Impact of Undergraduate Students' Mathematics Attainment on their Academic Performance in Computer Science and Engineering (CSE) Courses

Francis Avevor

Advanced School of System and Data Studies (ASSDAS), Accra Institute of Technology, Accra, Ghana

DOI: https://doi.org/10.51244/IJRSI.2025.12060083

Received: 26 May 2025; Accepted: 04 June 2025; Published: 10 July 2025

ABSTRACT

This descriptive study is underpinned by, and anchored on, the Transfer of Learning Theory (TLT); and it sought to determine the association between students' attainments in Mathematics at West African Senior School Certificate Examination (WASSCE) and their undergraduate Mathematics courses. In addition, it sought to establish the correlation between students' performance in undergraduate Mathematics courses and that of Computer Science and Engineering (CSE) courses. 872 undergraduate students were sampled from three public universities in Ghana using stratified random sampling technique; and data analysis was performed with ANOVA and descriptive statistics. The results revealed a moderate correlation among the students' attainments in Mathematics at WASSCE, in undergraduate Math courses, and in undergraduate CSE courses. Also, it showed a significant difference in the mean performances of male and female students in all the 3 performance variables/datasets, with the females outperforming the males. Furthermore, this study proffered policy and strategy recommendations for university administrators and academic deans.

Keywords: Academic performance, undergraduate mathematics, ANOVA, Likert scale, undergraduate grades

INTRODUCTION

Over the last two decades, West African Examinations Council in collaboration with the Ghana Education Service has been producing a competitive School Performance League Table (SPLT) that ranks the performance of public Senior High Schools at WASSCE annually. Based on the SPLT, schools are ranked as Category A, Category B and Category C. Typically, Category A schools are provided with more government-sponsored developmental projects; notably: well-equipped model Science, Technology, Engineering and Mathematics (STEM) facilities including robotics laboratory, and aeronautic engineering workshop/laboratory. Also, Ghana's Ministry of Education introduced a robust, inspirational, competitive, and innovation scheme, dubbed STEMNNOVATION, for students from public pre-university schools to compete in using their skills and knowledge in mechatronics, STEM, robotics, and Computer-Aided Design tools to find novel solutions to health and socio-economic problems. Furthermore, the Ghana Education Service has instituted annual National Teachers' Awards Scheme to motivate teachers and non-teaching staff in public Basic Schools and Senior High Schools. This scheme tends to inspire teaching and non-teaching staffs to be innovative and implement proactive strategies to promote teaching and learning in schools and boost their schools' academic performance and ranking.

Obtaining good grades (specifically: A1, B2, B3, C4, C5, or C6) in six subjects (with a minimum of aggregate 24) at WASSCE is an entry requirement into tertiary institutions in Ghana. To gain admission to pursue undergraduate CSE programmes in Ghanaian Universities, students are specifically required to obtain grade C6 or better in the following six subjects: Core Mathematics, Elective Mathematics, English Language, Social Studies, and two Science subjects. The tenacity of making students' performances in both Core Mathematics and Elective Mathematics at WASSCE as a precursor for admission to undergraduate CSE programmes is often questioned.

The general perception is that mathematics teaches problem-solving skills and emphasizes abstract and deductive reasoning required in CSE studies and careers (BYJU's Future School, 2022; Bohlmann & Pretorius, 2008; Venkat, 2007). It promotes analytical, logical, and critical reasoning which, in turn, tends to increase students' performance in CSE courses (Neri, 2021). Invariably, the fields of Mathematics and Computer Science and Engineering (CSE) are tightly intertwined. For instance, "mathematical reasoning complements Computer Science reasoning" (Baldwin, Walker & Henderson, 2013 p.74). Thus, the strength of students' mathematics background determines their level of performance in undergraduate CSE courses. (Duran, 2016; White & Sivitanides, 2015; Duran, 2015; Paulson (n.d.)).

Some students who get admission to pursue undergraduate Mathematics and CSE programmes lack understanding of some basic mathematical concepts and topics as well as logical problem-solving skills relevant for their undergraduate studies. This raises questions as to whether their attainment in mathematics at pre-tertiary educational level can significantly predict their performance in undergraduate Mathematics and CSE programmes. Similarly, people are skeptical about a relationship between students' performance in undergraduate mathematics courses and that of CSE courses.

Problem Statement and Motivation for Study

Students' overall pre-tertiary educational attainments predict their performances in undergraduate programmes in higher educational institutions (Gray et al., 2016; Mayston, 2003; Morgan et al., 2001). In students' quest to qualify for admission to pursue undergraduate CSE programmes, many of them struggle to pass Core Mathematics and Elective Mathematics at the WASSCE. The general perception among them is that once they gain admission into undergraduate CSE programmes, academic work would be smooth sailing for them. However, on entering the undergraduate CSE programmes, "students with weak mathematics background are often overwhelmed by the many mathematics courses that they have to take during their undergraduate Computer Science and Engineering (CSE) programmes; and tend to question the relevance of mathematics to their CSE studies" (Avevor, 2022a p. 30). Often, students who underperform in some of their undergraduate mathematics courses struggle to cope with, and sometimes trail, CSE courses.

As a computer scientist, educator, and counselor, the researcher had witnessed some of his undergraduate CSE students with grades C4, C5 or C6 (i.e., credit/average performance) in mathematics at WASSCE struggling to cope with undergraduate mathematical courses and/or CSE courses. The researcher was, therefore, driven to investigate the relationships (if any) among students' performances in mathematics at WASSCE, undergraduate mathematics courses, and undergraduate CSE courses. This study, therefore, sought to appraise the tenacity of making students' performances in both Core Mathematics and Elective Mathematics at WASSCE as a precursor for gaining admission to pursue undergraduate CSE education in Ghana; and determine the three-pronged relationships among students' performances in pre-university mathematics (at WASSCE), undergraduate mathematics courses, and undergraduate CSE courses.

Research Objectives and Research Questions

Objectives that guided this study are:

1. To assess the stipulation of using students' performances in both Core Mathematics and Elective Mathematics at WASSCE as a prerequisite for their admission to pursue undergraduate CSE education in Ghana.
2. To determine if there are any correlations among students' achievements in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses.
3. To determine if male and female students differ in their performances in Mathematics at WASSCE, undergraduate mathematics courses, and undergraduate CSE courses.

The corresponding research questions are:

RQ1. How relevant is making students' performances in Core Mathematics and Elective Mathematics at WASSCE a prerequisite for their admission to pursue undergraduate CSE education in Ghana?

RQ2. Do any relationships exist among students' achievements in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses?

RQ3. Do male and female students have significant differences in their performances in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses?

LITERATURE REVIEW

In this section, the researcher reviewed pertinent theoretical and empirical literature; and provided the conceptual framework for this study.

Theoretical Review

The theoretical underpinning for this study is expounded in this sub-section.

Transfer of Learning Theory (ToLT)

This theory, propounded by Edward Thorndike in 1901 and greatly transformed a century later by Robert Haskell with his 11 cognitive, instructional, and reasoning principles [outlined in Figure 1], succinctly explains how individuals utilize (or generalize) their prior skills and knowledge to perform inherently different tasks in different environments and contexts (Nakakoji & Wilson, 2020; Sala & Gobet, 2016; Kowalski, 2010; Haskell, 2001). In situations where the two contexts are explicitly close, the learner harnesses his/her prior knowledge precisely and steadfastly to perform the task on hand. However, in situations where the two contexts are distant, the learner applies his/her abstracts and merges principles and practices from different domains to perform the task at hand. The success of prior knowledge transfer depends on how explicitly and closely-associated the task-at-hand and the previous task(s) performed are (Nakakoji & Wilson, 2020; Lobato, 2012; Gick & Holyoak, 1987). Steiner (2001) postulates that "newly acquired knowledge structures need consolidation in order to be transferred" (p. 15845). A transfer of learning can be positive, negative, proactive, retroactive, or bilateral (Rashid, 2023). Table 1 describes the 5 types of learning transfer.

