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# A study of selected predictors of achievement in the computer science programs in the Nigerian universities

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Morgan State University, 1989



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# A STUDY OF SELECTED PREDICTORS OF ACHIEVEMENT IN THE COMPUTER SCIENCE PROGRAMS IN THE NIGERIAN UNIVERSITIES

A Dissertation Submitted to the Faculty of the
School of Graduate Studies, Morgan State University
in Partial Fulfillment of the Requirements for the Degree of
Doctor of Education

School of Graduate Studies

by

Longinus Obialor Anyanwu
Baltimore, Maryland
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SELECTED PREDICTORS OF ACHIEVEMENT IN THE COMPUTER SCIENCE PROGRAMS IN THE NIGERIAN UNIVERSITIES

Longinus Obialor Anyanwu, Ed.D.
Morgan State University, 1988

In the last decade, Nigeria has begun to integrate computer technology into its national life. As the academic institutions attempt to provide the needed trained personnel, questions relating to computer science program effectiveness and productivity at the universities have arisen.

This study was designed to: (1) identify among the computer science majors in Nigerian universities, the most reliable predictors of achievement in Computer Science, from a selected set of possible predictors; (2) determine the relative predictive power of each independent variable; (3) find the program levels at which the effects of these predictors are maximized; and (4) evaluate the extent to which achievement in the computer science program correlates with achievement in the mathematics component.

A sample of five universities, randomly selected from three strata (based on age of establishment and curriculum orientation) of the Nigerian universities with undergraduate computer science programs, was used. Data gathered from students' academic records and responses to questionnaires were analyzed utilizing the Pearson product-moment correlation, and the multiple regression and the stepwise multiple regression

analyses.

Although the Joint Admission and Matriculation Board(JAMB) total score correlated with achievement in the computer science program during the first two years, this predictor correlated more strongly with achievement in the mathematics component of the computer science program during the same period. The correlation between the JAMB(total) score and achievement in the nonmathematics subsection existed only in the first year. No relationship was found between the JAMB(mathematics) score and achievement in the computer science program at any of the three year-levels.

The results affirmed that achievement in the computer science program can be predicted based on the selected cognitive variables but not on the selected noncognitive variables. This is contrary to the literature which suggested that cognitive predictors are only effective in predicting college performance of the white (but not the black) students in the United States. This suggests that the differences in the findings may be due to cultural or social rather than racial or innate factors. In addition, potentially high achieving computer science majors can be detected at admission.

## ACKNOWLEDGMENTS

The development and completion of this dissertation took the dedicated efforts of many, both in Nigeria and in the United Staes. To all these I owe a great deal of sincere thanks. However, there are a few whose tireless efforts, commitment, and professionalism were beyond the call of duty.

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Secondly, the able and friendly university officials in the sample universities in Nigeria through whose lavish cooperation and kind assistance the voluminous data were extracted from students' confidential files. These include: (at the University of Nigeria, Nsukka): Dr. C. N. Chinema, Deputy Vice-Chancellor for Academics, Dr. A. O. Amadi, Acting Head of the Department of Computer Science, and Dr.

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Thirdly, my beloved wife, Edith Ifeoma Anyanwu, who worked tirelessly both in the typing of the manuscript and in relieving me of most domestic responsibilities so I could give this dissertation the attention it needed.

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# CHAPTER 1

# INTRODUCTION

The unavailability of university education to Nigerians up to the early 1940s was the reason for the nationwide agitation that challenged the British colonial education policy in Nigeria. These agitations resulted in the establishment of the Asquith and Elliot Commissions in 1943 which inquired into the state of higher education in West Africa. Upon the recommendations of the Elliot Commission, two institutions of higher learning were established in the continental region of West Africa.[1] These institutions (University Colleges), which were located at Fourah Bay in Sierra Leone and Ibadan in Nigeria, were mere extension units (overseas campuses with limited facilities) of the Universities of Durham and London, England, respectively. See Map 1 for the location of Sierra Leone and Nigeria on the west coast of Africa. However, the continued existence of a widespread demand for an indigenous university in the British West Africa,[2] among the educated elite in the mid-

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[1]Osuntoku Akinjide, Expansion of University Education in Nigeria (Washington, D.C.: Nigerian Universities Commission, 1982), 5.

[2]Chinelo A. Chizea, 20 Years of University Education in Nigeria (Lagos: Academy Press Limited, 1983), 1-9.


Map 1. Geographic Locations of Nigeria and Sierra Leone

to late 50s, was an indication that these institutions were scarcely meeting the educational needs of this huge regional expanse.[3]

This broad-based demand led to the establishment of the Ashby Commission at the time when the climate leading to independence was being established in Nigeria. This commission was assigned to investigate the prospects and feasibility of such an indigenous university. This project gave birth to, inter alia, five indigenous universities in Nigeria alone (between 1948 and 1962), thus creating the nucleus of what later became the Nigerian university system. See Map 2 for the state boundaries of Nigeria.

Since then, the Nigerian university system has grown from a system of coordination designed to operate within a unitary system of government to one controlled by and responsible to both the state and the federal governments. As may have been expected, during the new and subsequent administrations, the university system battled for centralized control and financing. Complicating the situation was the prevailing problem of a nationally unplanned rapid proliferation of programs (often in duplication of others). Many more universities were also being established, for purely ethnocentric motives, in fulfillment of election campaign promises or even in direct response to tribal

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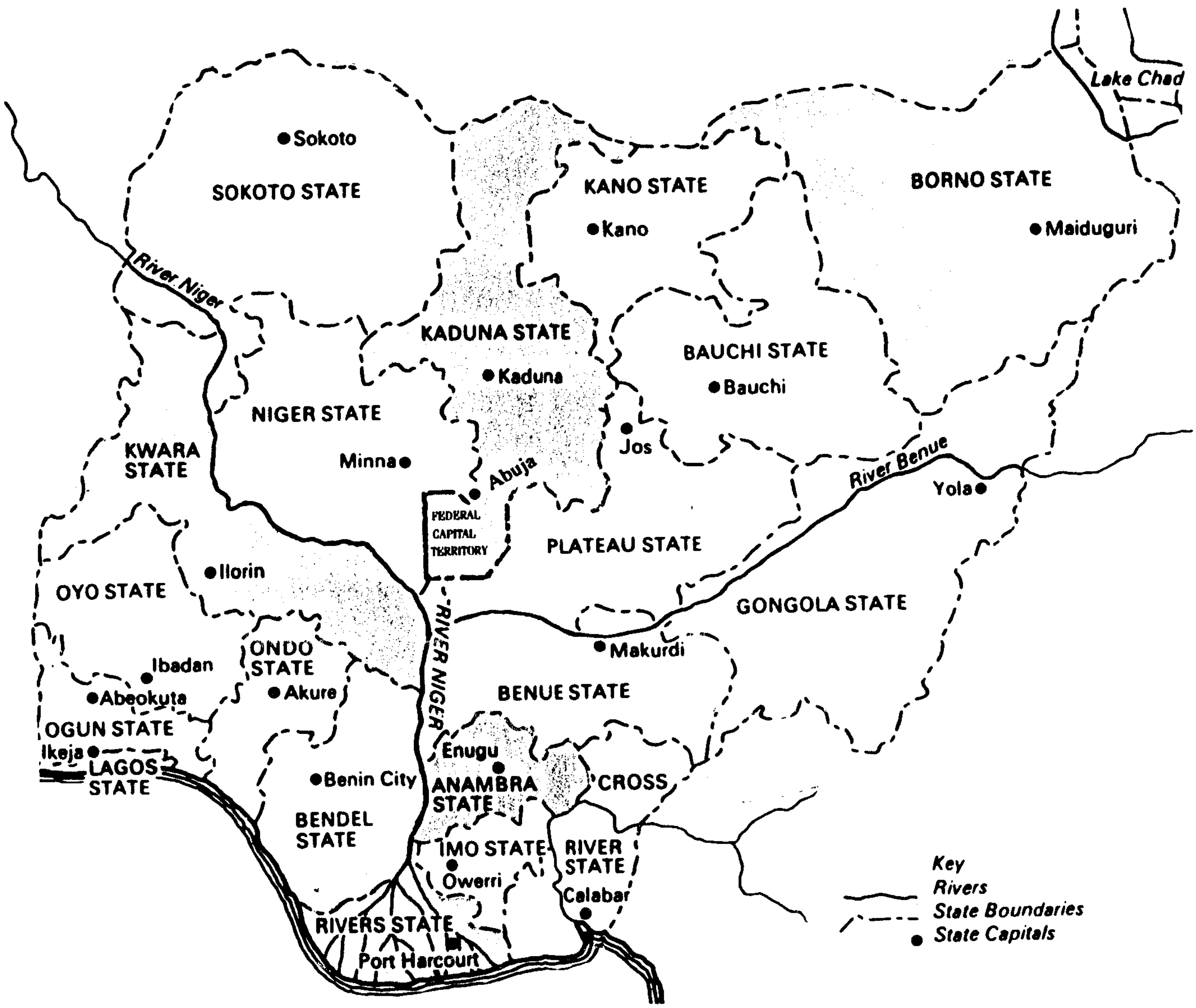
[3]Akinjide, 5.




Map 2. State Boundaries of Nigeria

demands.[4]

The impact of these unarticulated educational ventures was devastating to both the state and national economies (which were already staggering). Worse still, an educational imbalance (where some tribes or states produced a greater number of the educated elite than others) across the country became another major precipitate of this educational disarray.

In an attempt to find answers to this problem of educational imbalance in the country, the federal government initiated the establishment of a number of bodies to make and implement regulatory policies that would affect all the universities. These organizations included the National Universities Commission (NUC) and the Committee of Vice-Chancellors (CVC), neither of which has yet evolved a policymaking body that commands the respect of all the universities and states.[5] In addition, some other special-task bodies and guidelines were formed. These included the Agulu Commission on University Entrance, the Joint Admission and Matriculation Board (JAMB) and the Guidelines on Admission to Federal Universities, all of which aimed at remedying the educational imbalance and the lack of centralized control through regulated university

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[4]Ibid., 13-32.

[5]Jibril Aminu, "The Factor of Centralization in Two Decades of Nigerian University Development," in _20 Years of University Education in Nigeria,_ ed. Chinelo Amaka Chizea (Lagos: Academy Press Limited, 1983), 22-56.

admissions.

As these organizations tried to gather momentum to confront the prevailing problems, it was discovered that no national accreditation body existed other than the federal or state Ministries of Education for a wide range of academic and professional disciplines including computer science.[6] See Map 3 for the various locations of the federal and state universities.

The sole purpose and mission of the JAMB was to implement a centralized and balanced university access for the country, which would bring about a more even educational development as well as increase the likelihood that qualified students would be admitted into appropriate university programs of their choice (provided a sufficient number of vacancies existed in those institutions). This goal the JAMB attempted to achieve with an aptitude test instrument and/or the possession (on the part of the student) of the General Certificate of Education or the Higher School Certificate (HSC). HSC is the certificate awarded at the successful completion of two years of precollege work beyond the high school curriculum.

Furthermore, the nation, rather than grappling with the economic extravagance following the growth of unproductive university programs, has had a preference for a review of the university admissions process with the aim of improving its effectiveness and validity. Besides, the

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[6]Ibid., 32.


Map 3. Locations of Old and New Universities

increased validity of the university admission selection process will reduce student attrition rate.

In the wake of the computer revolution which has engulfed the entire developed world, the Nigerian academic institutions are attempting to meet the national manpower needs for an effective integration of this computer technology into the Nigerian life. These institutions, now more than ever, need articulation, direction and proper harnessing of the national efforts into effective and productive computer science programs to reflect the national needs and interests.

To improve the effectiveness and productivity of these computer science programs, some basic questions must be addressed namely: What kind of individuals are admitted into the programs? Are they the ones who should have been admitted? Thus, the selection mechanism utilized by the admissions office becomes a target for this examination. Naturally, one becomes concerned about the ability of these more traditional preadmission measures to predict accurately the future achievement in the computer science programs. Alongside this concern, is a similar one: Are there some nontraditional preadmission measures that can predict achievement more accurately in the computer science programs or can a better prediction be made using a combination of some traditional and nontraditional measures?

The rest of the chapter focuses on the problem and hypotheses, the assumptions and definition of the terms, and the delimitations and significance of this research.

## The Problem

Computer science and mathematics share many similar thought-processes such as the use of deductive logic and sequential reasoning. In spite of this premise, there is a growing concern (among teachers of computer science) that computer science majors do not perform as well in the mathematics component of the computer science programs as in the computer science courses. This inability to perform well in the mathematical portions of the courses may produce a poor overall performance in the program, or account for the tendency of students to change to other related majors where less emphasis is placed on mathematics. It is important to note that some students may have changed majors simply because of a preference for that major.

This shift of majors in computer science to other areas has occasioned serious questions concerning the development of the computer science programs. Despite these fundamental questions, the Association for Computing Machinery (ACM), the national professional organization for computer scientists, is currently field testing an accreditation process for programs in computer science. A tentative set of criteria for the accreditation of computer science programs in the U.S. has recently been developed. Apparently, the major question being addressed in this field test is: On what set of criteria will the computer science program accreditation be based? Rendering the problem more complex, is the lack of a clear rationale (other than recurrency in most programs) for the computer science (mathematics component) course selection according to the report of the ACM-curriculum committee, a portion of which is cited below:

> Suitable computer oriented mathematics course offerings constitute an important topic which should be explored more thoroughly both on local (i.e., individual institutions) and national levels. Specific course recommendations, however, are outside the domain of this report. Until such time as suitable courses become readily available, it will be necessary to rely on the most commonly offered mathematics courses for the mathematical background needed by computer science majors.[7]

In addition to the concerns of the ACM, the determination of the admission criteria for majors in computer science will, obviously, help cut down on the "float" of students with undecided majors on the campuses, reduce attrition rate and increase enrollment in both the various computer science programs and the institutions in Nigeria.

Obviously, without adequate knowledge of certain predictors, potentially successful students may be rejected, and unsuccessful ones accepted at admission. In the same way, students may be admitted into inappropriate programs. Enrolling students in programs for which they are inadequately prepared may lead to: (1) student frustration

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[7]Richard H. Austing et al., ed. "Curriculum '78: A Report of the ACM Curriculum Committee on Computer Science," Communications of the ACM 22 (March 1979): 161.

and thus attrition, (2) the deterioration of the quality of the academic program, and (3) reduction in the cost effectiveness of the programs.

## Statement of Problem

This study was designed to: (1) identify among the computer science majors in Nigerian universities, the most reliable predictors of success in Computer Science, from a selected set of possible predictor variables; (2) determine the relative predictive power of each independent variable; (3) find the levels of student classification (freshman, sophomore or junior) in the program at which the effects of these predictor variables are maximized; and (4) evaluate the extent to which achievement in the computer science program correlates with achievement in the mathematics components.

## Research Questions

This study was designed to answer the following research questions:

1. (a) Is there a relationship between a student's score on the Joint Admission and Matriculation Board (JAMB) test and the student's achievement in the computer science program?

   (b) Is there a relationship between the score on the JAMB test and achievement in the mathematics courses of the computer science program?

(c) Is there a relationship between the JAMB test score and the achievement in the nonmathematics courses of the computer science program?

2. Can achievement in the computer science program be predicted for entering freshmen based on their achievement in the mathematics component of the JAMB test?

3. Which of the following cognitive variables has greater predictive power in the prediction of achievement in the computer science program and its mathematics and nonmathematics courses? The cognitive predictor variables are:

   (a) high school GPA

   (b) high school GPA in mathematics courses

4. Which of the following noncognitive predictor variables has greater predictive power in the prediction of achievement in the computer science program and its mathematics and nonmathematics courses? The noncognitive predictor variables are:

   (a) amount of instructional support available to the students. This instructional support is measured by the number of the following attributes:

      - teacher-student conferences
      - tutor-student conferences
      - frequency of the laboratory attendant's help
      - computer terminals in working order;

   (b) number of mentally or emotionally destabilizing problems which include:

      - death of family member/close friend
      - accident/injury leading to the loss of any body part
      - loss of job
      - unforeseen financial incapacitation

   (c) number of times subject had previously used the computers;

(d) having computer-related goals, such as aspiration to become a computer scientist, computer software/hardware design engineer, computer programmer/analyst, etc.

5. In what year of study (freshman, sophomore, or junior) in the program are the effects of the cognitive predictor variables strongest?

6. In what year of study (freshman, sophomore, or junior) in the program are the effects of the noncognitive predictors strongest?

7. Which category of variables (cognitive and noncognitive) are better predictors of achievement in the computer science program (see figure 1 for the relationship of the independent variables and achievement in the computer science program), and the mathematics and the nonmathematics components of the computer science program?

8. Is there a relationship between achievement in the computer science program and achievement in the mathematics courses of the program for all three cohorts (freshman, sophomore, and junior years)?

9. Is there a relationship between achievement in the computer science program and achievement in the nonmathematics courses of the program for all three cohorts (freshman, sophomore, and junior years)?

## The Hypotheses

The research questions outlined in this study were translated into the following set of hypotheses:

1. (a) There is a positive relationship between the JAMB test score and achievement in the computer science program (as measured by the GPA in the core courses of the program) for the three cohorts: freshman, sophomore, and junior years.

   (b) There is a positive relationship between the score on the JAMB test and achievement in the mathematics courses of the computer science program (as measured by the GPA in the mathematics courses taken by the student from

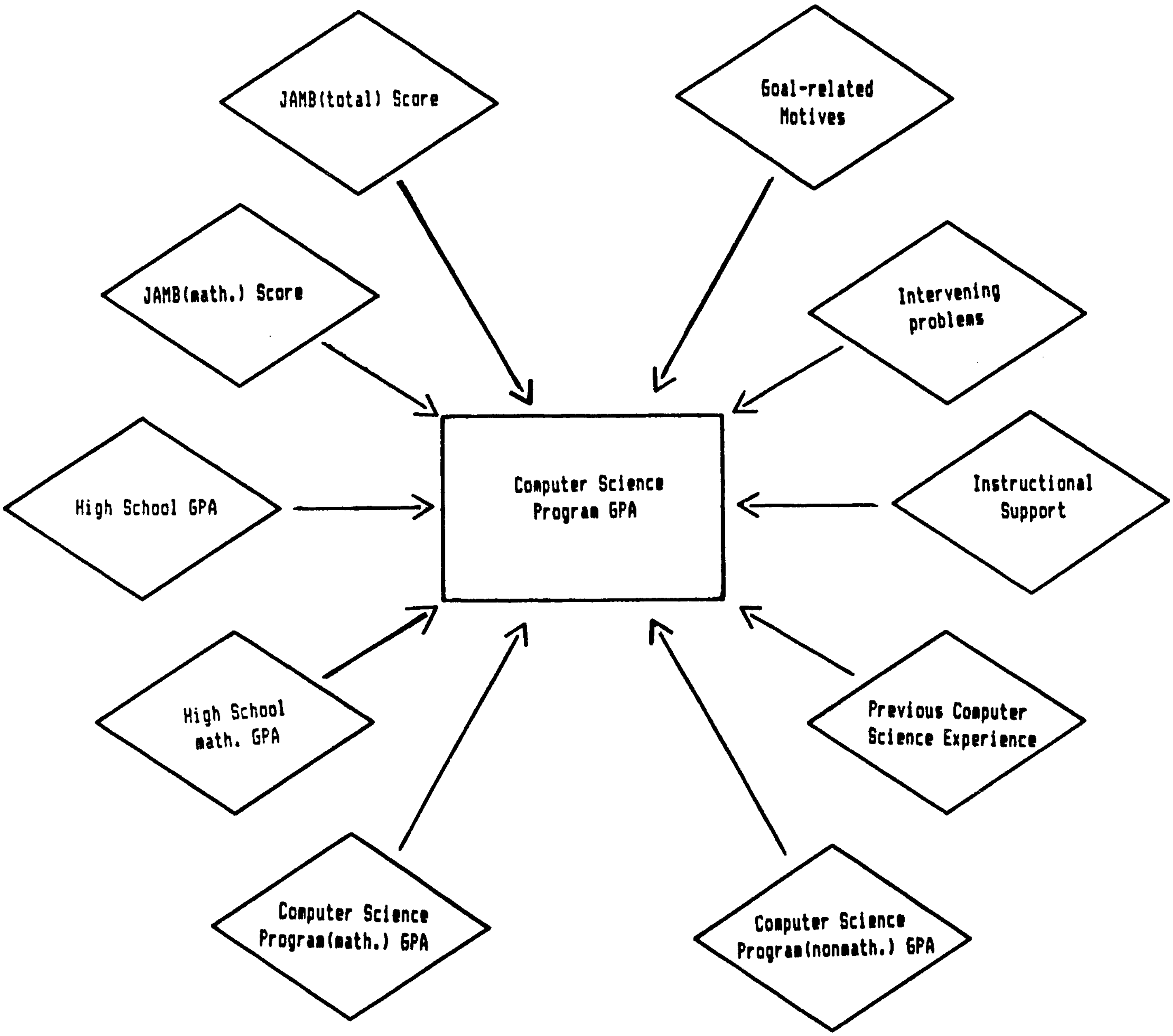


Fig. 1. Relationship of the variables.

the university listed computer science program core courses) for the three cohorts.

(c) There is a positive relationship between the JAMB test score and achievement in the non-mathematics courses of the computer science program (as measured by the GPA in the nonmathematics courses taken by the student from the university listed computer science program core courses) for the three cohorts.

2. There is a positive relationship between the score in the mathematics component of the JAMB test and achievement in the computer science program, for the three cohorts.

3. There is a positive relationship between the achievement in the computer science program and the joint effect of the listed cognitive variables (for the three cohorts):

   (a) high school GPA

   (b) high school GPA in mathematics courses

4. There is a positive relationship between the achievement in the computer science program, the mathematics courses and the nonmathematics courses of the program and the joint effect of the listed noncognitive variables (for the three cohorts):

   (a) amount of instructional support available to the students. This instructional support is measured by the number of the following attributes:

   - teacher-student conferences
   - tutor-student conferences
   - frequency of the laboratory attendant's help
   - computer terminals in working order

   (b) number of mentally or emotionally destabilizing problems which include:

   - death of a family member/close friend
   - accident/injury leading to the loss of any body part
   - loss of job

- unforeseen financial incapacitation

c) number of times the subject had previously used the computers

d) having computer-related goals, like aspiration to become a computer scientist, computer software/hardware design engineer, computer programmer/ analyst, etc.

5. The strength of the relationship between the listed cognitive predictor variables and achievement in the computer science program is greatest in the freshman year.

6. The strength of the relationship between the listed noncognitive variables and achievement in the computer science program is greater in the sophomore and junior years than in the freshman year.

7. The noncognitive variables have greater strength of prediction of the achievement in the computer science program, the mathematics and the nonmathematics courses of the program than the cognitive variables.

8. There is a positive relationship between achievement in the computer science program and achievement in the mathematics component for the three cohorts.

9. There is a positive relationship between achievement in the computer science program and achievement in the nonmathematics component for the three cohorts.

## Assumptions

The hypotheses of this study were supported by a series of basic assumptions. Among them are the following two:

1. Teachers' test scores are accurate, and correctly reflect the academic status of students.

2. The respondents to the questionnaire are mature, and can furnish correct information about themselves.

## Definition of Terms

In this section, operational definitions of critical terms used in the hypotheses of this study are presented in alphabetical order.

1. Achievement in a course was measured by the letter-grade (or its equivalent score) given by the instructor of the course to the student (as representative of his performance) in that course.

2. Achievement in the mathematics courses (or component) of a computer science program was measured by the GPA (or its equivalent score) in the mathematics courses taken from the institution's officially listed computer science program core courses.

3. Achievement in the nonmathematics courses (or component) of the computer science program, was measured by the GPA (or its equivalent) in the nonmathematics courses taken from the institution's officially listed computer science program core courses.

4. Achievement in a computer science program was measured as the cumulative GPA (or its equivalent) in all courses attempted by the student from the university's officially listed computer science program core courses (all components of the computer science program inclusive).

5. Attrition was used in this study to include two groups of students, namely:

   (a) those who were enrolled into the computer science program initially, but later changed their majors, had re-enrolled in other programs, in a given time interval (1983/84 to 1986/87)

   (b) those who were initially enrolled in the program, but later dropped out of college in the same time interval (1983/84 to 1986/87)

Thus, attrition (ATTR) in a computer science program was measured as the sum of the number of students in (a) and (b) above--ATTR = # of (a) + # of (b).

6. Attrition rate of a computer science program was evaluated as the ratio of attrition to the total number of students admitted to that computer science program within the same time interval--ATTR-RATE = ATTR / TOTAL PROG-ADMISSIONS.

7. Cohorts as used in this study meant the three groups of students' cumulative GPAs in a computer science program as outlined below:

   - students' GPAs after one year in the computer science program

   - students' GPAs after two years in the computer science program

   - students' GPAs after three years in the computer science program

8. The cognitive variables selected for this study included the following:

   (a) high school GPA

   (b) high school GPA in the mathematics courses

9. The courses of a computer science program were those courses officially identified (or listed) by the representative university as the required courses (in addition to the general education requirements) for the majors of computer science in that university.

10. JAMB test score was the total score (or achievement) of a student on the Joint Admission and Matriculation Board (JAMB) test.

11. The noncognitive variables selected for this study included the following:

    (a) amount of instructional support available to the students. This instructional support is measured by the sum of the frequencies of the following attributes:

        - teacher-student conferences

        - tutor-student conferences

- lab attendant's help

- computer terminals in working order

(b) number of mentally or emotionally destabilizing problems which included:

- death of family member/close friend

- accident/injury leading to the loss of any body part

- unforeseen financial incapacitation

The frequencies of these attributes to the variable are summed.

(c) number of times subject has previously used the computers

(d) having computer-related goals, such as aspiration to become a computer scientist, computer software/hardware design engineer, computer programmer/analyst, etc.

12. Success rate of a computer science program (SRCSP) was calculated as the sum of the number of graduates (from the program) and the number in the computer science program with at least 2.0 cumulative GPA, divided by the total number of students admitted into the program within same time interval (1983/1984 to 1986/1987)--SRCSP = (GRADS + NON-GRADS-WITH-GPA > = 2.0) / TOTAL PROG-ADMISSIONS.

In addition, the core courses of the computer science program as recommended by the ACM were as follows:

Nonmathematics Courses

1. Computer Programming I
2. Computer Programming II
3. Introduction to Computer Systems
4. Introduction to Computer Organization
5. Introduction to File Processing

6. Operating Systems and Computer Architecture I
7. Data Structures and Algorithm Analysis
8. Organization of Programming Languages

Mathematics (component) Core Courses

Similarly, the core courses that constituted the mathematics component of the computer science program as recommended by the ACM were as follows:

1. Introduction to Calculus
2. Mathematical Analysis I

2a. Probability

3. Linear Algebra
4. Discrete Structures

The courses below might be taken, depending on the elective courses of choice:

5. Mathematical Analysis II
6. Probability and Statistics

## Scope and Delimitations

In this study, the analysis of data and its conclusions were based on student records made available by the federal and state government universities listed below and the students' responses to the questionnaires. The Nigerian universities with undergraduate computer science programs are:

| Name | Location | Status |
|---|---|---|
| Ahmadu Bello University | Zaria | federal |
| Anambara State Univ. of Tech. | Enugu | state |
| Federal Univ. of Tech. | Owerri | federal |
| Ibadan University | Ibadan | federal |
| Ife University | Ile-Ife | federal |
| Lagos University | Lagos | federal |
| University of Maiduguri | Maiduguri | federal |
| University of Nigeria | Nsukka | federal |
| University of Port Harcourt | Port Harcourt | federal |

It may be mentioned that due to the enormity of data gathered, the many complexities of obtaining cooperation from the sample universities, coupled with the rather extensive amount of time involved, five universities were randomly selected from these nine, from which data were gathered. Furthermore, information was gathered from the first-year records of the freshmen, sophomores, and juniors (in the program) to provide longitudinal data for analysis. Obviously, data gathered through the questionnaire did not reflect the opinions of the dropouts from the program (since they simply were unavailable to complete the questionnaire).

Apart from the age of the institutions and their professional or liberal arts orientation, control for many other individualized characteristics of the universities in the sample was not necessary since this study does not aim at comparing the students' performances or success rates of the computer science programs in these institutions. If institutionally individualized analysis of the data is desired, another study may be conducted for this purpose.

Overall, the generalizability of the findings are limited to Nigerian universities with an undergraduate computer science program. It may, however, have some implications for similar programs in other African universities/colleges.

## The Significance of the Study

The results of this study can be useful in many ways both to potential computer science majors and to academic institutions/organizations in Nigeria and, to some degree, in the United States.

Student performance in the program can be improved through proper reinforcements in the appropriate subunit(s) of the mathematics component. Thus, the attrition rate can be reduced and the enrollment in the computer science programs can be increased.

Based on facts on the identified predictor variables, potentially successful (and unsuccessful) computer science majors can be identified at admission. This will undoubtedly cut down on the "float" of students with undecided majors at the institutional level, and also will reduce attrition rates and increase the institutional enrollment figures. Obviously, the positive effects on cost reduction and quality enhancement of the educational experience at the institutions which are guided by an effective predictive model in the admission process cannot be overemphasized.

As the ACM is in the process of field testing an accreditation process for programs in computer science, the results of this study can pave the way and raise pertinent issues and questions that may be addressed in later studies in this country and Africa.

A model computer science program can be designed for the Nigerian universities, especially as computer science programs are being established in most of those institutions. However, if a program already exists (in any university), recommendations for its improvement (or even for a better program) can be made.

# CHAPTER 2

## REVIEW OF THE LITERATURE

The effectiveness of using the more academic or scholastic achievement factors such as high school GPA and aptitude tests such as SAT and ACT, usually referred to as cognitive variables, and the less academically oriented factors (noncognitive variables) in predicting college success has been widely investigated. In the literature the cognitive variables have been referred to as traditional preadmission measures because they have been routinely used to select students for admission to colleges and universities. The noncognitive variables have been referred to as nontraditional preadmission measures because their usefulness as predictors of achievement has been investigated only in more recent studies.

Some investigators have examined these cognitive and noncognitive predictors along racial lines, while others have simply questioned the effectiveness of the use of these cognitive and noncognitive variables as admission criteria in predicting college success. However, the importance of considering both the race of the students and the cognitive or noncognitive dimension of the variables used in such studies for the purposes of comparison cannot be overemphasized. The pertinent literature was classified into four major categories: the traditional (cognitive) preadmission measures and college performance, the nontraditional (noncognitive) preadmission measures and college performance, the Nigeria-based studies, and the conclusions.

## Traditional/Cognitive Preadmission Measures and College Performance

In this section, the studies dealing with traditional preadmission measures and college performance are reviewed. One of those studies was designed to determine appropriate admission policies for oversubscribed majors at the University of California at Irvine (UCI). This study, titled "Predicting Cumulative and Major GPAs of UCI Engineering and Computer Science majors," was conducted by Judith S. Shoemaker.[8] The basic concern in the study was that while UCI had a general policy of accepting all eligible applicants, these applicants could not always be admitted into their first choice of major programs. Thus, the study used a statistical regression approach to identify those prospective engineering and computer science applicants who

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[8]Judith S. Shoemaker, Predicting Cumulative and Major GPAs of the University of California, Irvine Engineering and Computer Science Majors (Irvine, CA: ERIC Document Reproduction Service, ED 270 468, 1986), 7-17.

would be most likely to succeed at UCI. More specifically, that study was designed to determine, to what extent each of the preadmission measures (i.e., high school GPA and admission test scores) was able to predict college cumulative GPA and GPA in that major.

While the two criterion variables were college cumulative GPA and college major GPA, the predictor variables, on the other hand, included high school GPA, Mathematics Achievement Test, SAT-V, SAT-M, and English Composition Achievement Test. Multiple regression analysis and stepwise multiple regression analysis were used. Although considerable intercorrelation among the variables was observed, several conclusions were reached. One of those conclusions was that cumulative GPA and major GPA of the samples of UCI engineering and computer science majors can be "reliably" predicted using a linear combination of two preadmission measures: high school GPA and Mathematics Achievement Test. None of the other three predictor variables (SAT-V, SAT-M, and English Composition Achievement Test) added significantly to the prediction.

For engineering majors the single best predictor of both cumulative GPA and major GPA was the Mathematics Achievement Test, followed by high school GPA. Both criterion scores could be predicted to the same extent (the multiple correlations for both being equal to 0.62). However, the computer science major GPA was slightly more predictable than cumulative GPA. For the cumulative GPA, high school GPA was the single best predictor, followed by the Mathematics Achievement Test. But for the major GPA, the relative importance of the two predictors was reversed, the Mathematics Achievement Test being the single best predictor, followed by the high school GPA. No other variables significantly improved the prediction. This study was an excellent example of the power of traditional preadmission measures to predict college success of engineering and computer science majors.

Other researchers have investigated traditional preadmission measures as predictors of success in education programs. For example, in 1984, Mary Komorowski of West Virginia University investigated the predictors of success in mathematics for elementary teacher education majors. She found that both high school GPA and college GPA have a strong relationship with success in the mathematics component of the teacher education program.

The power of the traditional preadmission variables as predictors was demonstrated in another study which used a different analytical model. Michael Yost, in a paper presented at the Annual Conference of the Southern Association for Institutional Research, conducted two surveys to predict attrition in admissions using a discriminant model.[9] This model yielded predictive

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[9]Michael Yost, Predicting Attrition in Admission Using a Discriminant Model (Little Rock, AR: ERIC Document Reproduction Service, ED 258 493, 1984), 9.

accuracies of 75% and 68%, respectively. This study showed that regardless of the analytical model used, the cognitive variables are effective predictors of college success.

In a comprehensive review of a population validity study on college entrance and various population groups, Hunter Breland found that in the majority of studies, when identical regression equations using traditional admissions criteria (particularly SAT and ACT scores) were applied to black and white students, the tendency was to overpredict the college performance of black students.[10] