_{X(Y.Z)} b' \quad (5)$$

subject to, $a'^{T}\sum_{XX}a' = 1$ and $b'^{T}\sum_{YY.Z}b' = 1$.

The Part CCA is to determine the real impact of mathematics in Level 1 on engineering performance in Level 2 when the impact of mathematics in Level 2 is eliminated from engineering performance in Level 2.

III. Results and Discussion

A. Correlation Analysis

Pearson correlation coefficients between mathematics variables and engineering variables separately and between the variables in both sets are calculated and the results noted that the most pairs are significant and positively correlated ($p<0.05$) within the each variable set and between the variable sets. On the basis of correlation coefficients, the two variable sets are used for CCA, Part CCA and Partial CCA for two semesters in Level 2 (S3 and S4) separately.

B. Impact of mathematics in Level 1 and semester 3 on the engineering performance in semester 3

The dependent set is the engineering modules in S3 and it contains four engineering variables for all three cases. But, the predictor set and the control set are varied. The results of unadjusted and adjusted CCA for student performance in S3 are summarized in Table II.

1) Canonical Correlation Analysis (CCA)

Mathematics modules in S1, S2 (in Level 1) and S3 are taken as the predictor set and it contains four mathematics variables.

The number of canonical variate pairs is equal to four and the Wilks' lambda test statistic denote that out of four canonical variate pairs only the first canonical variate pair is statistically significant at the 0.01 level. It indicates that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. According to the results of unadjusted CCA, the first canonical correlation is 0.816 which implies a strong linear relationship between students' mathematics performance and engineering performance in S3. The proportion of the variance in the canonical variate of engineering performance explained by the canonical variate of the mathematics performance is 66.5%.

The standardized canonical coefficients of ME2122 engineering variable and MA1013 mathematics variable obtained negative values which indicate that two variables are weakly important to their first canonical variate. Considering the canonical loadings, it reflects that all observed variables in predictor set as well as dependent set are strongly associated with its first canonical variate except ME2122 in engineering set and MA1013 in mathematics set. The redundancy measure

TABLE II. Results of Unadjusted and Adjusted CCA for S3

	Unadjusted		Adjusted			
	CCA		Part CCA		Partial CCA	
Canonical Correlation	0.816		0.298		0.662	
Squared canonical correlation	0.665		0.089		0.438	
Wilks' Lambda	0.295		0.888		0.535	
P-value	0.000		0.442		0.000	
Engineering performance	(1)	(2)	(1)	(2)	(1)	(2)
CH2013	0.409	0.889	0.256	0.466	0.603	0.926
CH2023	0.165	0.798	0.081	0.409	0.154	0.734
CH2033	0.588	0.946	0.885	0.935	0.421	0.844
ME2122	-0.110	0.467	-0.395	-0.052	-0.051	0.530
Variance extracted	63.51		31.49		59.75	
Redundancy	42.26		2.79		26.18	
Mathematics performance	(1)	(2)	(1)	(2)	(1)	(2)
MA1013	-0.058	0.561	-0.303	0.349	-	-
MA1023	0.322	0.780	1.142	0.969	-	-
MA2013	0.525	0.926	-	-	0.680	0.928
MA2023	0.342	0.865	-	-	0.448	0.824
Variance extracted	63.19		53.01		76.93	
Redundancy	42.04		4.69		33.71	

(1) – Standardized canonical coefficients and (2) – Canonical loadings

of engineering denotes that 42.3% of the variance in the engineering performance is explained by the first canonical variate of mathematics performance.

2) Part CCA

The two mathematics variables in Level 1 are considered as the predictor set and it is performed, with the effect of two mathematics variables in S3 partialed out of the dependent set of engineering variables.

With reference to Wilks' lambda test statistic, it is clear that the first canonical variate pair of Part CCA is not statistically significant ($p=0.442$). That is, the first canonical variate pair in Part CCA is not sufficient to explain a significant amount of variability of the predictor set and dependent variable set.

The first canonical correlation is found to be equal to 0.298 and it confirmed a weak relationship between mathematics in Level 1 and engineering performance when the effect of mathematics in Level 2 is eliminated from engineering performance. Moreover, the amount of variation in the canonical variate of engineering performance explained by the canonical variate of the mathematics performance in Level 1 is 8.9%. Also, the redundancy measures in the analysis indicate that amount of variability in predictor and dependent sets explained by their opposite canonical variate are not sufficient.

3) Partial CCA

The Partial CCA comprises two mathematics variables in S3 as the predictor set and two mathematics variables in both S1 and S2 (in Level 1) as the control set, which eliminates its influence from both predictor and dependent sets.

The maximum number of canonical variate pairs is two and out of two canonical variate pairs only the first canonical variate pair is statistically significant ($p < 0.01$). As the effect of mathematics in Level 1 is statistically controlled by partial correlation, the results confirmed that the mathematics in S3 has a moderately strong relationship with the engineering performance in S3 (0.662). The squared canonical correlation indicates that 43.8% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics in S3.

The ME2122 engineering variable has the least association with mathematics in S3 as revealed by the standardized canonical coefficients and canonical loadings. Furthermore, the redundancy index of engineering reflects that canonical variate of mathematics performance accounted for 26.2% of the total variance of student engineering performance in S3.

By comparing the results of the adjusted canonical analysis (Partial CCA and Part CCA), it can be said that the individual effect of mathematics in S3 is significantly higher than the individual effect of mathematics in Level 1 on the students' engineering performance in S3 (in Level 2). Despite the redundancy indices are reduced in Partial CCA compared to CCA, it indicates that even after adjusting for mathematics in Level 1, there is a significant effect of mathematics in S3 on engineering performance. Nevertheless, when considering the redundancy measures of all three cases, it can be concluded that though the direct effect of mathematics in Level 1 is not significant, there is a sufficient indirect effect of mathematics in Level 1 on engineering performance.

C. *Impact of mathematics in Level 1 and Level 2 on the engineering performance in semester 4*

As in the case of S3 analysis, dependent set is the engineering modules in S4 and it consists of five engineering variables. Table III presents the summary of CCA, Part CCA and Partial CCA results for the academic performance in S4.

1) CCA

Mathematics in both Level 1 as well as Level 2 is the predictor set and it contains five mathematics variables (i.e. two variables in Level 1 and three variables in Level 2).

According to the results of CCA, it can be seen that only the first pair of canonical variate is statistically significant ($p<0.01$). That is, the remaining four canonical variate pairs are not sufficient to explain a significant amount of variability of the predictor set and dependent variable set. The first canonical correlation is equal to 0.812 which implies a strong relationship between mathematics in both Level 1 and Level 2 with their engineering performance in S4. The squared canonical correlation indicates that 65.9% of variation in the first canonical variate of engineering is explained by the first canonical variate of mathematics.

Based on the standardized canonical coefficient of CCA, the MA2033 mathematics variable has the largest weight, which is the most important to first canonical variate of mathematics and the MA1013 mathematics variable is the weakly important to first canonical variate of mathematics. The canonical loadings reflect that both engineering and mathematics variables are strongly correlated (>0.7) with their first canonical variates except MA1013 mathematics variable. The redundancy measures of engineering exhibits that the explainable variability of engineering performance in S4 is 52.8% by the first canonical variate of mathematics. It can be concluded that the first canonical variate of mathematics is a good predictor of student engineering performance in S4.

2) Part CCA

The two mathematics variables in Level 1 are considered as the predictor set while the control set which removes its effect from dependent set, comprises three mathematics variables in both S3 and S4.

By referring the Wilks' lambda test statistic, it can be seen that the first pair of canonical variate in Part CCA is not statistically significant ($p=0.682$). This implies that at least a first canonical variate pair of Part CCA does not explain a statistically significant amount of variability of the predictor and dependent sets. The part canonical correlation shows a weak linear relationship between mathematics in Level 1 and engineering performance in S4 with the effect of mathematics in Level 2 partialed out of the dependent set of engineering variables. In addition, first canonical variate of mathematics in Level 1 accounted for 8.6% of the variance of the first canonical variate of engineering. The redundancy index of engineering found that the amount of variability in engineering performance in S4 explained by the first canonical variate of mathematics in Level 1 is 1.4%. According to the results of

TABLE III. RESULTS OF UNADJUSTED AND ADJUSTED CCA FOR S4

	Unadjusted		Adjusted			
	CCA		Part CCA		Partial CCA	
Canonical Correlation	0.812		0.293		0.691	
Squared canonical correlation	0.659		0.086		0.478	
Wilks' Lambda	0.265		0.893		0.465	
P-value	0.000		0.682		0.000	
Engineering performance	(1)	(2)	(1)	(2)	(1)	(2)
CH2043	0.408	0.890	0.706	0.661	0.227	0.737
CH2053	0.259	0.913	0.538	0.483	0.103	0.828
CH2063	0.117	0.895	0.527	0.394	-0.031	0.824
CH2073	0.188	0.878	-0.269	0.034	0.337	0.895
CH2083	0.144	0.899	-0.88	-0.085	0.496	0.950
Variance extracted	80.14		16.67		72.21	
Redundancy	52.78		1.43		34.50	
Mathematics performance	(1)	(2)	(1)	(2)	(1)	(2)
MA1013	-0.055	0.541	0.034	0.594	-	-
MA1023	0.212	0.741	0.980	0.999	-	-
MA2013	0.054	0.815	-	-	0.174	0.752
MA2023	0.212	0.796	-	-	0.227	0.672
MA2033	0.683	0.966	-	-	0.747	0.959
Variance extracted	61.50		67.61		64.58	
Redundancy	40.50		5.80		30.85	

(1) – Standardized canonical coefficients and (2) – Canonical loadings

Part CCA, it can be said that the real effect of mathematics in Level 1 is not sufficient to explain the engineering performance in S4.

3) Partial CCA

The predictor set contains three mathematics variables in both S3 and S4, while the two mathematics variables in Level 1 are taken as the control set, which eliminates its effect from both predictor and dependent sets.

With reference to Wilks' lambda test statistic of Partial CCA, it confirmed that only the first of three canonical variate pairs is statistically significant ($p<0.01$). The first canonical correlation of 0.691 denotes that the students' mathematics performance in both S3 and S4 has a moderately strong linear relationship with their engineering performance in S4. Moreover, the first canonical variate of mathematics accounted for 47.8% of the variance in the first canonical variate of engineering. It is clear that, there is a significant influence of mathematics in both S3 and S4 on engineering performance in S4 even after the effect of mathematics in Level 1 is removed.

With respect to standardized canonical coefficients, MA2013 and MA2023 variables which are in S3, have smaller weights compared to mathematics variable in S4 (i.e. MA2033). It shows that mathematics variable in S4 (MA2033) is the most important, influential predictor of engineering performance in S4. The proportion of variance in engineering performance in S4 explained by the first canonical variate of mathematics in both S3 and S4 is 34.5% and it can be concluded that a considerable amount of variability in student engineering performance in S4 can be explained by the mathematics performance in both S3 and S4, after adjusted for mathematics in Level 1.

Based on the results of unadjusted and adjusted CCA, it is clear that the degrees of part canonical correlation as well as partial canonical correlation are reduced due to the relevant adjustments. That is, the combined effect of mathematics in Level 1 and Level 2 on engineering performance in S4 is significantly higher compared to the individual effects of mathematics in Level 1 and Level 2. Furthermore, the amount of variability in the canonical variate of engineering performance explained by the canonical variate of predictor set is reduced from 65.9% to 8.6% and 47.8% in Part CCA and Partial CCA respectively. It confirmed that the individual effect of mathematics in Level 2 is noteworthy compared to the individual effect of mathematics in Level 1 on the students' engineering performance. Similarly, dependent redundancy indices of engineering performance are also reduced in both Part CCA and Partial CCA. It denotes that the proportion of variance in student engineering performance in S4 explained by the first canonical variate of mathematics is reduced after eliminating the effect of mathematics in Level 1 or Level 2. As expected, it is not worth considering only the individual effect of mathematics in Level 1 on engineering performance in S4. But, there is a sufficient indirect effect of mathematics in Level 1 on engineering performance in S4.