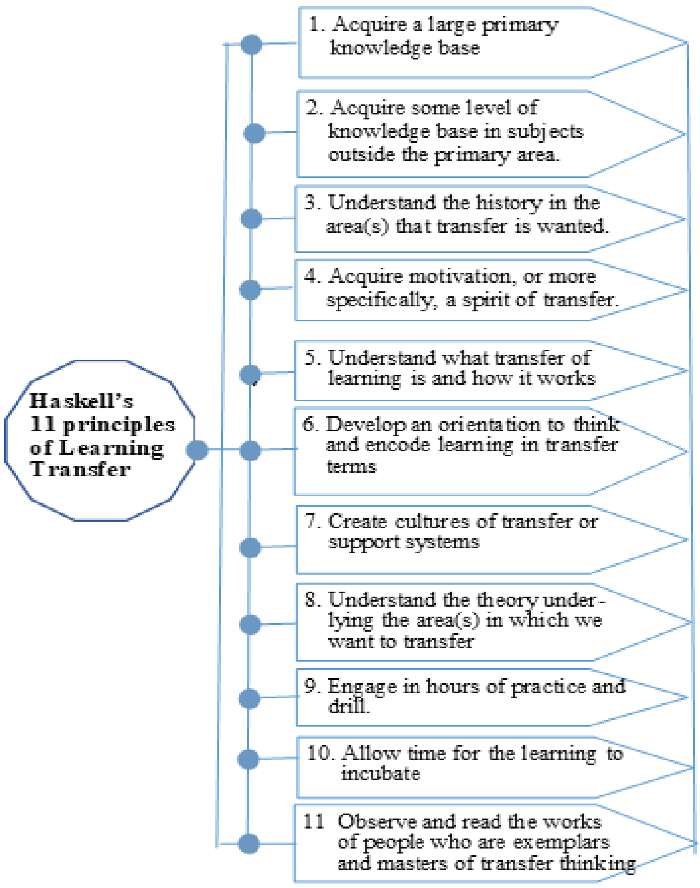

Figure 1. Haskell's 11 learning transfer principles (Haskell, 2001 p. xv).

Table 1. Types of learning transfer

Type of Transfer	Explanation
Positive	A positive learning transfer occurs when prior skill, knowledge, or strategy enhances a person's capability to execute a new task in a different context/domain.
Negative	A negative learning transfer occurs when prior skill, knowledge, or strategy impedes a person's capability to execute a new task in a different context/domain.
Bilateral	A bilateral learning transfer occurs when there is a bidirectional transfer of skills or knowledge between the two problem domains or tasks; and here, the skills from two domains (or simultaneous tasks) impact each other.
Proactive	A proactive learning transfer occurs when prior skills or knowledge foster(s) the acquisition of new related skills or knowledge.
Retroactive	Retroactive learning transfer occurs when an individual's efforts towards the acquisition of new skills or knowledge is hindered by the prior skills or knowledge that he/she had acquired.

Thus, a prior learning can either enhance or inhibit the subsequent task performance in another domain/context. Alternatively, the impact of a prior learning on the subsequent task performance can be nil (Sala & Gobet, 2016; Haskell, 2004). This theory may be influenced by several key factors, including the similarities between previous and new learning processes/contexts (Steiner, 2001), the learner's mental processes, personal characters, and motivation (Herring, 2010; Volet, 1999; Greeno et al., 1993); the learner's physical and social environments, and the learner's interaction with others (Royer, Mestre & Dufresne, 2005).

It is essential for educators to use this theory to identify "how transfer works and how transfer can be facilitated" (Royer, Mestre & Dufrene, 2005 p. viii) and device appropriate pedagogical strategies to achieve desired outcomes. Many mathematics courses are contextually and explicitly close to, and have loose intrinsic coupling with, many CSE courses (Baldwin, Walker & Henderson, 2013; Beaubouef & Mason, 2005; Beaubouef, 2002; Glass, 2000). For instance, prior skills and knowledge acquired from learning statistics, discrete mathematics, linear algebra, calculus, and probability can be positively transferred to learning topics such as cryptography, digital signature generation and verification algorithms, as well as data encryption and compression algorithms in undergraduate Computer Security course (Avevor, 2022a). This is because topics that are usually taught in the five mathematics courses listed above are closely related to topics that are taught in undergraduate Computer Security course. Invariably, a direct and smooth application of prior skills and knowledge acquired from the afore-listed mathematics courses enhances students' understanding and problem-solving in undergraduate Computer Security course.

Conceptual Framework

The conceptual framework to ascertain the relationships among students' performances in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses is shown in Figure 2.

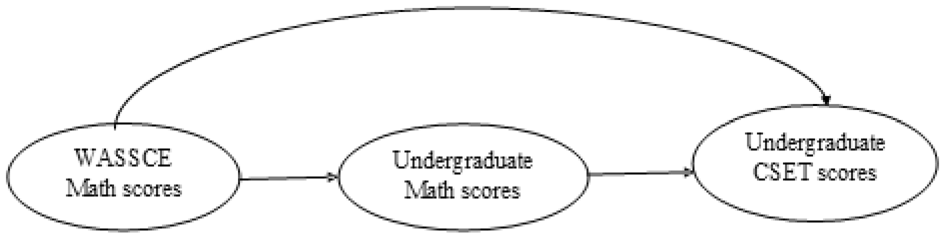

Figure 2. Conceptual framework for relationships among WASSCE Math scores, undergraduate Math scores and CSE scores

Empirical Review

This section explores pertinent literature regarding the relationships among students' performances in mathematics at WASSCE, undergraduate mathematics courses, and undergraduate CSE courses.

Relationship between Pre-University Math and Undergraduate Math Performance

According to Hourigan & O'Donoghue (2007), many students struggle to cope with undergraduate mathematics courses in situations where there is a mismatch between their "pre-tertiary mathematical experiences and subsequent tertiary level mathematics-intensive courses" (p. 461). By comparing students' performances in 4 undergraduate mathematics courses with their prior mathematics courses studied in final year secondary school, Rylands & Coady (2009) found that the students' pre-tertiary mathematics background greatly impacts their performance in undergraduate mathematics courses. They, thus, concluded that students who performed well in mathematics in secondary school will excel in their undergraduate mathematics courses.

Fioroni (2006) conducted a 3-year survey, using a total of 732 McMaster University's 1st year mathematics students, to determine the association between their performance in mathematics at high school and their attainment in a mandatory 1st year undergraduate Calculus course dubbed "Calculus for Science" (p.1). He administered a questionnaire with math aptitude test in it during the 1st week of the semester. He made the following key findings:

1. that participants who took one, two, and three high school math courses had an average score of 53.16%, 66.26%, and 74.66%, respectively, in their undergraduate Calculus course [where a score of ≥50% denotes Pass].
2. that students who studied a combination of Calculus, Geometry, and Algebra at high school outperformed those who studied other course combinations in their undergraduate Calculus course.
3. that a student's good score in the survey statistically correlates with his/her performance in the undergraduate Calculus course; but a student's poor score in the survey is inconclusive in predicting his/her performance in the undergraduate Calculus course.

He, therefore, contended that the more exposure students have to mathematics in high school and the more amount of time they devote to learning topics, the better they will ultimately understand the subject.

Islam Al-Ghassani & Al-hadhrami (2018) evaluated the attainment of 551 undergraduate students in a mathematics course (dubbed: "Mathematics Foundation Course" p. 96) in relation to their prior performance in mathematics at high school. They found that the students performed generally better in mathematics at high school than in the undergraduate mathematics course; and that the female students outperformed the male students in both courses. In addition, their study revealed that the students' attainment in mathematics at high school significantly predicts their performance in the undergraduate mathematics course. However, the ratio of the likelihood of success of the female and male students in the undergraduate mathematics course is 4:1 in favour of the female students. In related research using regression analysis, Husnira et al. (2018) used data on 2442 Engineering students and found a significant positive correlation between their attainment in Mathematics at Malaysian secondary school leaving certificate examination (SPM) and that of undergraduate Engineering Mathematics 2. In contrast, Shukri et al. (2022) used data on 179 undergraduate Medical and Engineering students and found a weak correlation ($r=.363$, producing effect size r^2 [i.e., coefficient of determination] of 13.18) between the students' performance in Mathematics at Malaysian secondary school leaving certificate examination (SPM) and that of undergraduate Mathematics 1.

Furthermore, Kpe-Nobana & Wonu (2019) used data on 67 undergraduate Computer Science students of Ignatus Ajuru University of Education in Nigeria to investigate whether students' performance in mathematics at 3 external high school leaving examinations (namely: UTME/JAMB, WASSCE, and post-UTME) can predict their performance in undergraduate Algebra. They found that students' performance in Mathematics at all the 3 external examinations strongly, positively and significantly correlated with their performance in undergraduate Algebra. They concluded that the predictive power of the students' performance in mathematics at WASSCE was the strongest among the 3 external examinations in gauging the students' success (or otherwise) in undergraduate Algebra.

Performance relationship between Undergraduate Math and Undergraduate CSE courses

A strong mathematics background is essential for great success in undergraduate CSE courses (Popanao, Smith & Pairor, 2022; Duran, 2016; Balmes, 2017; Buick, 2007; Meltzer, 2002). According to Wilson & Shrock

(2001) and Bergin & Riley (2006), students' attainment in undergraduate mathematics correlates with their performance in CSE courses. Similarly, using examination scores of 99 computer science graduates, Razak & Ismail (2018) found the existence of a strong association between their performance in mathematics courses and that of programming courses. Also, Duran (2015) conducted a study with 132 undergraduate students in the Philippines to determine how students' mathematics background influences their performance in two computer programming courses. He found that students' mathematics background correlated significantly with their attainment in the programming courses. He concluded that good mathematics students should expect to excel better in the two programming courses he used in his study. Using a sample of 19 undergraduate students of Lyceum of the Philippines University, Balmes (2017) found that students' score in mathematics is a predictor of their performance in all the 9 courses of the BSc Computer Science programme used in his study. Likewise, White & Sivitanides (2003) and Fan & Li (2002), in separate studies using 283 students in USA and 940 students in Taiwan, respectively, found that the students' performance in undergraduate mathematics courses correlates positively with their performance in undergraduate CSE courses.

Using 121 undergraduate students at Selangor International Islamic University College in Malaysia, Sofi, Khalid & Jalil (2010) found a "significant correlation between Discrete Mathematics course and Introduction to Programming course" (p. 649). Furthermore, Cornillez, Treceñe & Santos (2020) conducted a survey using 73 datasets and J48 datamining classification algorithm to determine the association between students' performances in 2 undergraduate mathematics courses and Computer Programming 1 course (i.e., C Programming Language) in the Philippines. They obtained the following two key results:

1. The relationship between a math course, dubbed "Mathematics in the modern world", and the programming course is statistically insignificant; while the other math course, (dubbed: "Mathematics Enhancement 1"), with strong analogous computational skills (typically learnt from undergraduate trigonometry and algebra) inherent therein, has an average correlation with the programming course.
2. The female students generally outperformed their male counterparts in the programming course.

Andrade-Arenas, Vasquez-Paragulla & Sotomayor-Beltran (2019) conducted a 4-year study (covering 8 semesters in 2015 – 2018), to determine the correlation between students' performance in undergraduate mathematics courses and that of Algorithms course. They found a moderate positive correlation between the 2 variables. Also, Patalay, Danguilan & Daligcon (2017) investigated the relationship between students' mean performance in 3 undergraduate mathematics courses and 4 programming courses. They found a strong association between the 2 variables and concluded that "if a student is good in Mathematics, the student will also perform better in programming" (p. 43).

Furthermore, Nanayakkara & Peiris (2016) used correlation analysis and PLS-Structural Equation Modeling to analyze the relationship between 626 undergraduate engineering students' performance in Level 1 (i.e., 1st and 2nd semester) mathematics courses and their performance in Level 2 (i.e., 3rd and 4th semester) core engineering courses. Correlating the mathematics performance variables separately with the engineering courses, they found that 2nd semester mathematics courses recorded a higher impact on the students' mean performance in Level 2 engineering courses than that of the 1st semester mathematics courses. Analyzing the joint impact of the Level 1 mathematics courses (i.e., both 1st semester and 2nd semester mathematics courses), they concluded that the students' mean performance in mathematics greatly predicts their mean performance in the various engineering courses; and that the levels of impact vary across the various engineering programmes/disciplines. They reported an effect size (i.e., coefficient of determination) of between 39% and 73% for the positive correlation between the students' performance in engineering courses and that of their prior undergraduate mathematics courses.

Relationship between Pre-university Math and Undergraduate CSE Performance

Students' prior attainment in mathematics at pre-tertiary educational level is a significant predictor of their undergraduate performance in CSE programmes (Gomes & Mendes, 2008; Bergin & Reilly, 2005; Spark, 2005; Golding & McNamarah (2005); Wilson & Shrock, 2001; Byrne & Lyons, 2001; Goold & Rimmer, 2000). Using 82 undergraduate Information Technology students, Barlow-Jones, Westhuizen & Coetzee, (2015) conducted a study to determine whether South African students' performance in Mathematics at Grade

12 National Senior Certificate (NSC) Examinations correlates with their performance in 2 undergraduate programming courses (dubbed: “Development Software 1A” and “Development Software 1B” p. 4). They found weak correlations between the students’ Grade 12 NSC Mathematics performance and each of the 2 programming courses. Similarly, Westhuizen & Barlow-Jones (2015) conducted a study using a sample of 398 undergraduate students in a South African University and found that statistically insignificant positive correlations exist between the students’ Mathematics attainment at secondary school leaving examination (NSC) and their performances in two mandatory undergraduate CSE courses (specifically) used in their study. Also, they found that the students’ mean scores in the 2 undergraduate CSE courses were higher than their mean score in Mathematics at NSC.

In contrast, Maharaj & Gokal (2006) found no association between students’ achievement in Mathematics at the secondary school leaving examination and that of CSE courses. Similarly, in their study of 9418 students from 118 US Universities, Chen et al. (2020) found that the students’ attainment in Calculus at the high school leaving examination had no significant effect on their success in undergraduate Computer Science courses. Thus, from the literature, the results for the relationship between students’ attainment in Mathematics at secondary school leaving examination and that of their undergraduate CSE courses is mixed. In the same vein, several other studies assert that the influence(s) of students’ performance in other pre-tertiary level courses on their attainment in undergraduate CSE programmes is inconclusive (Keane & Gray, 2019; Bergin & Reilly, 2005).

METHODOLOGY

This descriptive survey utilized a mixed research design (i.e., combining quantitative and qualitative approaches) so as to make data analysis very comprehensive (Creswell, 2009). Semi-structured questionnaire and focus-group discussion were the instruments used in this study. Quantitative data was collected on students’ biographical data and the following 3 datasets of students’ performance: (i). their performance in Core mathematics and Elective mathematics at WASSCE, (ii). their performance in undergraduate mathematics courses, and (iii). their performance in undergraduate CSE courses. These performance datasets were coded using a 9-point likert-scale. Prior to data analysis, a 56-minutes focus-group discussion was held with 9 heads of departments from the 3 universities selected for this study. Data from the questionnaires was triangulated with the data from the focus-group discussion “i. to enhance the credibility and validity of the findings of this study; and ii. explain the results in more detail.” (Avevor, 2024).

Two university professors, who are well-versed in designing questionnaires, validated a 16-item instrument that the researcher developed to gather students’ biographical data (comprising age, gender, institution, program, and level) and the 3 datasets of their performance (outlined above).

This study’s target population was all Level 300 and Level 400 students in public universities in Ghana that are (i). offering CSE programmes; (ii). offering the selected 4 mathematical courses that usually serve as prerequisites for CSE courses, and (iii). offering the 5 core CSE courses selected for this study. The researcher stratified the research population into regions; thereafter, convenience sampling technique was used to select 3 universities with an accessible population (i.e., target population’s eligible and available students who are willing to voluntarily participate in the study) of 2341 students. This accessible population comprised 1463, 681 and 197 students from University #1, University #2, and University #3, respectively. After further stratification into levels 300 and 400, and gender, the researcher used purposive random sampling to pick 872 students for this study; and the questionnaires were then administered to them.

The instrument for this study attained Cronbach alpha (i.e., internal consistency) value of 0.79, average variance extracted (i.e., convergent and discriminant validity) value of 0.61, and composite reliability (i.e., convergent validity) value of 0.86. These values are greater than their individual thresholds of 0.70 set by Hair et al. (2010), 0.50 set by Fornell & Larcker (1981), and 0.80 set by Ramayah, et al. (2016), respectively. Thus, the instrument passed the tests of internal consistency and validity.

Descriptive statistics as well as correlation coefficients and ANOVA were used to analyze the data on IBM SPSS 28.0.1.1 software.

RESULTS

Table 2 showed that 53.2% of the respondents for this study were males while and the remainder (46.8%) were females. It also showed that 53.3% of the respondents were from University #1, while 37.6% and 9.1% of them were from University #2 and University #3, respectively.

Table 2. Gender Distribution of Respondents by University

Gender	University #1 N (%)	University #2 N (%)	University #3 N (%)	Total (%)
Male	249 (28.5%)	171 (19.6%)	44 (5.1%)	464 (53.2%)
Female	216 (24.8%)	157 (18.0%)	35 (4.0%)	408 (46.8%)
Total	465 (53.3%)	328 (37.6%)	79 (9.1%)	872 (100%)

Table 3 showed that the Level 300 students and Level 400 students from University #1 were 33.2% and 20.1%, respectively; while the Level 300 students and Level 400 students from University #2 were 19.3% and 18.3%, respectively. Also, the Level 300 students and Level 400 students from University #3 were 5.1% and 3.9%, respectively. Table 3 also showed that the level 300 students from University #1 comprised 18.1% males and 15.1% females while Level 400 students comprised 10.4% males and 9.6% females. Also, the level 300 students from University #2 comprised 10.0% males and 9.2% females while Level 400 students comprised 9.6% males and 8.7% females. Furthermore, the level 300 students from University #3 comprised 3.3% males and 1.8% females while Level 400 students comprised 1.7% males and 2.2% females.

Table 3 Gender Distribution of Respondents by Undergraduate Level

Gender	University #1		University #2		University #3		Total
	L300	L400	L300	L400	L300	L400	(%)
Male	158 (18.1%)	91 (10.4%)	87 (10.0%)	84 (9.6%)	29 (3.3%)	15 (1.7%)	464 (53.2%)
Female	132 (15.1%)	84 (9.6%)	81 (9.2%)	76 (8.7%)	16 (1.8%)	19 (2.2%)	408 (46.8%)
Total	290 (33.2%)	175 (20.1%)	168 (19.3%)	160 (18.3%)	45 (5.1%)	34 (3.9%)	872 (100%)

L300 = Level 300,   L400 = Level 400

RQ1. How relevant is making students' performances in Core Mathematics and Elective Mathematics at WASSCE a prerequisite for their admission to pursue undergraduate CSE education in Ghana?

Many universities require students to take several Mathematics courses in the first 3 or 4 semesters of their CSE programmes. Some authors attribute this phenomenon to the seemingly loose intrinsic coupling of Mathematics to various CSE courses (Pospiech, et al. 2015; Baldwin, Walker & Henderson, 2013; Beaubouef & Mason, 2005; Beaubouef, 2002; Glass, 2000). Invariably, CSE students and professionals utilize mathematical concepts and skills to develop and analyze CSE theories and applications, as well as for solving problems in CSE courses and careers. The Core Mathematics and Elective Mathematics that students studied at Senior High School and wrote the WASSCE in, underpin and/or provide the background of their mathematical and critical thinking skills needed for understanding and coping with undergraduate CSE courses. Thus, it is imperative for students who are seeking admission to pursue undergraduate CSE education to pass Core Mathematics and Elective Mathematics at WASSCE (or analogous senior high school leaving examinations). This requirement not only augurs well with the several undergraduate mathematics courses that they take in CSE programmes, but also helps them to understand and cope with undergraduate CSE courses. Therefore, a good mathematics background is required for success in undergraduate CSE education. An overview of the relevance of mathematics for CSE education is provided for the 5 core undergraduate CSE courses that were used for this study.

Data Structures and Algorithms

Students require a strong background in discrete mathematics (specifically proof techniques, set theory and graph theory) to understand topics like algorithm analysis, searching and sorting, and data structures (such as hash tables, symbol tables, graphs, maps, and trees) in Data Structure and Algorithms. Thus, this course invariably requires "strong Mathematical skills such as abstraction ability and algorithmic thinking but do not require strong rigorous mathematical reasoning skill" (Sritharan, 2018 p. 3). Apart from discrete mathematics, Data Structures and Algorithms course also requires knowledge and skills from abstract algebra, and geometry.

Computer Security

Undergraduate students require knowledge of probability, calculus, statistics, linear algebra, abstract algebra, and discrete mathematics to understand cryptography, digital signature generation and verification algorithms, and data encryption and compression algorithms in undergraduate Computer Security course.

Computer Programming II

Students require a good knowledge of abstract algebra, linear algebra, calculus, geometry, and discrete mathematics to understand and appreciate topics in Computer Programming II such as coding theory, programming principles and tools for VB-Net, Java, Python and C++, graph algorithms, software error correcting strategies, and proofs of program correctness. Their mathematics background will also enable them to understand "algorithm analysis, software quality metrics, code optimization, dynamic storage allocation principles, parallelism and parallelization techniques, and computational complexity of algorithms" (Avevor, 2022a p. 32).

Computer Networks and Data Communication

CSE students require knowledge of statistics, probability, abstract algebra, discrete mathematics, linear algebra, and geometry to understand topics such as network topology construction, and network protocols, routing and security in undergraduate Computer Networks and Data Communication course; to enable them to "solve various problems such as routing issues, security issues, network load issues, recovery issues and efficiency-related issues" (Avevor, 2022a p. 33).

Artificial Intelligence and Machine Learning

Students require knowledge of abstract algebra, linear algebra, discrete mathematics, geometry, statistics, calculus, and probability to understand topics like vision and image analysis, data compression, data mining, patterns generation, simulation, speech recognition, and abstract problem analysis in undergraduate Artificial Intelligence and Machine Learning course (The University of Sheffield, n.d.). Specifically, for the students "to create axioms and rules for machine learning operations, they require mathematical logic and proofs from discrete mathematics and abstract algebra, respectively" (Avevor, 2022a p.33).

From the foregoing, the importance of mathematics in CSE education cannot be overstated. It is, therefore, apt, imperative, and appropriate that Core Mathematics and Elective Mathematics are made as pre-requisites for gaining admission to undergraduate CSE programmes in universities in Ghana.

RQ2. Do any relationships exist among students' achievements in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses?

Table 4 revealed that the students performed modestly in Mathematics at WASSCE, in undergraduate Math courses, and in the undergraduate CSE courses. On average, they performed best in mathematics at WASSCE (with consolidated mean=7.20, SD=2.28), followed by their performance in undergraduate Mathematics courses (with consolidated mean= 5.89, SD=3.27) and trailed by their performance in undergraduate CSE courses (with consolidated mean=5.81, SD=3.17).

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

Table 4. Descriptive statistics of grades for WASSCE Courses

Course	Mean	SD
WASSCE Math Scores		
Core Mathematics	7.40	2.25
Elective Mathematics	7.00	2.30
Consolidated WASSCE Math score	7.20	2.28
Undergraduate Mathematics Scores		
Calculus I	6.13	3.00
Discrete Mathematics	5.65	3.37
Calculus II	5.98	3.26
Linear Algebra	5.80	3.44
Consolidated Undergraduate Math score	5.89	3.27
Undergraduate CSE Scores		
Data Structures & Algorithms	5.47	3.09
Computer Security	5.72	3.17
Computer Programming II	5.81	2.89
AI and Machine Learning	5.64	3.37
Networking & Data Communications	6.41	3.32
Consolidated undergraduate CSE score	5.81	3.17

N = 872, Scale: 1 – 9 (*WASSCE*: F9=1, A1=9; *Undergraduate*: F=1, A=9)

Tables 5 and Figure 3 revealed a moderate positive correlation (r=.649, and effect size (r^2)=.4212) between the students' performance in undergraduate Mathematics courses and that of undergraduate CSE courses. Thus, 42.12% of the variation in students' performance in CSE courses can be explained by their prior performance in undergraduate Mathematics courses. Similarly, a moderate positive correlation (r=.598, and effect size (r^2) = .3576) is found between the students' performance in Mathematics at WASSCE and that of undergraduate Mathematics courses. Thus, 35.76% of the variation in students' performance in undergraduate Mathematics courses can be explained by their prior performance in Mathematics at WASSCE. Also, there is a moderate positive correlation (r=.514, and effect size (r^2) = .2642) between the students' performance in Mathematics at WASSCE and that of undergraduate CSE courses. Thus, 26.42% of the variation in students' performance in undergraduate CSE courses can be explained by their prior performance in Mathematics at WASSCE.

Table 5. Pearson's Correlation Coefficients and P-values

Course	1 WMS	2 UMS	3 UCS
1. WASSCE Math score (WMS)	1	.598* p<.00001	.514* p<.00001
2. Undergraduate Math score (UMS)		1	.649* p<.00001
3. Undergraduate CSE score (UCS)			1

α=.05 sig. level

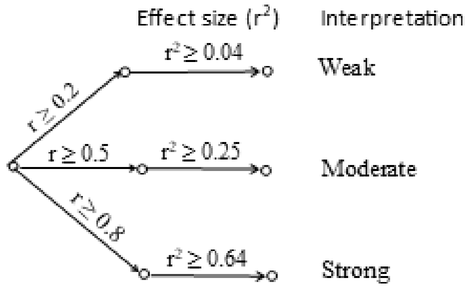

Figure 3. Effect Size (Correlation Strength) Interpretation.

Adopted from Ferguson (2009)

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

Table 6 showed that the differences among the students' 3 performance variables (viz. their performances in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses) are statistically significant since the p value (.00000) is less than the test's significant level of α=.05.

Table 6. One way ANOVA for differences in WASSCE Math, Undergraduate Math courses and Undergraduate CSE courses

Course Type	df	SS	MS	F	p value
Between Groups	2	1062.2704	531.1352	189.0393	.00000
Within Groups	2613	7341.6296	2.8097		
Total	2615	8403.9			

N = 872 α = .05 sig. level

Table 7 revealed that the statistically significant differences among the 3 performance variables cannot be attributed to any pair of them because from the Studentized (Tukey) q tables q(3, 2613)=3.32, which is greater than all the values of HSD (q_{calc}).

Table 7. One way Tukey-Kramer ANOVA for performance across Course/Exam Types

Exam Type (I)	Exam Type (J)	Absolute Mean Diff. |I-J|	HSD (q_{calc})	Decision
WASSCE Math	Undergrad Math	1.31	1.562459	Insignificant
	Undergrad CSE	1.39	1,657876	Insignificant
Undergrad Math	Undergrad CSE	0.08	0.095417	Insignificant

α = 0.05, q(3, 2613) = 3.32 from Studentized (Tukey) q tables

RQ2. Do male and female students have significant differences in their performances in Mathematics at WASSCE, undergraduate Mathematics courses, and CSE courses?

Table 8 showed that on average, female students outperformed the male students in all the 3 performance datasets; i.e., in Math at WASSCE, in undergraduate math courses and in undergraduate CSE courses. Specifically, in Mathematics at WASSCE, the females obtained a consolidated mean score of 7.34 while the males got 7.08. In the undergraduate Mathematics courses, while the females obtained a consolidated mean score of 6.23, the males got 5.59. Similarly, while the females scored a consolidated mean of 6.03 in the CSE courses, the males obtained 5.61. Table 8 also revealed that, on average, the male students' performances had both the highest and the least variability. Specifically, the male students obtained the highest consolidated standard deviation of 3.22 in undergraduate Mathematics courses; and they also got the lowest consolidated standard deviation of 2.23 in Mathematics at WASSCE.

Table 8. Gender Distribution of WASSCE Math, Undergraduate Mathematics, and CSE Scores

	Male		Female	
Course	Mean	SD	Mean	SD
WASSCE Math Scores				
Core Mathematics	7.34	2.27	7.46	2.17
Elective Mathematics	6.81	2.19	7.22	2.42
Consolidated WASSCE Math score	7.08	2.23	7.34	2.30
Undergraduate Mathematics Scores				
Calculus I	5.87	3.05	6.42	2.87
Discrete Mathematics	5.28	2.98	6.08	3.11

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue VI June 2025

Calculus II	5.88	3.29	6.08	3.21
Linear Algebra	5.32	3.56	6.35	3.28
Consolidated undergraduate Math score	5.59	3.22	6.23	3.12
Undergraduate CSE Scores				
Data Structures & Algorithms	5.41	3.06	5.53	3.33
Computer Security	5.47	3.32	6.01	3.04
Computer Programming II	5.32	2.81	6.32	2.97
AI & Machine Learning	5.52	3.37	5.78	3.33
Networking & Data Communications	6.33	3.22	6.50	3.38
Consolidated CSE score	5.61	3.16	6.03	3.21

Scale: 1 – 9 (*WASSCE*: F9=1, A1=9; *Undergraduate*: F=1, A=9)

(Male = 464, Female = 408, Total = 872)

Table 9 revealed a statistically significant difference in the mean performances of male and female students at WASSCE Mathematics since the p value (.00000) is below the test's significance criterion/level of α=.05.

Table 9. One way ANOVA for WASSCE Math Performance across Genders

Gender	df	SS	MS	F	p value
Between Groups	1	90.2408	90.2408	86.26302	.00000
Within Groups	870	910.118	1.046112		
Total	871	1000.36			

N = 872 α = .05 sig. level

Table 10 showed a statistically significant difference in the mean performances of male and female students in their undergraduate Mathematics courses since the p value (.000002) is below the test’s significant criterion/level of α=.05.

Table 10. One way ANOVA for Undergraduate Math Performance across Genders

Gender	df	SS	MS	F	p value
Between Groups	1	128.89	128.89	22.4725	.000002
Within Groups	870	4989.84	5.73545		
Total	871	1807214.897			

N = 872 α = .05 sig. level

Table 11 showed a statistically significant difference in the mean performances of male and female students in their undergraduate CSE courses since the p value (.00000) is below the test’s significant criterion/level of α=.05.

Table 11. One way ANOVA for Undergraduate CSE Performance across Genders

Gender	df	SS	MS	F	p value
Between Groups	1	98.4312	98.4312	77.3563	.00000
Within Groups	870	1107.02	1.27244		
Total	871	1205.45			

N = 872 α = .05 sig. level

DISCUSSION

RQ1. How relevant is making students' performances in Core Mathematics and Elective Mathematics at WASSCE a prerequisite for their admission to pursue undergraduate CSE education in Ghana?

Various CSE programmes that universities in Ghana offer at the bachelor's degree level require strong mathematics backgrounds and skills since there is a loose coupling of mathematics to CSE courses (Pospiech, et al. 2015; Baldwin, Walker & Henderson, 2013; Beaubouef & Mason, 2005; Beaubouef, 2002; Glass, 2000). Also, mathematics "encourages logical reasoning, critical thinking, abstract thinking, problem-solving as well as creativity" (Twum, Yarkwah & Arthur, 2020 p. 1328) and these skills are required for success in CSE (and/or STEM) courses and careers. Specifically, students utilize mathematical skills and concepts in CSE education for 2 basic reasons: (i). to foster their grasp and understanding of the principles and practices of the various CSE courses and careers; and (ii). to solve real-life socio-economic problems using a blend of their knowledge from mathematics and CSE courses (Avevor 2022a). Thus, many universities require students pass Mathematics (both Core Mathematics and Elective Mathematics) at WASSCE to gain admission to CSE programmes; they also require the students to take several mathematics courses during the first 3 or 4 semesters of their undergraduate CSE programmes.

Undergraduate CSE programmes in Ghana have the following core courses that students take: Data structures and algorithms, Computer security, Computer programming II, Computer networks and data communications, and Artificial intelligence and machine learning. Table 12 showed the key undergraduate mathematics courses that students are required to pass as pre-requisites for taking each of these core CSE courses.

Table 12. Key undergraduate mathematics courses required for core CSE courses.

Core CSE Course	Key Mathematics Courses Required
Data structures and algorithms	Discrete mathematics, abstract algebra, and geometry.
Computer security	Discrete mathematics, abstract algebra, probability, calculus, statistics, and linear algebra.
Computer Programming II	Discrete mathematics, geometry, linear algebra. calculus, and abstract algebra.
Computer networks and data communications	Discrete mathematics, geometry, abstract algebra, statistics, linear algebra, and probability.
Artificial intelligence and machine learning	Discrete mathematics, abstract algebra, geometry, linear algebra, statistics, calculus, and probability.

Universities in Ghana do not offer any bridging Mathematics course(s) to help students who have weak mathematics backgrounds from senior high school. It is, therefore, both imperative and relevant for universities to make students' performance in Core Mathematics and Elective Mathematics at WASSCE as a requirement for admission to undergraduate CSE programmes in Ghana. Their prior mathematical backgrounds from Core Mathematics and Elective Mathematics prepare them to cope with the several undergraduate mathematics courses that they take "prior to their registration for various undergraduate CSE courses" (Avevor, 2022a p. 33). This finding, however, contradicts the study of Westhuizen & Barlow-Jones (2015) which correlated students high school Mathematics performance with that of 2 undergraduate computer programming courses; and found insignificant marginal correlation between them. They, therefore, asserted that "the mark achieved for school mathematics cannot be considered as a valid admission criterion for programming courses in the South African context" (p. 37).

RQ2. Do any relationships exist among students' achievements in Mathematics at WASSCE, undergraduate Mathematics courses, and undergraduate CSE courses?

This study found a statistically moderate positive correlation between the mean performance of the students in Mathematics at WASSCE and that of undergraduate Mathematics courses. Specifically, it showed that 35.76% of the variation in the students' mean performance in undergraduate Mathematics courses can be explained by their prior mean performance in Mathematics at WASSCE. This finding supports those of Kpe-Nobana &

Wonu (2019), Husnira et al. (2018), Islam Al-Ghassani & Al-hadhrami (2018), Rylands & Coady (2009), and Fioroni (2006); who all concluded that students' attainment in Mathematics at high school certificate examinations (such as WASSCE, UTME/JAMB, NSC, et cetera) is a good predictor of their success, or otherwise, in undergraduate mathematics courses. This finding, however, contradicts that of Shukri et al. (2022) who used data on 179 undergraduate Medical and Engineering students and found a weak correlation (r=.363, producing effect size r^2 [i.e. coefficient of determination] of .1318) between their mean performance in Mathematics at Malaysian secondary school leaving certificate examination (SPM) and that of their undergraduate Mathematics 1.

This study also found that the students' mean performance in Mathematics at WASSCE is better than that of their undergraduate Mathematics courses. This finding supports those of Islam, Al-Ghassani & Al-hadhrami (2018) and Fioroni (2006). For instance, Islam, Al-Ghassani & Al-hadhrami (2018) evaluated the attainment of 551 undergraduate students in a mathematics course in relation to their prior performance in mathematics at high school final examinations; and concluded that the students performed generally better in mathematics at high school than in the undergraduate mathematics course.

In addition, this study found a statistically moderate positive correlation between the mean performance of the students in Mathematics at WASSCE and that of undergraduate CSE courses. Specifically, 26.42% of the variation in their mean performance in undergraduate CSE courses can be explained by their prior mean performance in Mathematics at WASSCE. This finding supports by those of Spark (2005), Gomes & Mendes (2008), Golding & McNamarah (2005) and Bergin & Reilly 2005). This finding, however, contradicts that of Westhuizen & Barlow-Jones (2015) who found a statistically insignificant positive correlation between the students' Mathematics attainment at secondary school leaving examination and their performances in two mandatory undergraduate CSE courses (specifically) used in their study. It also contradicts the research of Maharaj & Gokal (2006) and Chen et al. (2020) who found no association between students' achievement in Mathematics at the secondary school leaving examination and that of CSE courses.

Also, this study found that the students' mean performance in mathematics at WASSCE is better than that of their undergraduate CSE courses. This finding contradicts that of Westhuizen & Barlow-Jones (2015) who found that the students' mean performance at National School Certificate (NSC) examination were less than their mean performances in the 2 undergraduate CSE courses that they used in their study.

Furthermore, this study found a statistically moderate positive correlation between the mean performance of the students in undergraduate Mathematics courses and that of undergraduate CSE courses. Specifically, 42.12% of the variation in their mean performance in CSE courses can be explained by their prior mean performance in undergraduate Mathematics courses. This finding corroborates those of Andrade-Arenas, Vasquez-Paragulla & Sotomayor-Beltran (2019), Razak & Ismail (2018), Balmes (2017), Nanayakkara & Peiris (2016), Duran (2015), Sofi, Khalid & Jalil (2010), White & Sivitanides (2003), and Bergin & Riley (2006). However, the finding of this study contradicts that of Cornillez, Treceñe & Santos (2020). In their survey to determine the association between students' performances in 2 undergraduate mathematics courses and Computer Programming 1 course, Cornillez, Treceñe & Santos (2020) found that the relationship between a math course (i.e., "Mathematics in the modern world") and the programming course is statistically insignificant.

In addition, this study found that the students' mean performance in undergraduate Mathematics courses is better than that of their undergraduate CSE courses. This finding contradicts that of Patalay, Danguilan & Daligcon (2017) who concluded that "if a student is good in Mathematics, the student will also perform better in programming" (p. 43).

RQ3. Do male and female students have significant differences in their performances in Mathematics at WASSCE, undergraduate Mathematics courses, and CSE courses?

This study found that on average, female students outperformed the male students in all the 3 performance variables/datasets: Math at WASSCE, in undergraduate math courses and in undergraduate CSE courses. It also revealed the existence of a statistically significant difference in the performances of male and female students in all the 3 performance variables/datasets for this study. This finding supports those of Avevor (2022b), Cornillez, Treceñe & Santos (2020) and Islam, Al-Ghassani & Al-hadhrami (2018). Avevor (2022b), for instance, analyzed data on 140 undergraduate Information Technology students and found a "statistically significant difference in the academic performances of male and female students" (p. 675); and concluded that the female students generally outperformed their male counterparts in Data Structures and Algorithms course. Similarly, Islam, Al-Ghassani & Al-hadhrami (2018) concluded that the ratio of the likelihood of success of the female and male students in undergraduate mathematics course is 4:1 in favour of the female students.

CONCLUSION AND RECOMMENDATIONS

This study provided an insight to the discourse on the impact of students' prior performance in mathematics on their performance in undergraduate CSE programmes. Specifically, it established that students should have strong mathematics backgrounds and skills from their high school mathematics courses and pre-requisite undergraduate mathematics courses to succeed in their undergraduate CSE courses. Thus, it is prudent, apt, and relevant for universities to make students' performance in Core Mathematics and Elective Mathematics at WASSCE as a prerequisite for their admission to undergraduate CSE programmes. This study also revealed that there are statistically moderate correlations between the following 3 pairs of performance variables:

(i). students' performance in Mathematics at WASSCE and that of undergraduate Mathematics courses.
(ii). students' performance in Mathematics at WASSCE and that of undergraduate CSE courses.
(iii). students' performance in undergraduate Mathematics courses and that of undergraduate CSE courses.

Furthermore, this study showed the existence of a statistically significant difference in the performances of male and female students in all the 3 performance variables/datasets used in the study.

The remainder of this section provides policy and strategy recommendations for university management towards boosting students' performance in CSE programmes as well as recommendations for future research.

Recommendations to University Management

1. For undergraduate CSE or STEM programmes that do not require rigorous mathematics background (such as Information Technology, Software Engineering, and Information Systems), universities should make only Core Mathematics (thus, removing Elective Mathematics) as the mathematics prerequisite for gaining admission into those programmes; to ostensibly avoid alienating students who have potentials to succeed in such programmes and related careers but could not obtain at least a credit (i.e., grade C6) in Elective Mathematics at WASSCE.
2. For undergraduate CSE or STEM programmes requiring very strong mathematics backgrounds (such as Engineering, the Physical Sciences, and Computer Science), universities may consider offering an optional 3-credit bridging course in Mathematics to help students who perceive themselves as not having adequate mathematics efficacy.
3. Universities should design prudent student-centered CSE courses with lots of tutorials, multi-disciplinary projects, and assignments to enable students to utilize their knowledge, creativity, and critical-thinking skills cogently to solve pertinent real-life societal and economic problems.

Recommendations for Future Research

1. Researchers may consider determining whether significant differences exist among universities between the following pairs of variables:

i. students' attainment in Mathematics (i.e., Core Mathematics and Elective Mathematics) at WASSCE and their performance in undergraduate Mathematics courses.
ii. students' attainment in undergraduate Mathematics courses and their performance in undergraduate CSE courses.
iii. students' attainment in Mathematics (i.e., Core Mathematics and Elective Mathematics) at WASSCE and their performance in undergraduate CSE courses.

2. Future research may also consider assessing the impact of government sponsored schemes (such as Schools performance league table, National annual teachers' awards scheme, STEMNNOVATION, and analogous ones) on students' performance at pre-tertiary school leaving examinations (such as WASSCE, NSC, and SPM).

ACKNOWLEDGEMENT

I acknowledge Dr. Gideon Thompson for editing the manuscript. My sincere gratitude also goes to the students from the 3 public universities in Ghana who voluntarily and enthusiastically participated in this study as well as their heads of departments who eagerly coordinated the data collection process.

REFERENCES

1. Ali, P., & Farag, W. (2014). "An Instrument to Measure Math Attitudes of Computer Science Students". International Journal of Information and Education Technology, 4(5) 459-462.
2. Andrade-Arenas, L., Vasquez-Paragulla, J., & Sotomayor-Beltran, C. (2019). "On the Impact of Mathematics in a First Year Algorithms Course of a Computer Science Program in a University of Lima, Peru," 2019 International Symposium on Engineering Accreditation and Education (ICACIT), Cusco, Peru, 2019, pp. 1-4, Doi: 10.1109/ICACIT46824.2019.9130278.
3. Avevor, F. (2022a). Importance of Mathematics in Computer Science, Engineering and Technology (CSET) Education. International Journal of Research and Scientific Innovation (IJRSI), IX(VIII): 30-34. DOI: 10.51244/IJRSI.2022.9801
4. Avevor, F. (2022b). Effects of using blended instruction on undergraduate Information Technology students' achievement in post COVID-19 era. International Journal of Scientific Development and Research (IJSDR) 7(8): 668-678. DOI: http://doi.one/10.1729/Journal.31582 Retrieved https://www.ijsdr.org/papers/IJSDR2208098.pdf
5. Avevor, F. (2024). Impact of Parental Involvement with Homework on Pupils' Mathematics Performance in Public Basic Schools in Ghana. International Journal of Research and Innovation in Social Science (IJRISS), XVIII(VI): 1705-1721. DOI: https://dx.doi.org/10.47772/IJRISS.2024.806128
6. Baldwin, D., Walker, H. M., & Henderson, P. B. (2013). The Roles of Mathematics in Computer Science. ACM Inroads, 4(4): 74–80. https://doi.org/10.1145/2537753.2537777
7. Balmes, I. L. (2017). Correlation of Mathematical Ability and Programming Ability of the Computer Science Students. Asia Pacific Journal of Education, Arts and Sciences, 4(3), 85-88.
8. Barlow-Jones, G., Westhuizen, D., & Coetzee, C. (2015). Is Mathematics still Relevant as an Admission Criterion for Entry into an Information and Communication Technology Course at a South African University? International Conference on Information Communication Technologies in Education (ICICTE) 2015 Conference, Kos, Greece.
9. Beaubouef, T. (2002). Why Computer Science Students Need Math. SIGCSE Bulletin, 34(4) 57-59.
10. Beaubouef, T. (2005). Why the high attrition rate for computer science students: some thoughts and observations ACM SIGSCE Bull. 37(2): 103–106. DOI: https://doi.org/10.1145/1083431.1083474
11. Bergin, S., & Reilly, R. (2005). Programming: factors that influence success. ACM SIGCSE Bulletin, 37(1) 411 – 415. https://doi.org/10.1145/1047124.1047480
12. Bergin, S., & Reilly, R. (2006). Predicting introductory programming performance: A multi-institutional
    multivariate study. Computer Science Education, 16(4), 303-323.
13. Buick, J. M. (2007). Investigating the correlation between mathematical pre-knowledge and learning gains in service physics European Journal of Physics **28:** 1073–1080 doi:10.1088/0143-0807/28/6/004
14. BYJU's Future School (2022). "What is the Importance of Math in Computer Science?" Retrieved from https://www.byjusfutureschool.com/blog/what-is-the-importance-of-math-in-computer-science/#What_are_the_Benefits_of_Studying_Math_in_Computer_Science
15. Byrne P., & Lyons G. (2001). The Effect of Student Attributes on Success in Programming. ITiCSE 2001 Proceedings of the 6th annual conference on Innovation and technology in computer science education. pp 49-52. ACM: New York.

16. Cheema, J.R., & Galluzzo, G. (2013). Analyzing the gender gap in math achievement: Evidence from a large-scale US sample. Research in Education 90(1), 98–112.
17. Chen C., Kang, J. M., Sonnert, G., & Sadler, P. M. (2020). High School Calculus and Computer Science Course Taking as Predictors of Success in Introductory College Computer Science. ACM Trans. Computing Education 21(1): 1-21. https://doi.org/10.1145/3433169
18. Cornillez, E. E. C., Treceñe, J. K.D., Santos, J. R. N. (2020). Mining educational data in predicting the influence of Mathematics on the programming performance of university students. Indian Journal of Science and Technology, 13(26): 2668-2677. DOI: https://doi.org/10.17485/IJST/v13i26.719
19. Creswell, J. W. (2009). Research design: Qualitative, quantitative, and mixed method approaches (3rd ed.). Sage.
20. Devlin, K. (2003). Why Universities Require Computer Science Students to take Math. Communications of the ACM, 46(9), 37-39
21. Duran, I. L. (2016). The Role of Mathematics Background in the Performance of BSCS students in Computer Programming Subject, International Journal of Multidisciplinary Research and Modern Education (IJMRME), 2(1).
22. Ferguson, C. J. (2009). An effect size primer: A guide to clinicians and researchers. Professional Psychology: Research and Practice 40(5): 532-538
23. Fioroni, M. (2006). A study on the transition of students from High School to University Calculus at McMaster University. McMaster University.
24. Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1): 39-50.
25. Gick, M. L., & Holyoak, K. J. (1987). The cognitive basis of knowledge transfer. In Transfer of Learning, S. M. Cornier and J. D. Hagman (Eds.). New York: Academic, 81–120. DOI: https://doi.org/10.1016/b978-0-12-188950-0.50008-4
26. Glass, R.L. (2000). A New Answer to How Important is Mathematics to the Software Practitioner? IEEE Software. 135-136
27. Golding, P. & McNamarah, S. (2005). Predicting academic performance in the School of Computing & Information Technology (SCIT). In Proceedings of the Frontiers in Education Conference. DOI: https://doi.org/10.1109/fie.2005.1612248
28. Gomes, A., & Mendes, A. (2008). A study on student's characteristics and programming learning. In J. Luca & E. Weippl (Eds.), Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications 2008 (pp. 2895-2904). Chesapeake, VA: AACE. Retrieved from http://www.editlib.org/p/28776
29. Goold, A., & Rimmer, R (2000). Factors affecting performance in first-year computing. ACM SIGCSE Bulletin 32(2): 39-43. DOI:10.1145/355354.355369
30. Gray, G., Mcguinness, C., & Owende, P. (2016). Non-cognitive factors of learning as early indicators of students at-risk of failing in tertiary education. In M.S. Khine & S. Areepattamannil (eds). Non-cognitive Skills and Factors in Educational Attainment. Rotterdam: Sense Publishers, 199-237.
31. Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). "Multivariate data analysis". Pearson College Division.
32. Haskell, R. E. (2001). Transfer of Learning: Cognition, Instruction and Reasoning. A volume in the Educational Psychology Series. New York: Academic Press.
33. Haskell R. E. (2004). Transfer of Learning. Encyclopedia of Applied Psychology.
34. Henderson, P. B. (2005). The role of mathematics in computer science and software engineering education. Advances in Computers, 65: 350-396.
35. Herring, J. E. (2010). Year 12 students' use of information literacy skills: A constructivist grounded analysis. Practicing Information Literacy.
36. Hourigan, M., & O'Donoghue, J. (2007). Mathematical under-preparedness: the influence of the pre-tertiary mathematics experience on students' ability to make a successful transition to tertiary level mathematics courses in Ireland. International Journal of Mathematical Education in Science and Technology, 38(4): 461-476 https://doi.org/10.1080/00207390601129279.

37. Husnira, H., Marina, M., & Rohayu, A. W. (2018). Relationship of secondary school Mathematics Achievement with Engineering Mathematics 2 in Polytechnics. Jurnal Konseling dan Pendidikan, 6(3), 160-169.
38. Islam, M., Al-Ghassani, A., & Al-hadhrami, A. (2018). AN evaluation of the Mathematics Foundation Course in Sultan Qaboos University: Does High School Performance Matter? Sultan Qaboos University Journal for Science, 22(2): 96-107. DOI:10.24200/squjs.vol22iss2pp96-105
39. Keane, M., & Gray, G. (2019). An Investigation into the Pre-enrolment Characteristics of Students to Identify Factors Predictive of Academic Performance within First Year Computing and Engineering Programmes of Study in a Higher Educational Institution. All Ireland Journal of Teaching and Learning in Higher Education (AISHE-J), 11(1).
40. Kpe-Nobana, P., & Wonu, N. (2019). The predictive validity of public examinations in Mathematics on performance in university Algebra, 4(6): 158-164.
41. Kowalski, T. (2010). True North: Navigating for the Transfer of Learning in Legal Education. Seattle University Law Review, 51
42. Lobato, J. (2012). The actor-oriented transfer perspective and its contributions to educational research and practice. Educ. Psychol. 47(3), 232–247. DOI: https://doi.org/10.1080/00461520.2012.693353
43. Maharaj, M.S., & Gokal, H., (2006). An Investigation into the Performance of First Year, First Entry Students in Information Systems and Technology in Relation to their Matriculation Results. 36th Annual Conference of the Southern African Computer Lecturers Association. Retrieved from http://www.sacla.org.za/SACLA2006/Papers/
44. Meltzer, D. E. (2002). The relationship between mathematics preparation and conceptual learning gains in physics: a possible ‘hidden variable’ diagnostic pretest scores American Journal of Physics. 70
45. Pospiech, G., Evlon, B., Bagno, E., Lehanvi, Y., & Geyer, M.A. (2015). The role of mathematics for physics teaching and understanding. Il nuovo cimento C, 38(3), 1-10.
46. Popanao, M., Smith, M. F., & Pairor, P. (2023). Analyzing pre-instruction math knowledge and its correlation with introductory physics exam results. Journal of Physics: Conference Series 2431 012026. doi:10.1088/1742-6596/2431/1/012026.
47. Morgan, M., Flanagan, R., & Kellaghan, T. (2001). A Study of Non-Completion in Undergraduate University Courses. Dublin: Higher Education Authority.
48. Nakakoji, Y., & Wilson, R. (2020). Interdisciplinary learning in mathematics and science: Transfer of learning for 21st century problem solving at university. Journal of Intelligence. 8, 3 (2020), 32. DOI: https://doi.org/10.3390/jintelligence8030032
49. Nanayakkara, K. A. D. S. A., & Peiris, T. S. G. (2016a). Impact of Mathematics in Level 1 on the Academic Performance of Engineering Students: A Case Study. International Journal of Applied Mathematics & Statistical Sciences (IJAMSS), 5(4): 1-8.
50. Nanayakkara, K. A. D. S. A &. Peiris, T. S. G. (2016b). Impact of mathematics on academic performance of engineering students: A canonical correlation analysis. International Research Symposium on Pure and Applied Sciences, 2016; Faculty of Science, University of Kelaniya, Sri Lanka
51. Neri, F (2021). Teaching Mathematics to Computer Scientists: Reflections and a Case Study. SN Computer Science, SpringerLink. Retrieved from https://link.springer.com/article/10.1007/s42979-021-00461-7
52. Patalay, M. M., Danguilan, G. M. & Daligcon, A. G. (2017). The Relationship of Mathematics to the Performance of SHCT IT Students in Programming Courses. International Journal of Computing Algorithm, 6(1): 41-44.
53. Paulson, H. G. (n.d.). “Computer Science Students Need Adequate Mathematical Background,” Retrieved from http://www.math.uoc.gr/~ictm2/Proceedings/pap398.pdf
54. Priulla, A., Vittorietti, M., & Attanasio, M. (2023). Does taking additional Maths classes in high school affect academic outcomes? Socio-Economic Planning Sciences, 89: 1-9. DOI: https://doi.org/10.1016/j.seps.2023.101674
55. Ramayah, T., Cheah. J., Chuah, F., Ting, H., and Memon, M. A. (2016). “Partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3.0: An updated and practical guide to statistical analysis”. Singapore: Pearson.

56. Rashid, M. H. A. (2023). "Teaching & Learning". Retrieved from https://limbd.org/different-types-of-transfer-of-learning/
57. Razak, M.R. B., & Ismail, N. Z. B. (2018). Influence of mathematics in programming subject. In: AIP Conference Proceedings; 1974: 50011. AIP Publishing LLC. Retrieved from: https://doi.org/10.1063/1.5041711.
58. Rylands, L. J., & Coady, C. (2009). Performance of students with weak mathematics in first-year mathematics and science. International Journal of Mathematical Education in Science and Technology, 40(6): 741-753. DOI: https://doi.org/10.1080/00207390902914130
59. Sala, G., & Gobet, F. (2016). Do the benefits of chess instruction transfer to academic and cognitive skills? A meta-analysis. Educational Research Review.
60. Schoer V., Ntuli M., Rankin N., Sebastiao C., & Hunt K. (2010). A Blurred Signal? The usefulness of National Senior Certificate (NSC) Mathematics Marks as Predictors of Academic Performance at University Level. Perspectives in Education 28(2), 9-18.
61. Shukri, F. A., Wamin, A., Arif, A. M., & Rahin, N. F. (2022). A Relationship Between Secondary and Tertiary Mathematics Grades: A Case Study for Foundation Students. Jurnal Personalia Pelajar 25(2): 111-118 Retrieved from http://www.ukm.my/personalia/publication/a11-dis-2022/
62. Sofi, A. Z. M., Khalid, N., & Jalil, A. (2010). Correlation between Mathematics and Programming. Proceedings of Regional Conference on Knowledge Integration in ICT, 647-651
63. Spark L. (2005). Matric Maths as a Predictor of Success in Information Systems A Study of Information Systems Students at the University of the Witwatersrand. In Proceedings of the 35th Conference of SACLA, pp 268-271, Kasane, Botswana, 2005.
64. Sritharan, T. (2018). Impact of mathematics on the theoretical computer science course units in the general degree program in computer science at Sri Lankan state universities. Issues in Informing Science and Information Technology, 15: 1-14. Retrieved from https://doi.org/10.28945/4007
65. Steiner, G. (2001). Transfer of Learning, Cognitive Psychology of. International Encyclopedia of the Social & Behavioral Sciences, pp. 15845-15851. DOI: https://doi.org/10.1016/B0-08-043076-7/01481-9. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/B0080430767014819
66. Tai-sheng, F. and Yi-ching, L, (2002). Is math ability beneficial to performance in college computer science programs. J. Nat. Taipei Teach. Coll. 15(1), 69–98.
67. The University of Sheffield. (n.d.). "Maths in Computer Science. What I wish I knew before starting university, part 2". Retrieved from https://www.sheffield.ac.uk/dcs/blog/maths-computer-science
68. Twum, R., Yarkwah, C., & Arthur, B. E. (2020). Factors that Influence Attitudes of Computer Science Students towards Mathematics and Related Courses at the Tertiary Level of Education. International Journal of Innovative Science and Research Technology, 5(8): 1328-1335.
69. Westhuizen, D., & Barlow-Jones, G. (2015). Is mathematics still relevant as an admission criterion for entry into an Information and Communication Technology Course at a South African University? The Independent Journal of Teaching and Learning, 10: 37-50. Retrieved from https://www.researchgate.net/publication/284493544
70. White, G., & Sivitanides, M. (2003). An empirical investigation of the relationship between success in mathematics and visual programming courses. Journal of Information System Education, 14(4) 409-416.
71. Wilson, B.C., & Shrock, S. (2001). Contributing to success in an introductory computer science course: A study of twelve factors. ACM SIGCSE Bulletin 33(1), 184–188.