IV. Conclusion

The students' performance in mathematics in Level 1 and Level 2 is positive and strongly correlated with their engineering performance in Level 2. The joint effect of mathematics in Level 1 and Level 2 on students' engineering performance in Level 2 is significantly higher compared with both individual effects of mathematics in Level 1 and Level 2. Furthermore, the individual effect of mathematics in Level 2 is considerably higher compared with the individual effect of mathematics in Level 1 on the students' engineering performance. Besides that, the individual effect of mathematics in Level 1 on engineering performance in Level 2 can be negligible. It can be concluded that, there exists a notable indirect effect of mathematics in Level 1 on engineering performance in Level 2. Therefore, students are encouraged to achieve high marks in mathematics modules for better performance in engineering.

This study only focuses on academic performance of students from Chemical and Process Engineering discipline and it can be further extended to explore the individual impact of mathematics on academic performance of engineering students from other engineering disciplines at the Faculty of Engineering, University of Moratuwa as well. Furthermore, it is suggested to investigate the impact of preceding engineering courses on the academic performance of engineering students. As Partial CCA and Part CCA are not widely used in applied work, it is recommended to explore this methodology to various applications in other fields.

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Application of Canonical Correlation Analysis to Study the Influence of Mathematics on Engineering Programs: A Case Study

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***Abstract*—Mathematical knowledge is essential to improve the analytical thinking of engineering undergraduates. Exploring more information from existing academic data is an essential aspect of the educational research. The objective of this study is to explore the impact of mathematics performance on different engineering programs. The study was conducted with 626 engineering students from seven different disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka. Canonical Correlation Analysis (CCA) was employed to investigate the relationship between mathematics courses and other engineering courses with respect to their disciplines. Results of CCA revealed that the mathematics performance in both semester 1 and 2 influences significantly on the students' academic performance in Level 2 of the seven engineering disciplines considered. Wilk's lambda test statistic confirmed that only the first canonical variate pair is significant for all disciplines. The squared canonical correlations of first canonical variate pair indicated that the amount of variance between the mathematics performance and academic performance in Level 2 explained varied among seven disciplines from 42% to 68%. The impact is higher from mathematics in semester 2 than that from semester 1 in all disciplines except for Material Science and Engineering discipline. The explainable variability of student academic performance in Level 2 by the canonical variate of mathematics is varied from 27% to 50% among seven disciplines. Based on preliminary analysis, it can be concluded that the performance in mathematics in Level 1 could indicate the trend towards the student academic performance in all engineering programs.**

Keywords—canonical correlation analysis; engineering mathematics; student academic performance

I. Introduction

Mathematics is more than a tool for solving problems and it can develop intellectual maturity and logical thinking of students. The skills in mathematics would certainly assist to enhance students' knowledge in other subjects such as engineering, physics, chemistry, accounting, etc. [1-4]. Pyle [5] and Sazhin [6] stated the importance of mathematical knowledge for engineering students to improve their analytical thinking. The mathematical knowledge gained prior and during engineering education is highly essential in engineering practice as they use a high level of curriculum mathematics and mathematical thinking in their work [7].

The majority of the students who admitted to the Faculty of Engineering, University of Moratuwa have obtained higher grades for mathematics in the General Certificate of Examination (G.C.E.) Advanced Level. In a recent study by Nanayakkara and Peiris [8] have shown that mathematics performance of engineering students in their undergraduate degree programs at the Faculty of Engineering, University of Moratuwa, varies significantly between and within different engineering disciplines. Besides that, performance in mathematics and its impact on other subjects have not been studied. Therefore, it is desired to understand the impact of mathematical knowledge that students acquired from their undergraduate degree programs.

Much research effort has been devoted to student academic performance in various subjects and its impact on different study programs using various statistical techniques in univariate analysis [1-4] as well as in multivariate analysis [9], in particularly canonical correlation analysis (CCA). CCA employed in several studies, have argued that the presence of joint production, OLS regression, or even a simultaneous equation system, gives inconsistent estimates while CCA is more suitable when the research problem has multiple independent variables and multiple dependent variables [10].

A study carried out in Malaysia, by Ismail and Cheng [10] used CCA to examine the effects of school inputs, environmental inputs and gender influence in the production of a joint educational production function in mathematics and science subjects for eighth grade students. Gyimah-Brempong and Gyapong [11] examined the effects of socioeconomic characteristics of communities in the production of high school education in the state of Michigan. Rovai and Ponton [12] investigated how a set of three classroom community variables was related to a set of two students learning variables in a predominantly White sample of 108 online African American and Caucasian graduate students using CCA. A study by Sliusarenko and Clemmensen [13], applied CCA to explore the association between the evaluation of the course and the evaluation of the teacher at the Technical University of Denmark. Abedi [14] conducted a study on academic performance to examine the efficiency of the undergraduate grade average point (GPA) as a predictor of graduate academic

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success and compared it with other predictors. CCA was applied on three measures of graduate academic success and eight demographic and undergraduate academic variables including undergraduate GPA. It was found a weak relationship among graduate academic success and predictors and the graduate academic success was not associated with undergraduate GPA. A study carried out by Dai et al. [9] focused on the context of student score analysis and CCA was used to investigate the relationship of scores of different classes of courses; i.e. basic courses and major courses. The study was based on course scores of the first and second academic year of 76 college students. It summarized that three mathematical basic courses were strongly related with major courses.

In our study CCA is explored with a few modification in order to find the impact of mathematics performance in Level 1 on overall performance in Level 2 for seven engineering programs conducted by the Faculty of Engineering, University of Moratuwa.

II. Materials and Methods

A. Data Description

The study was conducted with 626 engineering students from seven different disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka for the academic year, 2011/2012. Data were collected from Examination division, University of Moratuwa. Seven engineering disciplines used are: (i) Chemical and Process Engineering (CPE), (ii) Civil Engineering (CE), (iii) Computer Science and Engineering (CSE), (iv) Electrical Engineering (EE), (v) Electronic and Telecommunications Engineering (ENTC), (vi) Materials Science and Engineering (MSE) and (vii) Mechanical Engineering (ME). Students' examination marks of mathematics courses in both semesters (semester 1 and semester 2) in Level 1 and all compulsory courses other than mathematics courses in both semesters (semester 3 and semester 4) in Level 2 were used.

B. Canonical Correlation Analysis (CCA)

CCA is a powerful multivariate statistical technique for measuring the linear relationship between two multidimensional systems [15]. Let two vectors $X = (X_1, X_2, \dots, X_p)$ and $Y = (Y_1, Y_2, \dots, Y_q)$ of random variables, and there are correlations among the variables, then CCA will find a linear combination of the X_i and Y_j which have maximum correlation with each other. The CCA computes two projection vectors, a and b such that the correlation coefficient:

$$R_c = \frac{cov(a^T X, b^T Y)}{\sqrt{var(a^T X).var(b^T Y)}} = \frac{a^T \Sigma_{XY} b}{\sqrt{a^T \Sigma_X a}\sqrt{b^T \Sigma_Y b}} \quad (1)$$

is maximized, where $\sum_{XY}$ is the covariance matrix between X and Y, and $\sum_X$ and $\sum_Y$ are the covariance matrices of X and Y respectively. Since R_c is invariant to the scaling of vectors a and b, CCA can be formulated equivalently as,

$$\max_{a,b} a^T \Sigma_{XY} b \quad (2)$$

subject to, $a^T \sum_X a = 1$ and $b^T \sum_Y b = 1$

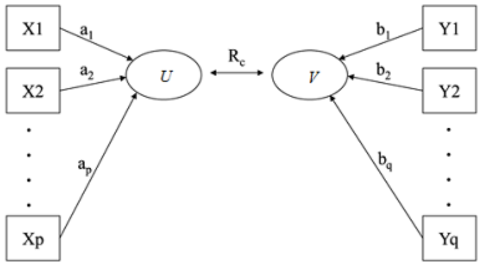

Fig. 1. Illustration of the conceptual framework in CCA

The first pair of canonical variables or first canonical variate pair (U_1, V_1) is the pair of linear combinations of X and Y respectively, having the highest correlation between the two systems. If the optimum values of (a, b) are denoted as (a_1^T, b_1^T) and then,

$$U_1 = a_1^T X \quad (3)$$

$$V_1 = b_1^T Y \quad (4)$$

is the pair of first canonical variables.

This procedure continues by seeking the second pair of canonical variables uncorrelated with the first pair of canonical variables, which has maximal correlation.

Canonical correlation (R_c) measures the strength of the overall relationships between the two canonical variates, which are the linear combination of the two sets of variables separately. The statistical significance of R_c is tested based on Wilk's Lambda test statistic. Canonical roots or squared canonical correlation (R_c^2) represents the proportion of variance shared between the two sets of variables. Canonical loading is the linear correlation between the variable and its respective canonical variate. Redundancy index is the amount of variance in a canonical variate (dependent or independent) explained by the other canonical variate in the canonical function. For an example, the amount of variance in the dependent variables explained by the independent canonical variate is represented by the redundancy index of the dependent variate. The conceptual framework of the canonical correlation function is illustrated in Fig. 1.

In this study, mathematics marks in semester 1 and 2 are taken as the one set of variables (predictor set) while the marks of all compulsory modules in Level 2 as the dependent set of variables. CCA was performed separately for seven engineering disciplines. The maximum number of canonical variate pairs is two.

III. Results and Discussion

A. Initial Analysis

Prior to determining the relationship among the two sets, Pearson correlation coefficients between variables of the two sets separately as well as between the variables in both sets were calculated for each discipline. The results noted that the most pairs are significantly and positively correlated ($p < 0.05$)

within the set and between sets for all disciplines. It indicates that there is a strong significant impact from the mathematics in semester 1 and 2 on the other modules in Level 2 irrespective of disciplines and the two sets can be used for CCA separately for each discipline.

The number of variables in the predictor set is two for all disciplines while the number of variables in the dependent set is varied among the disciplines. The corresponding number of dependent variables in CPE, CE, CSE, EE, ENTC, MSE and ME disciplines are 12, 15, 16, 20, 12, 17 and 16 respectively.

B. *Canonical Variates and Canonical Correlations*

Table I presents the results of statistical significance tests of the canonical correlation by engineering disciplines. The sample size for each discipline is shown in column 2 of Table I. The test statistic Wilk's lambda is used to test the significance of canonical correlations and it confirmed that out of two canonical variate pairs only the first canonical variate pair is statistically significant ($p < 0.005$) for all disciplines. It indicates that the first canonical variate pair is sufficient to explain a significant amount of variability of the predictor set and dependent variable set. In other words, the second canonical variant pair cannot be relied upon to describe the data.

The results of CCA were summarized mainly focusing on the student performance in mathematics. Table II illustrates the results of CCA by engineering disciplines. Results in Table II indicate that canonical correlations are strong for all disciplines ($R_c > 0.64$). The highest canonical correlation is in MSE discipline (0.824) and the lowest is in CE discipline (0.648). This implies that students' overall performance in Level 2 in MSE discipline has the highest impact of the performance of mathematics in Level 1 compared with other disciplines.

The squared canonical correlation (R_c^2) indicate that the amount of variation between the mathematics performance and academic performance in Level 2, explained by the first canonical variate. Results in Table II confirmed that the amount of variability explained is varied from 42% (in CE) to 68% (in MSE). This is due to the correlation between the two linear functions in two sets of data. Nevertheless, as the squared canonical correlation coefficients for all disciplines ($R_c^2 > 0.4$) suggested that mathematics courses in Level 1 has a strong and positive impact on the overall performance in Level 2 irrespective of the engineering disciplines.

TABLE I. RESULTS OF WILK'S LAMBDA TEST

Discipline	Sample size	Wilk's Lambda	P-value
CPE	71	0.3648	0.000
CE	125	0.5122	0.000
CSE	95	0.4614	0.000
EE	99	0.3013	0.000
ENTC	96	0.3306	0.000
MSE	44	0.1486	0.003
ME	96	0.4133	0.000

TABLE II. RESULTS OF FIRST CANONICAL CORRELATION

Discipline	Canonical correlation (R_C)	Squared Canonical correlation (R_C^2)
CPE	0.778	0.605
CE	0.648	0.420
CSE	0.686	0.471
EE	0.779	0.607
ENTC	0.783	0.612
MSE	0.824	0.679
ME	0.721	0.520

The results of the canonical and squared canonical loadings are shown in Table III. According to the results of Table III, the squared canonical loadings, the amount of variance explained by mathematics course in semester 2 (Math_S2) is higher compared with mathematics course in semester 1 (Math_S1) for all disciplines except in MSE discipline. Nevertheless, that difference can be negligible.

The canonical loadings of both mathematics courses are high in all disciplines (>0.60) with exceptional for Math_S1 for ENTC and ME disciplines. These results indicate that there is a significant impact from both Math_S1 and Math_S2 on the overall performance in Level 2, irrespective of the discipline and the impact from Math_S2 is higher than that from Math_S1.

The results of the canonical redundancy analysis are provided in Table IV. Redundancy analysis is carried out to assess the effectiveness of canonical analysis in capturing variances of the original variables by canonical variate pair.

The results indicate that the first canonical variate of performance in mathematics is a good predictor of the opposite set of variables. The amount of variance in student academic performance in Level 2 explained by the first canonical variate of mathematics is varied from 27.0% (in CE) to 49.6% (in MSE) and the proportion of variance explained by the first canonical variate of courses in Level 2 is varied from 12.9% (in CE) to 29.1% (in CPE) for mathematics performance.

TABLE III. CANONICAL LOADINGS OF PREDICTORS

Discipline	Canonical loadings		Squared canonical loadings	
	Math_S1	Math_S2	Math_S1	Math_S2
CPE	0.789	0.955	0.623	0.912
CE	0.702	0.891	0.493	0.794
CSE	0.778	0.862	0.605	0.743
EE	0.636	0.931	0.404	0.867
ENTC	0.491	0.986	0.241	0.972
MSE	0.881	0.825	0.776	0.681
ME	0.366	0.995	0.134	0.990

TABLE IV. RESULTS OF CANONICAL REDUNDANCY ANALYSIS

Discipline	Can. Var. of performance in mathematics		Can. Var. of performance in Level 2	
	% Var DEP	% Var PRE	% Var DEP	% Var PRE
CPE	46.40	76.73	48.12	29.13
CE	26.99	64.33	30.82	12.93
CSE	31.76	67.44	43.60	20.53
EE	38.51	63.49	28.31	17.17
ENTC	37.17	60.69	37.23	22.80
MSE	49.56	72.92	20.53	13.95
ME	29.24	56.27	32.89	17.09

The explainable variability of performance in mathematics by its canonical variate is varied from 56.3% (in ME) to 76.7% (in CPE) while the proportion of variance in student academic performance in Level 2 explained by its canonical variate is varied from 20.5% (in MSE) to 48.1% (in CPE). These redundancy coefficients denote that the variability of performance in mathematics explained by its canonical variate is higher compared with the variability of student overall performance in Level 2 explained by its canonical variate.

The following Fig. 2 illustrates the behavior of the first canonical variate pair by engineering disciplines. These graphs indicate that the overall academic performance in Level 2 has a moderately strong and positive relationship with mathematics courses in Level 1 for all disciplines. It was found that all correlations are high and positive and significantly different from zero.

In order to determine the students' overall academic performance in Level 2, the weighted mean was calculated. The weights were assigned based on the number of credits. Then, the Pearson correlation between the weighted mean and the first canonical variate of modules in Level 2 was computed to discover the relationship between them. The correlation coefficients by engineering disciplines are shown in Table V.

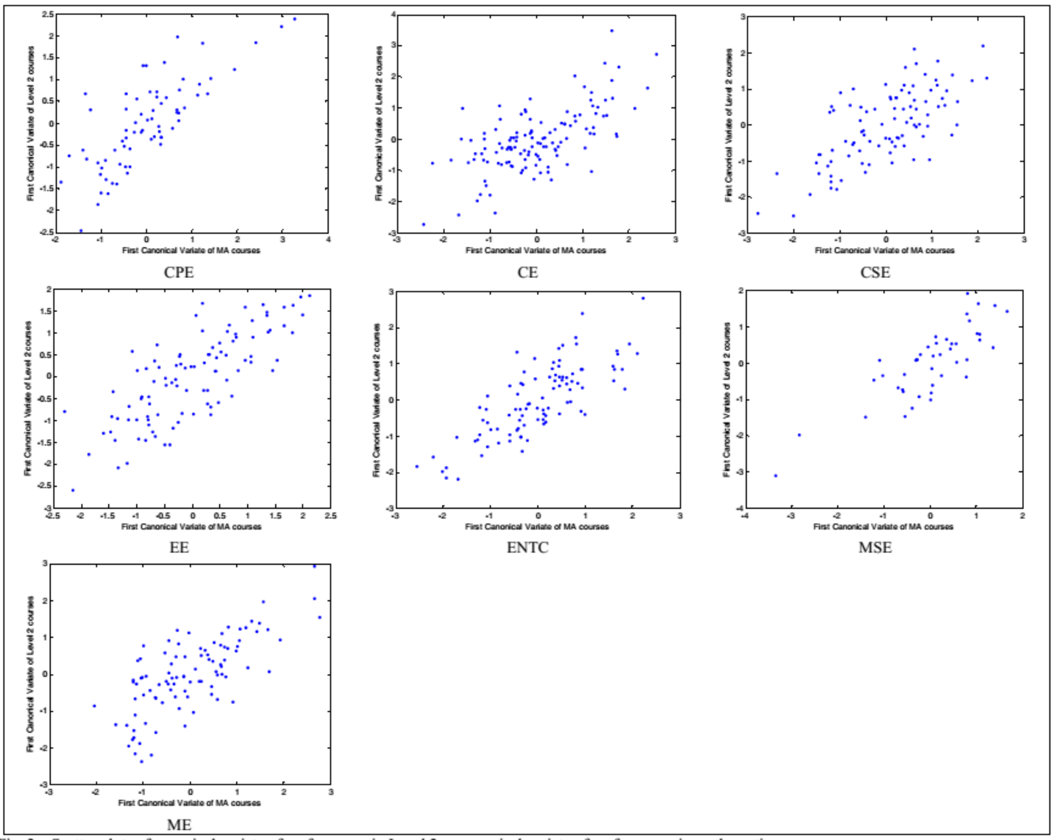

Fig. 2. Scatter plots of canonical variate of performance in Level 2 vs canonical variate of performance in mathematics

TABLE V. PEARSON CORRELATION BETWEEN WEIGHTED MEAN AND CANONICAL VARIATE OF LEVEL 2 COURSES

Discipline	Correlation coefficient
CPE	0.822*
CE	0.854*
CSE	0.910*
EE	0.874*
ENTC	0.841*
MSE	0.573*
ME	0.859*

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

The coefficients of correlation reveal that there is a strong positive significant correlation ($p < 0.05$) between canonical variate derived from the students' marks in Level 2 and the weighted average of the students' marks in Level 2, irrespective of the disciplines. This confirms that the canonical variate of modules in Level 2 can be considered as a proxy estimator for the student actual performance. In this study, we did not compare the values of the canonical variate of level 2 courses and the students GPA in level 2.

The results obtained are not possible to explain why Math_S2 is more influential than Math_S1 and why the impact is different between-and-within disciplines as we use only raw marks.

IV. CONCLUSION

The performance in Mathematics in semester 1 and 2 has a significant impact on the performance in Level 2 by all students irrespective of the engineering discipline. The impact of mathematics in semester 2 was significantly higher than the impact of mathematics in semester 1 on the students' academic performance in Level 2 in all the seven engineering disciplines considered except MSE. It is suggested to continue this study for more years and find the reasons for the variability of the impact between-and-within disciplines before implement various decisions.

It is also suggested to conduct a separate study to find out why mathematics in Semester 2 is more influential than mathematics in Semester 1 by discipline wise.

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Abstract No: PO-06 **Physical Sciences**

Impact of mathematics on academic performance of engineering students: A canonical correlation analysis

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Mathematics plays a key role in higher education as it is particularly essential to develop the analytical thinking of students. Mathematical skills would certainly assist to enhance students' knowledge in a wide range of disciplines, especially, in engineering sciences. Therefore, exploring the student academic performance has received great attention among researchers recently. The main objective of this study is to investigate the impact of mathematics on students' academic performance at the end of Level 2, in different engineering programs. The study was conducted with engineering undergraduates from seven different disciplines at the Faculty of Engineering, University of Moratuwa, Sri Lanka in academic year 2011/2012. Students' examination marks of mathematics courses in Level 1 and Level 2 and all compulsory engineering courses in Level 2 were used for the study. Explanatory data analysis techniques and canonical correlation analysis were used to achieve the objectives. Statistical testing confirmed that only the first canonical function is significant for all engineering disciplines. The amount of variance between the students' performance in mathematics and engineering courses in Level 2 explained is varied from 39% to 73%. The students' performance in engineering courses in both semesters of Level 2 is positively and strongly related to mathematics performance irrespective of the engineering disciplines. Furthermore, the combined effects of mathematics in Level 1 and Level 2 on students' performance in engineering courses in Level 2 are significantly higher compared with the individual effect of mathematics in Level 1 or Level 2. The combined effects of mathematics in both Level 1 and Level 2 are immensely beneficial to improve the overall academic performance at the end of Level 2 of the engineering students. However, the impact of mathematics varies among engineering disciplines. The students are encouraged to achieve high marks in mathematics courses for better performance in engineering courses.

Keywords: Canonical correlation analysis, Engineering mathematics, Students' academic performance

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Influence of Mathematics in Level 1 on Students' Performance in Engineering Programs: A Case Study

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Mathematics is more than a tool for solving problems as it can develop intellectual maturity and logical thinking of students. In engineering sciences, mathematical knowledge is highly essential to improve the analytical thinking of engineering undergraduates. Therefore, a significant component of advance mathematics has been included in the engineering degree programs. The objective of this study is to explore the impact of mathematics in level 1 on academic performance of undergraduate engineering students in level 2. The study was conducted with 1256 engineering students from seven different disciplines at Faculty of Engineering, University of Moratuwa, Sri Lanka for two academic years 2010/2011 and 2011/2012. Students' examination marks of mathematics courses in level 1: semester 1 (S1) and semester 2 (S2) and all compulsory courses from level 2: semester 3 (S3) and semester 4 (S4) were used. Average marks of subjects were used as the students' academic performance for S3 and S4 separately as well as level 2 (combining courses of S3 and S4). The response variable was the students' academic performance and the explanatory variables were the marks of mathematics courses in S1 and S2. Analyses revealed that the marks of mathematics were significantly positively correlated ($P < 0.05$) with students' performance in all engineering disciplines in S3 and S4 irrespective of the engineering discipline. The impact of mathematics in S2 was significantly higher than the impact of mathematics in S1 on the students' performance in S3 and S4. The same trend was found for the overall performance in level 2. Furthermore, the impact of mathematics was significantly different among various engineering disciplines. A similar trend was found for the pooled data across the discipline. The study concluded that the performance in mathematics in level 1 could indicate the trend toward students' academic performance in engineering programs in level 2. It is recommended to continue this analyze to other years as well.

Keywords: *Engineering Mathematics, Student Academic Performance, Correlation, Stepwise Regression*

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APPENDIX 1

Curriculum of B.Sc. Engineering Degree Programme

Table A1.1: Details of Modules - Academic Year 2010/2011

Department	Module code	Module Name
CE	CE2012	Structural Mechanics II
	CE2022	Design of Steel Structures
	CE2032	Hydraulic Engineering I
	CE2042	Soil Mechanics & Geology I
	CE2052	Construction Planning and Cost Estimation
	CE2062	Surveying I
	CE2112	Structural Analysis I
	CE2122	Design of Concrete Structures I
	CE2132	Soil Mechanics & Geology II
	CE2142	Surveying II
	CE3012	Hydraulic Engineering II
	CE1822	Aspects of Civil Engineering
CH	CH2042	Fuels and Lubricants
	CH2052	Transport Phenomena 1
	CH2062	Transport Phenomena II
	CH2072	Chemical Kinetics and Thermodynamics
	CH2082	Mass Transfer Operations 1
	CH3092	Environmental Science
	CH3102	Polymer Science and Technology
CS	CS2032	Principles of Computer Communication
	CS2042	Operating Systems
	CS2062	Object Oriented Software Development
	CS3022	Software Engineering
	CS3042	Database Systems
	CS3242	Micro-controllers and Applications
	CS3032	Computer Networks

Table A1.1 continued

EE	EE2802	Applied Electricity
	EE2012	Circuit Theory
	EE2022	Electrical Machines & Drives I
	EE2033	Power Systems I
	EE2042	Electrical Measurements and Instrumentation
	EE2132	Electromagnetic Field Theory
	EE2052	Control Systems I
	EE3072	Electrical Installations I
	EE2072	Electrical Machines & Drives II
	EE2083	Power Systems II
EN	EN2052	Communication Systems
	EE2092	Theory of Electricity
	EN3022	Electronic Design and Realization
	EN2072	Communications I
	EN2082	Electromagnetics
	EN2142	Electronic Control Systems
	EN2022	Digital Electronics
	EN2062	Signals and Systems
	EN2012	Analog Electronics
	EN2852	Applied Electronics
MA	MA1013	Mathematics
	MA1023	Methods of Mathematics
	MA1032	Numerical Methods for Computer Science
	MA2013	Differential Equation
	MA2023	Calculus
	MA2033	Linear Algebra
	MA3013	Applied Statistics
	MA2042	Discrete Mathematics
ME	ME2022	Manufacturing Engineering I
	ME2112	Fluid Dynamics
	ME2092	Mechanics of Machines I
	ME2012	Mechanics of Materials I
	ME2032	Thermodynamics of Heat Engines & Work Transfer Devices
	ME3072	Manufacturing Engineering II
	ME3032	Mechanics of Machines II
	ME3062	Mechanics of Materials II
	ME2142	Machine Elements and Innovative Design
	ME1802	Introduction to Manufacturing Engineering
	ME1822	Basic Engineering Thermodynamics

Table A1.1 continued

	ME2122	Engineering Drawing & Computer Aided Modeling
	ME2842	Basic Thermal Sciences and Applications
	ME2832	Mechanics of Machines
	ME3062	Mechanics of Materials II
MT	MT2122	Principles of Materials Science & Engineering II
	MT2042	Ceramic Science
	MT2142	Electrical and Magnetic Properties of Materials
	MT2072	Metal Forming and Machining
	MT2032	Degradation of Materials
	MT2152	Polymer Technology

Table A1.2: Curriculum for Academic Year 2010/2011

	Level	Semester	CE	CH	CS	EE	EN	ME	MT
Mathematics	Level 1	S1	MA1013	MA1013	MA1013	MA1013	MA1013	MA1013	MA1013
		S2	MA1023	MA1023	MA1032	MA1023	MA1023	MA1023	MA1023
	Level 2	S3	MA2013 MA2023	MA2013 MA2023	MA2023 MA2042	MA2013 MA2023	MA2013 MA2023	MA2013 MA2023	MA2013 MA2023
		S4	MA2033 MA3013	MA2033	MA2033 MA2013	MA2033 MA2042	MA2033 MA2042	MA2033 MA2042	MA2033 MA3013
Engineering	Level 2	S3	CE 2012 CE 2022 CE 2032 CE 2042 CE 2052 CE 2062	CH 2042 CH 2052 EE 2802 EN 2852 ME 2012 ME 2122 ME 1822	CE 1822 CS 2032 CS 2042 CS 2062 EN 2022 ME 1822	CE 1822 EE 2012 EE 2022 EE 2033 EE 2292 EN 2012 EN 2022 ME 2012	EE 2092 EN 2012 EN 2022 EN 2052 EN 2062	EE 2802 EN 2852 ME 2022 ME 2112 ME 2092 ME 2012	EE 2802 EN 2852 ME 1822 ME 2012 MT 2042 MT 2122
		S4	CE 2112 CE 2122 CE 2132 CE 2142 CE 3012	CH 2062 CH 2072 CH 2082 CH 3092 CH 3102 CH 2952	CS 2212 CS 3022 CS 3032 CS 3042 CS 3242 CS 3952 EN 2062 ME 1802	EE 2042 EE 2132 EE 2052 EE 3072 EE 2072 EE 2083 EE 2192 EE 3202 ME 2842	EN 2142 EN 2072 EN 3022 EN 2902 EN 2962 EN 2082	ME 2032 ME 3072 ME 3032 ME 3062 ME 2142	ME 2832 ME 2142 ME 3062 MT 2142 MT 2072 MT 2032 MT 2152

Table A1.3: Details of Modules - Academic Year 2011/2012

Department	Module code	Module name
CE	CE 1822	Aspects of Civil Engineering
	CE 2012	Structural Mechanics II
	CE 2022	Design of Steel Structures
	CE 2032	Hydraulic Engineering I
	CE 2042	Soil Mechanics & Geology I
	CE 2052	Construction Planning and Cost Estimation
	CE 2062	Surveying I
	CE 2112	Structural Analysis I
	CE 2122	Design of Concrete Structures I
	CE 2132	Soil Mechanics & Geology II
	CE 2142	Surveying II
	CE 3012	Hydraulic Engineering II
CH	CH 2013	Heat and Mass Transfer
	CH 2023	Unit Operations 1
	CH 2033	Thermodynamics
	CH 2043	Particle Technology
	CH 2053	Fuels and Lubricants
	CH 2063	Principles of Biological Engineering Fundamentals
	CH 2073	Polymer Science and Technology
	CH 2083	Environmental Science and Technology
CS	CS 2032	Principles of Computer Communication
	CS 2042	Operating Systems
	CS 2062	Object Oriented Software Development
	CS 3022	Software Engineering
	CS 3032	Computer Networks
	CS 3042	Database Systems
	CS 3242	Micro-controllers and Applications
EE	EE 2013	Circuit Theory
	EE 2023	Electrical Machines & Drives I
	EE 2033	Power Systems I
	EE 2043	Electrical Measurements and Instrumentation
	EE 2053	Control Systems I

Table A1.3 continued

	EE 2063	Electromagnetic Field Theory
	EE 2073	Electrical Machines & Drives II
	EE 2083	Power Systems II
	EE 2092	Theory of Electricity
	EE 2803	Applied Electricity
EN	EN 2012	Analog Electronics
	EN 2022	Digital Electronics
	EN 2052	Communication Systems
	EN 2062	Signals and Systems
	EN 2072	Communications I
	EN 2142	Electronic Control Systems
	EN 2082	Electromagnetics
	EN 3022	Electronic Design and Realization
	EN 2852	Applied Electronics
MA	MA 1013	Mathematics
	MA 1023	Methods of Mathematics
	MA 2013	Differential Equation
	MA 2023	Calculus
	MA 2033	Linear Algebra
	MA 2053	Graph Theory
	MA 2063	Differential Equations and Applications
	MA 2073	Calculus for System Modeling
	MA 3013	Applied Statistics
ME	ME 2012	Mechanics of Materials 1
	ME 2023	Manufacturing Engineering I
	ME 2092	Mechanics of Machines I
	ME 2112	Fluid Dynamics
	ME 2602	Motor Vehicle Technology
	ME 2032	Thermodynamics of Heat Engines & Work Transfer Devices
	ME 2153	Design of Machine Elements
	ME 3032	Mechanics of Machines II
	ME 3062	Mechanics of Materials II
	ME 3073	Manufacturing Engineering II
	ME 1802	Introduction to Manufacturing Engineering
	ME 1822	Basic Engineering Thermodynamics
	ME 2122	Engineering Drawing & Computer Aided Modeling
	ME 2832	Mechanics of Machines
	ME 2842	Basic Thermal Sciences and Applications
	ME 2850	Fundamentals of Machine Element Design

Table A1.3 continued

MT	MT 2042	Ceramic Science
	MT 2122	Principles of Materials Science & Engineering II
	MT 2152	Polymer Technology
	MT 2032	Degradation of Materials
	MT 2072	Metal Forming and Machining
	MT 2142	Electrical and Magnetic Properties of Materials

Table A1.4: Curriculum for Academic Year 2011/2012

	Level	Semester	CE	CH	CS	EE	EN	ME	MT
Mathematics	Level 1	S1	MA1013	MA1013	MA1013	MA1013	MA1013	MA1013	MA1013
		S2	MA1023	MA1023	MA1032	MA1023	MA1023	MA1023	MA1023
	Level 2	S3	MA2013 MA2023	MA2013 MA2023	MA 2053 MA2073	MA2013 MA2023	MA2013 MA2023	MA2013 MA2023	MA2013 MA2023
		S4	MA2033 MA3013	MA2033	MA2033 MA2063	MA2033 MA2053	MA2033	MA 2033 MA 2053	MA 2033 MA 3013
Engineering	Level 2	S3	CE 2012 CE 2022 CE 2032 CE 2042 CE 2052 CE 2062	CH 2013 CH 2023 CH 2033 ME 2122	CE 1822 CS 2032 CS 2042 CS 2062 EN 2022 ME 1822	CE 1822 EE 2013 EE 2023 EE 2033 EE 2183 EN 2012 EN 2022 ME 2012	EE 2092 EN 2012 EN 2022 EN 2052 EN 2062	EE 2803 EN 2852 ME 2012 ME 2023 ME 2092 ME 2112 ME 2602	EE 2803 EN 2852 ME 1822 ME 2012 MT 2042 MT 2122 MT 2152
		S4	CE 2112 CE 2122 CE 2132 CE 2142 CE 3012	CH 2043 CH 2053 CH 2063 CH 2073 CH 2083	CS 3022 CS 3032 CS 3042 CS 3242 EN 2062 ME 1802	EE 2043 EE 2053 EE 2063 EE 2073 EE 2083 EE 2193 EE 3203 ME 2842	EN 2072 EN 2142 EN 2082 EN 3022	ME 2032 ME 2153 ME 3032 ME 3062 ME 3073	ME 2832 ME 2850 ME 3062 MT 2032 MT 2072 MT 2142

APPENDIX 2

Correlation Coefficient Matrix between Mathematics and Engineering Modules

Table A2.1: Results for CH Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	CH2042	CH2052	EE2802	EN2852	ME1822	ME2012	ME2122
MA1023	.486**	1.00									
MA2013	.380**	.467**	1.00								
MA2023	.301**	.342**	.339**	1.00							
CH2042	.297**	.462**	.444**	.560**	1.00						
CH2052	.250*	.469**	.562**	.480**	.655**	1.00					
EE2802	.354**	.473**	.530**	.557**	.786**	.707**	1.00				
EN2852	.131	.245*	.249*	.197*	.491**	.418**	.655**	1.00			
ME1822	.142	.118	.054	.332**	.509**	.259*	.426**	.304**	1.00		
ME2012	.262*	.463**	.464**	.507**	.496**	.584**	.542**	.268**	.183	1.00	
ME2122	.014	.173	.316**	.295**	.338**	.400**	.457**	.323**	.262*	.536**	1.00

Table A2.2: Results for CH Performance in S4 (2010)

.	MA1013	MA1023	MA2013	MA2023	MA2033	CH2062	CH2072	CH2082	CH3092	CH3102
MA1023	.486**	1.00								
MA2013	.380**	.467**	1.00							
MA2023	.301**	.342**	.339**	1.00						
MA2033	.311**	.417**	.407**	.279**	1.00					
CH2062	.345**	.522**	.434**	.338**	.438**	1.00				
CH2072	.244*	.261*	.283**	.353**	.266**	.327**	1.00			
CH2082	.273**	.482**	.508**	.471**	.469**	.646**	.346**	1.00		
CH3092	.368**	.450**	.403**	.476**	.499**	.629**	.535**	.625**	1.00	
CH3102	.286**	.473**	.465**	.476**	.437**	.617**	.434**	.643**	.779**	1.00

Table A2.3: Results for CH Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	CH2013	CH2023	CH2033	ME2122
MA1023	.571**	1.00						
MA2013	.474**	.571**	1.00					
MA2023	.544**	.558**	.715**	1.00				
MA2033	.489**	.602**	.754**	.670**				
CH2013	.330**	.508**	.693**	.633**	1.00			
CH2023	.386**	.482**	.576**	.632**	.727**	1.00		
CH2033	.468**	.633**	.708**	.655**	.723**	.665**	1.00	
ME2122	.152	.213*	.361**	.383**	.595**	.499**	.427**	1.00

Table A2.4: Results for CH Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	CH2043	CH2053	CH2063	CH2073	CH2083
MA1023	.571**	1.00								
MA2013	.474**	.571**	1.00							
MA2023	.544**	.558**	.715**	1.00						
MA2033	.489**	.602**	.754**	.670**	1.00					
CH2043	.430**	.587**	.563**	.591**	.683**	1.00				
CH2053	.420**	.561**	.610**	.574**	.718**	.690**	1.00			
CH2063	.391**	.530**	.560**	.545**	.717**	.684**	.860**	1.00		
CH2073	.318**	.469**	.613**	.589**	.692**	.642**	.822**	.814**	1.00	
CH2083	.340**	.456**	.644**	.565**	.728**	.709**	.811**	.847**	.830**	1.00

Table A2.5: Results for CE Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	CE2012	CE2022	CE2032	CE2042	CE2052	CE2062
MA1023	.477**	1.00								
MA2013	.296**	.233**	1.00							
MA2023	.388**	.397**	.275**	1.00						
CE2012	-.003	.262**	.125	.158*	1.00					
CE2022	.125	.232**	.094	.155*	.326**	1.00				
CE2032	.328**	.518**	.335**	.270**	.329**	.506**	1.00			
CE2042	.192*	.401**	.192*	.253**	.372**	.547**	.571**	1.00		
CE2052	.197*	.300**	.132	.153*	.357**	.445**	.443**	.460**	1.00	
CE2062	.258**	.323**	.104	.243**	.197*	.379**	.484**	.480**	.199*	1.00

Table A2.6: Results for CE Performance in S4 (2010)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA3013	CE2112	CE2122	CE2132	CE2142	CE3012
MA1023	.477**	1.00									
MA2013	.296**	.233**	1.00								
MA2023	.388**	.397**	.275**	1.00							
MA2033	.192*	.356**	.230**	.171*	1.00						
MA3013	.168*	.241**	.082	.093	.334**	1.00					
CE2112	.181*	.299**	.204*	.349**	.623**	.322**	1.00				
CE2122	.194*	.401**	.242**	.242**	.391**	.343**	.550**	1.00			
CE2132	.092	.290**	.180*	.204*	.452**	.405**	.638**	.583**	1.00		
CE2142	-.003	.223**	.117	.066	.325**	.232**	.470**	.474**	.565**	1.00	
CE3012	.029	.262**	.150	.204*	.506**	.500**	.610**	.586**	.633**	.488**	1.00

Table A2.7: Results for CE Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	CE2012	CE2022	CE2032	CE2042	CE2052	CE2062
MA1023	.302**	1.00								
MA2013	.385**	.338**	1.00							
MA2023	.301**	.450**	.570**	1.00						
CE2012	.257**	.400**	.404**	.517**	1.00					
CE2022	.111	.107	.104	.044	-.028	1.00				
CE2032	.069	.026	.015	.017	-.009	.372**	1.00			
CE2042	.204*	.380**	.350**	.350**	.424**	.088	.168*	1.00		
CE2052	.024	.213**	.242**	.288**	.326**	.064	.049	.294**	1.00	
CE2062	.016	.280**	.270**	.174*	.243**	.056	.017	.465**	.361**	1.00

Table A2.8: Results for CE Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA3013	CE2112	CE2122	CE2132	CE2142	CE3012
MA1023	.302**	1.00									
MA2013	.385**	.338**	1.00								
MA2023	.301**	.450**	.570**	1.00							
MA2033	.353**	.406**	.442**	.439**	1.00						
MA3013	.311**	.429**	.351**	.364**	.455**	1.00					
CE2112	.202*	.392**	.430**	.512**	.476**	.498**	1.00				
CE2122	.214**	.368**	.275**	.386**	.402**	.547**	.535**	1.00			
CE2132	.243**	.395**	.326**	.344**	.432**	.566**	.558**	.504**	1.00		
CE2142	.187*	.237**	.285**	.265**	.350**	.453**	.348**	.505**	.530**	1.00	
CE3012	.249**	.317**	.405**	.412**	.452**	.494**	.450**	.483**	.464**	.460**	1.00

Table A2.9: Results for CS Performance in S3 (2010)

	MA1013	MA1032	MA2023	MA2042	CE1822	CS2032	CS2042	CS2062	EN2022	ME1822
MA1032	.397**	1.00								
MA2023	.349**	.417**	1.00							
MA2042	.303**	.423**	.327**	1.00						
CE1822	.192*	.373**	.318**	.430**	1.00					
CS2032	.193*	.380**	.256**	.475**	.369**	1.00				
CS2042	.263**	.430**	.396**	.541**	.391**	.669**	1.00			
CS2062	.187*	.447**	.231*	.499**	.408**	.389**	.477**	1.00		
EN2022	.227*	.419**	.455**	.469**	.403**	.465**	.438**	.363**	1.00	
ME1822	.266**	.470**	.300**	.376**	.294**	.399**	.399**	.405**	.388**	1.00

Table A2.10: Results for CS Performance in S4 (2010)

	MA1013	MA1032	MA2023	MA2042	MA2013	MA2033	CS3022	CS3032	CS3042	CS3242	EN2062	ME1802
MA1032	.397**	1.00										
MA2023	.349**	.417**	1.00									
MA2042	.303**	.423**	.327**	1.00								
MA2013	.306**	.324**	.191*	.262**	1.00							
MA2033	.421**	.412**	.422**	.285**	.458**	1.00						
CS3022	.213*	.503**	.246**	.412**	.417**	.507**	1.00					
CS3032	.176*	.380**	.101	.324**	.380**	.353**	.567**	1.00				
CS3042	.166	.397**	.251**	.309**	.389**	.489**	.572**	.507**	1.00			
CS3242	.010	.141	.100	.243**	.062	.228*	.380**	.310**	.465**	1.00		
EN2062	.407**	.464**	.325**	.417**	.513**	.472**	.607**	.480**	.454**	.263**	1.00	
ME1802	.237*	.361**	.142	.360**	.445**	.392**	.554**	.566**	.485**	.321**	.525**	1.00

Table A2.11: Results for CS Performance in S3 (2011)

	MA1013	MA1032	MA2053	MA2073	CE1822	CS2032	CS2042	CS2062	EN2022	ME1822
MA1032	.353**	1.00								
MA2053	.484**	.308**	1.00							
MA2073	.427**	.389**	.620**	1.00						
CE1822	.264**	.236*	.518**	.425**	1.00					
CS2032	.428**	.417**	.596**	.590**	.438**	1.00				
CS2042	.301**	.404**	.375**	.312**	.262**	.562**	1.00			
CS2062	.341**	.395**	.561**	.519**	.572**	.669**	.537**	1.00		
EN2022	.310**	.480**	.360**	.542**	.384**	.534**	.435**	.398**	1.00	
ME1822	.217*	.281**	.326**	.378**	.303**	.500**	.291**	.475**	.355**	1.00

Table A2.12: Results for CS Performance in S4 (2011)

	MA1013	MA1032	MA2053	MA2073	MA2033	MA2063	CS3022	CS3032	CS3042	CS3242	EN2062	ME1802
MA1032	.353**	1.00										
MA2053	.484**	.308**	1.00									
MA2073	.427**	.389**	.620**	1.00								
MA2033	.432**	.345**	.537**	.606**	1.00							
MA2063	.445**	.376**	.588**	.485**	.674**	1.00						
CS3022	.377**	.361**	.539**	.410**	.455**	.507**	1.00					
CS3032	.412**	.453**	.613**	.535**	.591**	.679**	.742**	1.00				
CS3042	.379**	.401**	.525**	.418**	.459**	.524**	.673**	.653**	1.00			
CS3242	.190*	.299**	.332**	.249**	.372**	.334**	.495**	.501**	.442**	1.00		
EN2062	.454**	.530**	.563**	.535**	.688**	.675**	.494**	.673**	.564**	.347**	1.00	
ME1802	.275**	.312**	.455**	.359**	.517**	.508**	.493**	.535**	.446**	.391**	.553**	1.00

Table A2.13: Results for EE Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	EE2012	EE2022	EE2033	EN2012	EN2022	ME2012	CE1822
MA1023	.355**	1.00									
MA2013	.242*	.362**	1.00								
MA2023	.354**	.391**	.458**	1.00							
EE2012	.324**	.417**	.574**	.398**	1.00						
EE2022	.135	.368**	.427**	.426**	.445**	1.00					
EE2033	.162	.152	.395**	.221*	.291**	.344**	1.00				
EN2012	.085	.330**	.400**	.442**	.507**	.638**	.239*	1.00			
EN2022	.159	.435**	.267*	.462**	.351**	.557**	.164	.507**	1.00		
ME2012	.187	.365**	.379**	.467**	.384**	.444**	.218*	.505**	.437**	1.00	
CE1822	-.005	.205*	.116	.084	.200	.208*	.143	.176	.340**	.255*	1.00

Table A2.14: Results for EE Performance in S4 (2010)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA2042	EE2042	EE2052	EE2072	EE2083	EE2132	EE3072	ME2842	EE3202
MA1023	.355**	1.00												
MA2013	.242*	.362**	1.00											
MA2023	.354**	.391**	.458**	1.00										
MA2033	.372**	.421**	.386**	.545**	1.00									
MA2042	.349**	.344**	.402**	.236*	.539**	1.00								
EE2042	.260*	.306**	.335**	.244*	.576**	.559**	1.00							
EE2052	.239*	.328**	.204*	.237*	.504**	.383**	.336**	1.00						
EE2072	.253*	.403**	.435**	.395**	.575**	.419**	.457**	.415**	1.00					
EE2083	.376**	.414**	.531**	.475**	.658**	.396**	.441**	.320**	.621**	1.00				
EE2132	.243*	.356**	.362**	.305**	.591**	.413**	.438**	.285**	.512**	.600**	1.00			
EE3072	.167	.478**	.325**	.335**	.499**	.260*	.340**	.401**	.489**	.436**	.385**	1.00		
ME2842	.180	.251*	.341**	.378**	.580**	.432**	.338**	.400**	.613**	.583**	.659**	.505**	1.00	
EE3202	-.194	-.149	.013	.015	.307**	.057	.113	.096	.158	.204*	.248*	.272*	.295**	1.00

Table A2.15: Results for EE Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	CE1822	EE2013	EE2023	EE2033	EE2183	EN2012	EN2022	ME2012
MA1023	.308**	1.00										
MA2013	.395**	.517**	1.00									
MA2023	.457**	.490**	.560**	1.00								
CE1822	.220*	.330**	.140	.297**	1.00							
EE2013	.340**	.458**	.476**	.468**	.307**	1.00						
EE2023	.305**	.317**	.376**	.515**	.127	.436**	1.00					
EE2033	.190*	.398**	.309**	.480**	.458**	.461**	.304**	1.00				
EE2183	.151	.130	.201*	.064	.291**	.259**	.040	.169*	1.00			
EN2012	.272**	.356**	.325**	.379**	.317**	.320**	.340**	.370**	.031	1.00		
EN2022	.219*	.337**	.281**	.430**	.299**	.371**	.362**	.484**	.262**	.388**	1.00	
ME2012	.350**	.477**	.479**	.571**	.272**	.549**	.435**	.414**	.180*	.431**	.456**	1.00

Table A2.16: Results for EE Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA2053	EE2043	EE2053	EE2063	EE2073	EE2083	EE2193	EE3203	ME2842
MA1023	.308**	1.00												
MA2013	.395**	.517**	1.00											
MA2023	.457**	.490**	.560**	1.00										
MA2033	.403**	.609**	.490**	.550**	1.00									
MA2053	.180*	.149	.237**	.197*	.300**	1.00								
EE2043	.310**	.222*	.229*	.309**	.319**	.042	1.00							
EE2053	.213*	.286**	.120	.154	.374**	.158	.143	1.00						
EE2063	.292**	.311**	.337**	.484**	.455**	.110	.309**	.136	1.00					
EE2073	.310**	.546**	.421**	.546**	.526**	.390**	.387**	.195*	.325**	1.00				
EE2083	.252**	.408**	.421**	.473**	.525**	.419**	.522**	.184*	.415**	.616**	1.00			
EE2193	.132	.212*	.122	-.004	.191*	.311**	.167*	.275**	-.088	.244**	0.139	1.00		
EE3203	-.093	.233*	.101	.143	.098	.150	.064	-.049	.039	.330**	.235**	.058	1.00	
ME2842	.171*	.423**	.347**	.425**	.511**	.181*	.351**	.197*	.500**	.403**	.423**	.080	.190*	1.00

Table A2.17: Results for EN Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	EE2092	EN2012	EN2022	EN2052	EN2062
MA1023	.335**	1.00							
MA2013	.320**	.522**	1.00						
MA2023	.411**	.439**	.540**	1.00					
EE2092	.348**	.530**	.636**	.594**	1.00				
EN2012	.455**	.434**	.607**	.622**	.705**	1.00			
EN2022	.346**	.479**	.489**	.538**	.673**	.531**	1.00		
EN2052	.255**	.316**	.346**	.462**	.566**	.561**	.495**	1.00	
EN2062	.401**	.459**	.549**	.499**	.572**	.533**	.489**	.417**	1.00

Table A2.18: Results for EN Performance in S4 (2010)

	MA1013	MA1023	MA2013	MA2023	EN2072	EN2082	EN2142	EN3022
MA1023	.335**	1.00						
MA2013	.320**	.522**	1.00					
MA2023	.411**	.439**	.540**	1.00				
EN2072	.392**	.380**	.442**	.469**	1.00			
EN2082	.441**	.457**	.570**	.626**	.525**	1.00		
EN2142	.149	.210*	.281**	.442**	.533**	.529**	1.00	
EN3022	.106	.070	.130	.122	.331**	.194*	.364**	1.00

Table A2.19: Results for EN Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	EE2092	EN2012	EN2022	EN2052	EN2062
MA1013	1.00								
MA1023	.341**	1.00							
MA2013	.220*	.548**	1.00						
MA2023	.356**	.575**	.623**	1.00					
EE2092	.263**	.487**	.669**	.652**	1.00				
EN2012	.251**	.318**	.397**	.567**	.443**	1.00			
EN2022	.216*	.402**	.489**	.568**	.522**	.451**	1.00		
EN2052	.215*	.464**	.368**	.462**	.554**	.614**	.503**	1.00	
EN2062	.282**	.625**	.580**	.706**	.665**	.572**	.533**	.612**	1.00

Table A2.20: Results for EN Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	EN2142	EN2072	EN2542	EN3022
MA1023	.341**	1.00							
MA2013	.220*	.548**	1.00						
MA2023	.356**	.575**	.623**	1.00					
MA2033	.357**	.598**	.485**	.602**	1.00				
EN2142	-.094	.284**	.291**	.271**	.301**	1.00			
EN2072	.143	.483**	.406**	.588**	.533**	.337**	1.00		
EN2542	.116	.300**	.334**	.369**	.406**	.202*	.382**	1.00	
EN3022	.250**	.421**	.183*	.231*	.299**	.157	.267**	.353**	1.00

Table A2.21: Results for ME Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	EE2802	EN2852	ME2012	ME2022	ME2092	ME2112
MA1023	.333**	1.00								
MA2013	.280**	.452**	1.00							
MA2023	.229*	.297**	.421**	1.00						
EE2802	.235**	.297**	.388**	.281**	1.00					
EN2852	.316**	.182*	.154	.247**	.482**	1.00				
ME2012	.154	.280**	.406**	.320**	.215*	.020	1.00			
ME2022	.191*	.290**	.260**	.241**	.498**	.444**	.170*	1.00		
ME2092	.333**	.553**	.379**	.426**	.334**	.249**	.498**	.369**	1.00	
ME2112	.178*	.256**	.282**	.401**	.442**	.418**	.190*	.536**	.279**	1.00

Table A2.22: Results for ME Performance in S4 (2010)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA2042	ME2032	ME3072	ME3032	ME3062	ME2142
MA1023	.333**	1.00									
MA2013	.280**	.452**	1.00								
MA2023	.229*	.297**	.421**	1.00							
MA2033	.135	.025	.118	.255**	1.00						
MA2042	.021	.285**	.282**	.330**	.404**	1.00					
ME2032	.330**	.242**	.119	.251**	.297**	.413**	1.00				
ME3072	.182*	.280**	.268**	.360**	.260**	.395**	.430**	1.00			
ME3032	.278**	.299**	.210*	.370**	.463**	.513**	.412**	.430**	1.00		
ME3062	.034	.113	.011	.070	.081	.171*	.358**	.414**	.293**	1.00	
ME2142	.188*	.225*	.170*	.199*	.246**	.414**	.446**	.517**	.406**	.554**	1.00

Table A2.23: Results for ME Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	EE2803	EN2852	ME2012	ME2023	ME2092	ME2112	ME2602
MA1023	.279**	1.00									
MA2013	.264**	.430**	1.00								
MA2023	.365**	.488**	.624**	1.00							
EE2803	.108	.341**	.485**	.490**	1.00						
EN2852	-.022	.433**	.228*	.200*	.436**	1.00					
ME2012	.223*	.406**	.437**	.582**	.524**	.331**	1.00				
ME2023	.135	.380**	.273**	.318**	.453**	.426**	.376**	1.00			
ME2092	.121	.314**	.366**	.274**	.421**	.312**	.225*	.369**	1.00		
ME2112	.211*	.452**	.586**	.575**	.504**	.293**	.445**	.428**	.420**	1.00	
ME2602	.038	.376**	.237*	.256**	.587**	.480**	.408**	.643**	.389**	.483**	1.00

Table A2.24: Results for ME Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA2053	ME2032	ME2153	ME3032	ME3062	ME3073
MA1023	.279**	1.00									
MA2013	.264**	.430**	1.00								
MA2023	.365**	.488**	.624**	1.00							
MA2033	.222*	.429**	.456**	.449**	1.00						
MA2053	.018	.353**	.253**	.111	.260**	1.00					
ME2032	.078	.457**	.340**	.414**	.339**	.353**	1.00				
ME2153	.207*	.499**	.310**	.481**	.332**	.487**	.487**	1.00			
ME3032	.228*	.477**	.345**	.466**	.356**	.269**	.442**	.472**	1.00		
ME3062	.255**	.321**	.424**	.530**	.288**	.165	.512**	.402**	.348**	1.00	
ME3073	.089	.344**	.163	.301**	.149	.416**	.551**	.559**	.221*	.395**	1.00

Table A2.25: Results for MT Performance in S3 (2010)

	MA1013	MA1023	MA2013	MA2023	EE2802	EN2852	ME1822	ME2012	MT2042	MT2122
MA1023	$.401^{**}$	1.00								
MA2013	$.460^{**}$	$.540^{**}$	1.00							
MA2023	.233	$.568^{**}$	$.513^{**}$	1.00						
EE2802	.161	$.470^{**}$	$.409^{**}$	$.383^{**}$	1.00					
EN2852	.224	$.467^{**}$	.244	$.275^{*}$	$.735^{**}$	1.00				
ME1822	.191	.241	$.299^{*}$	.197	$.499^{**}$	$.469^{**}$	1.00			
ME2012	.245	$.512^{**}$	$.491^{**}$	$.577^{**}$	$.519^{**}$	$.352^{*}$	$.329^{*}$	1.00		
MT2042	.089	$.689^{**}$	$.521^{**}$	$.420^{**}$	$.721^{**}$	$.690^{**}$	$.400^{**}$	$.517^{**}$	1.00	
MT2122	.248	$.631^{**}$	$.526^{**}$	$.349^{*}$	$.681^{**}$	$.646^{**}$	$.601^{**}$	$.517^{**}$	$.889^{**}$	1.00

Table A2.26: Results for MT Performance in S4 (2010)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA3013	ME2142	ME2832	ME3062	MT2032	MT2072	MT2142	MT2152
MA1023	$.401^{**}$	1.00											
MA2013	$.460^{**}$	$.540^{**}$	1.00										
MA2023	.233	$.568^{**}$	$.513^{**}$	1.00									
MA2033	$.273^{*}$	$.432^{**}$	$.365^{**}$	$.645^{**}$	1.00								
MA3013	.142	$.501^{**}$	$.402^{**}$	$.380^{**}$	$.482^{**}$	1.00							
ME2142	.101	$.473^{**}$	$.344^{*}$	$.524^{**}$	$.551^{**}$	$.544^{**}$	1.00						
ME2832	.153	$.648^{**}$	$.278^{*}$	$.485^{**}$	$.581^{**}$	$.632^{**}$	$.590^{**}$	1.00					
ME3062	$.368^{**}$	$.487^{**}$	$.550^{**}$	$.559^{**}$	$.624^{**}$	$.514^{**}$	$.684^{**}$	$.458^{**}$	1.00				
MT2032	-.051	$.601^{**}$	$.416^{**}$	$.407^{**}$	$.373^{**}$	$.601^{**}$	$.516^{**}$	$.734^{**}$	$.450^{**}$	1.00			
MT2072	.032	$.543^{**}$	$.453^{**}$	$.266^{*}$	$.389^{**}$	$.553^{**}$	$.526^{**}$	$.592^{**}$	$.476^{**}$	$.820^{**}$	1.00		
MT2142	.099	$.572^{**}$	$.423^{**}$	$.399^{**}$	$.389^{**}$	$.576^{**}$	$.428^{**}$	$.687^{**}$	$.413^{**}$	$.758^{**}$	$.663^{**}$	1.00	
MT2152	.025	$.560^{**}$	$.394^{**}$	$.437^{**}$	$.491^{**}$	$.614^{**}$	$.488^{**}$	$.644^{**}$	$.411^{**}$	$.827^{**}$	$.791^{**}$	$.735^{**}$	1.00

Table A2.27: Results for MT Performance in S3 (2011)

	MA1013	MA1023	MA2013	MA2023	EE2803	EN2852	ME1822	ME2012	MT2042	MT2122	MT2152
MA1013	1.00										
MA1023	.460**	1.00									
MA2013	.657**	.525**	1.00								
MA2023	.461**	.581**	.734**	1.00							
EE2803	.196	.441**	.312*	.449**	1.00						
EN2852	.189	.371**	.242	.266*	.568**	1.00					
ME1822	.277*	.090	.178	.259*	.358**	.154	1.00				
ME2012	.239	.577**	.458**	.577**	.627**	.437**	.419**	1.00			
MT2042	-.021	.228	-.032	.000	.454**	.649**	.266*	.353**	1.00		
MT2122	.181	.206	.042	.139	.517**	.508**	.253*	.251*	.637**	1.00	
MT2152	.096	.272*	.226	.303*	.512**	.521**	.277*	.436**	.750**	.621**	1.00

Table A2.28: Results for MT Performance in S4 (2011)

	MA1013	MA1023	MA2013	MA2023	MA2033	MA3013	ME2832	ME2850	ME3062	MT2032	MT2072	MT2142
MA1023	.460**	1.00										
MA2013	.657**	.525**	1.00									
MA2023	.461**	.581**	.734**	1.00								
MA2033	.461**	.578**	.571**	.702**	1.00							
MA3013	.321*	.300*	.382**	.336*	.319*	1.00						
ME2832	.187	.405**	.211	.385**	.354**	.296*	1.00					
ME2850	.190	.360**	.243	.408**	.370**	.519**	.589**	1.00				
ME3062	.250	.409**	.476**	.589**	.460**	.464**	.561**	.556**	1.00			
MT2032	.088	.287*	.219	.143	.110	.559**	.545**	.706**	.467**	1.00		
MT2072	-.034	.234	.033	.074	.023	.559**	.436**	.565**	.455**	.777**	1.00	
MT2142	-.047	.391**	.169	.311*	.382**	.444**	.562**	.753**	.523**	.727**	.724**	1.00

APPENDIX 3

Results of CCA – CE Student Performance

Table A3.1: Results of CCA – Performance of CH in S3 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.592206	0.553967	0.060285	0.350708
2	0.255006	0.132121	0.086810	0.065028
3	0.185275	.	0.089661	0.034327
4	0.039313	-.163882	0.092704	0.001546

	Eigenvalue	Difference	Proportion	Cumulative	likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.5401	0.4706	0.8351	0.8351	0.58532466	2.59	24	374.49	<.0001
2	0.0696	0.0340	0.1075	0.9426	0.90148208	0.76	15	298.54	0.7195
3	0.0355	0.0340	0.0550	0.9976	0.96418086	0.50	8	218	0.8544
4	0.0015		0.0024	1.0000	0.99845450	0.06	3	110	0.9821

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.58532466	2.59	24	374.49	<.0001
Pillai's Trace	0.45160871	2.33	24	440	0.0004
Hotelling-Lawley Trace	0.64678583	2.85	24	244.36	<.0001
Roy's Greatest Root	0.54014026	9.90	6	110	<.0001

Standardized Canonical Coefficients for the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4
CE2012	CE2012	0.1239	-0.8777	0.2507	-0.1516
CE2022	CE2022	-0.2697	-0.0123	0.2183	0.1875
CE2032	CE2032	0.8216	0.1226	-0.9702	0.3174
CE2042	CE2042	0.2453	-0.4245	0.3049	0.2029
CE2052	CE2052	0.0962	0.5012	0.1097	-1.0955
CE2062	CE2062	0.0887	0.5902	0.8333	0.2081

Standardized Canonical Coefficients for the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4
MA1012	MA1012	0.0320	1.1855	-0.1163	0.0400
MA1022	MA1022	0.8050	-0.4152	0.1397	-0.7460
MA2012	MA2012	0.3458	-0.2944	-0.8304	0.4924
MA2022	MA2022	0.0755	-0.1921	0.7991	0.7849

Canonical Structure

Correlations Between the Engineering Measurements and Their Canonical Variables

		ENG1	ENG2	ENG3	ENG4
CE2012	CE2012	0.4491	-0.7040	0.3195	-0.2613
CE2022	CE2022	0.3965	-0.0217	0.3405	0.0004
CE2032	CE2032	0.9515	0.0926	-0.1517	0.0938
CE2042	CE2042	0.7002	-0.1738	0.4133	0.0261
CE2052	CE2052	0.5146	0.1583	0.1728	-0.7909
CE2062	CE2062	0.5450	0.3682	0.6642	0.2823

Table A3.1 continued

Correlations Between the Mathematics Measurements and Their Canonical Variables

		MAT1	MAT2	MAT3	MAT4
MA1012	MA1012	0.5477	0.8257	0.0149	0.1342
MA1022	MA1022	0.9310	0.0054	0.2079	-0.2999
MA2012	MA2012	0.5640	-0.0937	-0.6123	0.5461
MA2022	MA2022	0.5031	0.0218	0.5809	0.6395

Correlations Between the Engineering Measurements and the Canonical Variables of the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4
CE2012	CE2012	0.2659	-0.1795	0.0592	-0.0103
CE2022	CE2022	0.2348	-0.0055	0.0631	0.0000
CE2032	CE2032	0.5635	0.0236	-0.0281	0.0037
CE2042	CE2042	0.4147	-0.0443	0.0766	0.0010
CE2052	CE2052	0.3048	0.0404	0.0320	-0.0311
CE2062	CE2062	0.3227	0.0939	0.1231	0.0111

Correlations Between the Mathematics Measurements and the Canonical Variables of the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4
MA1012	MA1012	0.3244	0.2106	0.0028	0.0053
MA1022	MA1022	0.5514	0.0014	0.0385	-0.0118
MA2012	MA2012	0.3340	-0.0239	-0.1134	0.0215
MA2022	MA2022	0.2979	0.0056	0.1076	0.0251

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.3861	0.3861	0.3507	0.1354	0.1354
2	0.1159	0.5020	0.0650	0.0075	0.1429
3	0.1471	0.6491	0.0343	0.0051	0.1480
4	0.1305	0.7796	0.0015	0.0002	0.1482

Standardized Variance of the Mathematics Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.4345	0.4345	0.3507	0.1524	0.1524
2	0.1728	0.6073	0.0650	0.0112	0.1636
3	0.1889	0.7962	0.0343	0.0065	0.1701
4	0.2038	1.0000	0.0015	0.0003	0.1704

Table A3.2: Results of CCA – Performance of CH in S4 (2010)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.723606	0.697686	0.044232	0.523606
2	0.392196	0.303442	0.078566	0.153818
3	0.308681	0.275805	0.084001	0.095284
4	0.159312	0.107476	0.090491	0.025380
5	0.019951	-.186466	0.092811	0.000398

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.0991	0.9173	0.7780	0.7780	0.35530797	4.19	30	426	<.0001
2	0.1818	0.0765	0.1287	0.9067	0.74582787	1.64	20	355.83	0.0407
3	0.1053	0.0793	0.0746	0.9813	0.88140316	1.16	12	286.03	0.3081
4	0.0260	0.0256	0.0184	0.9997	0.97423187	0.48	6	218	0.8248
5	0.0004		0.0003	1.0000	0.99960194	0.02	2	110	0.9783

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.35530797	4.19	30	426	<.0001
Pillai's Trace	0.79848574	3.48	30	550	<.0001
Hotelling-Lawley Trace	1.41263938	4.93	30	271.75	<.0001
Roy's Greatest Root	1.09910257	20.15	6	110	<.0001

Standardized Canonical Coefficients for the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4	ENG5
CE2112	CE2112	0.5878	-1.2724	-0.1046	0.1155	-0.1111
CE2122	CE2122	0.0634	0.2017	1.2367	-0.2531	-0.4229
CE2132	CE2132	0.1129	0.4115	0.0021	-0.3958	1.4053
CE2142	CE2142	-0.0973	0.1912	0.0083	1.2370	-0.0759
CE3012	CE3012	0.4418	0.7343	-0.8497	-0.2844	-0.7346

Standardized Canonical Coefficients for the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4	MAT5
MA1012	MA1012	-0.1666	-0.5009	0.3157	-0.5501	0.6173
MA1022	MA1022	0.0527	0.5122	0.8070	0.5404	-0.5304
MA2012	MA2012	0.0466	0.1975	0.3560	0.0747	0.5233
MA2022	MA2022	0.3294	-0.4205	-0.1665	-0.5468	-0.7180
MA2032	MA2032	0.6955	-0.5568	-0.3444	0.5136	0.2448
MA3012	MA3012	0.3772	0.7741	-0.2456	-0.5736	0.1233

Correlations Between the Engineering Measurements and Their Canonical Variables

		ENG1	ENG2	ENG3	ENG4	ENG5
CE2112	CE2112	0.9186	-0.3607	0.0623	0.1319	0.0689
CE2122	CE2122	0.6652	0.2623	0.6866	-0.0009	-0.1315
CE2132	CE2132	0.7497	0.2900	0.1226	0.0489	0.5800
CE2142	CE2142	0.4882	0.2789	0.1316	0.8094	0.1068
CE3012	CE3012	0.8618	0.4296	-0.1837	-0.0095	-0.1974

Correlations Between the Mathematics Measurements and Their Canonical Variables

		MAT1	MAT2	MAT3	MAT4	MAT5
MA1012	MA1012	0.1966	-0.3380	0.6343	-0.4802	0.3079
MA1022	MA1022	0.4533	0.1409	0.7928	0.1223	-0.2822
MA2012	MA2012	0.2909	-0.0113	0.4927	-0.0412	0.4506
MA2022	MA2022	0.4528	-0.3805	0.2928	-0.4901	-0.4918
MA2032	MA2032	0.8756	-0.2385	-0.0259	0.3321	0.2127
MA3012	MA3012	0.6289	0.6046	-0.0994	-0.4085	0.1568

Table A3.2 continued

Correlations Between the Engineering Measurements and the Canonical Variables of the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4	MAT5
CE2112	CE2112	0.6647	-0.1415	0.0192	0.0210	0.0014
CE2122	CE2122	0.4814	0.1029	0.2119	-0.0001	-0.0026
CE2132	CE2132	0.5425	0.1138	0.0378	0.0078	0.0116
CE2142	CE2142	0.3533	0.1094	0.0406	0.1289	0.0021
CE3012	CE3012	0.6236	0.1685	-0.0567	-0.0015	-0.0039

Correlations Between the Mathematics Measurements and the Canonical Variables of the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4	ENG5
MA1012	MA1012	0.1423	-0.1326	0.1958	-0.0765	0.0061
MA1022	MA1022	0.3280	0.0553	0.2447	0.0195	-0.0056
MA2012	MA2012	0.2105	-0.0044	0.1521	-0.0066	0.0090
MA2022	MA2022	0.3276	-0.1492	0.0904	-0.0781	-0.0098
MA2032	MA2032	0.6336	-0.0935	-0.0080	0.0529	0.0042
MA3012	MA3012	0.4551	0.2371	-0.0307	-0.0651	0.0031

Standardized Variance of the Engineering Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.5659	0.5659	0.5236	0.2963	0.2963
2	0.1091	0.6750	0.1538	0.0168	0.3131
3	0.1083	0.7832	0.0953	0.0103	0.3234
4	0.1350	0.9182	0.0254	0.0034	0.3268
5	0.0818	1.0000	0.0004	0.0000	0.3269

Standardized Variance of the Mathematics Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.2827	0.2827	0.5236	0.1480	0.1480
2	0.1169	0.3996	0.1538	0.0180	0.1660
3	0.2283	0.6279	0.0953	0.0218	0.1877
4	0.1274	0.7553	0.0254	0.0032	0.1910
5	0.1149	0.8702	0.0004	0.0000	0.1910

Table A3.3: Results of CCA – Performance of CH in S3 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.623157	0.591551	0.054930	0.388324
2	0.260196	0.152498	0.083723	0.067702
3	0.181356	0.135503	0.086849	0.032890
4	0.025870	-.276066	0.089743	0.000669

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.6349	0.5622	0.8554	0.8554	0.55113923	3.12	24	402.4	<.0001
2	0.0726	0.0386	0.0978	0.9533	0.90103152	0.82	15	320.63	0.6525
3	0.0340	0.0333	0.0458	0.9991	0.96646286	0.50	8	234	0.8533
4	0.0007		0.0009	1.0000	0.99933075	0.03	3	118	0.9942

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.55113923	3.12	24	402.4	<.0001
Pillai's Trace	0.48958516	2.74	24	472	<.0001
Hotelling-Lawley Trace	0.74214920	3.52	24	263.26	<.0001
Roy's Greatest Root	0.63485280	12.49	6	118	<.0001

Standardized Canonical Coefficients for the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4
CE2012	CE2012	0.6855	-0.5350	0.0306	0.2283
CE2022	CE2022	0.1746	0.1436	-0.5493	0.8507
CE2032	CE2032	-0.0847	-0.2038	-0.0663	-0.2047
CE2042	CE2042	0.3535	0.0262	-0.4951	-0.6930
CE2052	CE2052	0.1305	-0.0069	0.8034	0.2984
CE2062	CE2062	0.0854	0.9490	0.0587	0.0310

Standardized Canonical Coefficients for the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4
MA1013	MA1013	0.0271	-0.6592	-0.8756	0.1491
MA1023	MA1023	0.4332	0.6128	-0.3335	-0.7962
MA2013	MA2013	0.3350	0.8024	-0.0249	0.9217
MA2023	MA2023	0.4677	-0.9232	0.7525	-0.1784

Correlations Between the Engineering Measurements and Their Canonical Variables

		ENG1	ENG2	ENG3	ENG4
CE2012	CE2012	0.8948	-0.2980	0.1128	0.0172
CE2022	CE2022	0.1682	0.1373	-0.5639	0.7279
CE2032	CE2032	0.0415	-0.1252	-0.3133	0.0084
CE2042	CE2042	0.7237	0.2169	-0.2781	-0.4534
CE2052	CE2052	0.4958	0.1676	0.6507	0.2245
CE2062	CE2062	0.4715	0.8333	0.0941	-0.0845

Table A3.3 continued

Correlations Between the Mathematics Measurements and Their Canonical Variables

		MAT1	MAT2	MAT3	MAT4
MA1013	MA1013	0.4276	-0.4430	-0.7595	0.2098
MA1023	MA1023	0.7649	0.2697	-0.2679	-0.5200
MA2013	MA2013	0.7584	0.2295	-0.0457	0.6083
MA2023	MA2023	0.8617	-0.3884	0.3249	0.0338

Correlations Between the Engineering Measurements and the Canonical Variables of the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4
CE2012	CE2012	0.5576	-0.0775	0.0205	0.0004
CE2022	CE2022	0.1048	0.0357	-0.1023	0.0188
CE2032	CE2032	0.0259	-0.0326	-0.0568	0.0002
CE2042	CE2042	0.4510	0.0564	-0.0504	-0.0117
CE2052	CE2052	0.3090	0.0436	0.1180	0.0058
CE2062	CE2062	0.2938	0.2168	0.0171	-0.0022

Correlations Between the Mathematics Measurements and the Canonical Variables of the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4
MA1013	MA1013	0.2664	-0.1153	-0.1377	0.0054
MA1023	MA1023	0.4767	0.0702	-0.0486	-0.0135
MA2013	MA2013	0.4726	0.0597	-0.0083	0.0157
MA2023	MA2023	0.5369	-0.1011	0.0589	0.0009

Canonical Redundancy Analysis

Standardized Variance of the Engineering Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.3037	0.3037	0.3883	0.1180	0.1180
2	0.1488	0.4526	0.0677	0.0101	0.1280
3	0.1564	0.6090	0.0329	0.0051	0.1332
4	0.1322	0.7412	0.0007	0.0001	0.1333

Standardized Variance of the Mathematics Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.5214	0.5214	0.3883	0.2025	0.2025
2	0.1181	0.6395	0.0677	0.0080	0.2105
3	0.1891	0.8286	0.0329	0.0062	0.2167
4	0.1714	1.0000	0.0007	0.0001	0.2168

Table A3.4: Results of CCA – Performance of CH in S4 (2011)

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation
1	0.766469	0.747800	0.037046	0.587475
2	0.285908	0.181809	0.082462	0.081743
3	0.170767	0.062308	0.087184	0.029161
4	0.085904	.	0.089140	0.007380
5	0.047681	.	0.089598	0.002273

	Eigenvalue	Difference	Proportion	Cumulative	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	1.4241	1.3351	0.9171	0.9171	0.36421360	4.39	30	458	<.0001
2	0.0890	0.0590	0.0573	0.9744	0.88288874	0.73	20	382.36	0.7936
3	0.0300	0.0226	0.0193	0.9937	0.96148341	0.38	12	307.2	0.9691
4	0.0074	0.0052	0.0048	0.9985	0.99036374	0.19	6	234	0.9796
5	0.0023		0.0015	1.0000	0.99772654	0.13	2	118	0.8743

Multivariate Statistics and F Approximations

Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.36421360	4.39	30	458	<.0001
Pillai's Trace	0.70803259	3.24	30	590	<.0001
Hotelling-Lawley Trace	1.55286626	5.84	30	293.07	<.0001
Roy's Greatest Root	1.42409601	28.01	6	118	<.0001

Standardized Canonical Coefficients for the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4	ENG5
CE2112	CE2112	0.3881	-1.0140	-0.4203	-0.1604	-0.5799
CE2122	CE2122	0.2293	0.6729	-0.8222	0.7070	0.2955
CE2132	CE2132	0.2597	0.8338	0.1179	-1.0383	0.0045
CE2142	CE2142	0.0859	-0.0467	0.7647	0.6041	-0.8196
CE3012	CE3012	0.3202	-0.3922	0.5358	0.0423	0.9938

Standardized Canonical Coefficients for the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4	MAT5
MA1013	MA1013	-0.0624	0.2776	0.2223	0.0290	1.0543
MA1023	MA1023	0.0985	0.2967	-0.5460	-1.0217	-0.0732
MA2013	MA2013	0.1249	-0.5702	0.7938	-0.5128	-0.3734
MA2023	MA2023	0.2625	-0.5728	-0.8587	0.6942	0.2906
MA2033	MA2033	0.2874	-0.1952	0.2622	-0.0470	0.0256
MA3013	MA3013	0.5716	0.7024	0.1875	0.5444	-0.3957

Canonical Structure

Correlations Between the Engineering Measurements and Their Canonical Variables

		ENG1	ENG2	ENG3	ENG4	ENG5
CE2112	CE2112	0.8295	-0.3815	-0.2874	-0.1327	-0.2572
CE2122	CE2122	0.7655	0.3375	-0.3429	0.4238	0.0534
CE2132	CE2132	0.7858	0.4000	0.1235	-0.4319	-0.1436
CE2142	CE2142	0.6215	0.2023	0.5123	0.3742	-0.4126
CE3012	CE3012	0.7655	-0.1580	0.3563	0.1072	0.5006

Table A3.4 continued

Correlations Between the Mathematics Measurements and Their Canonical Variables

		MAT1	MAT2	MAT3	MAT4	MAT5
MA1013	MA1013	0.3739	0.1251	0.2557	-0.1152	0.8617
MA1023	MA1023	0.6015	0.1522	-0.4101	-0.6596	0.0904
MA2013	MA2013	0.6116	-0.5292	0.3871	-0.2807	0.0456
MA2023	MA2023	0.6933	-0.5113	-0.4015	0.1284	0.2293
MA2033	MA2033	0.7361	-0.1607	0.1785	-0.1249	0.1510
MA3013	MA3013	0.8646	0.4187	0.1086	0.1662	-0.1127

Correlations Between the Engineering Measurements and the
Canonical Variables of the Mathematics Measurements

		MAT1	MAT2	MAT3	MAT4	MAT5
CE2112	CE2112	0.6358	-0.1091	-0.0491	-0.0114	-0.0123
CE2122	CE2122	0.5868	0.0965	-0.0586	0.0364	0.0025
CE2132	CE2132	0.6023	0.1144	0.0211	-0.0371	-0.0068
CE2142	CE2142	0.4764	0.0578	0.0875	0.0321	-0.0197
CE3012	CE3012	0.5867	-0.0452	0.0608	0.0092	0.0239

Correlations Between the Mathematics Measurements and the
Canonical Variables of the Engineering Measurements

		ENG1	ENG2	ENG3	ENG4	ENG5
MA1013	MA1013	0.2866	0.0358	0.0437	-0.0099	0.0411
MA1023	MA1023	0.4611	0.0435	-0.0700	-0.0567	0.0043
MA2013	MA2013	0.4688	-0.1513	0.0661	-0.0241	0.0022
MA2023	MA2023	0.5314	-0.1462	-0.0686	0.0110	0.0109
MA2033	MA2033	0.5642	-0.0459	0.0305	-0.0107	0.0072
MA3013	MA3013	0.6627	0.1197	0.0185	0.0143	-0.0054

Standardized Variance of the Engineering Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.5728	0.5728	0.5875	0.3365	0.3365
2	0.0971	0.6699	0.0817	0.0079	0.3444
3	0.1210	0.7908	0.0292	0.0035	0.3480
4	0.1071	0.8979	0.0074	0.0008	0.3488
5	0.1021	1.0000	0.0023	0.0002	0.3490

Standardized Variance of the Mathematics Measurements Explained by

	Their Own Canonical Variables			The Opposite Canonical Variables	
Canonical Variable Number	Proportion	Cumulative Proportion	Canonical R-Square	Proportion	Cumulative Proportion
1	0.4409	0.4409	0.5875	0.2590	0.2590
2	0.1302	0.5712	0.0817	0.0106	0.2697
3	0.0980	0.6692	0.0292	0.0029	0.2726
4	0.0978	0.7670	0.0074	0.0007	0.2733
5	0.1402	0.9072	0.0023	0.0003	0.2736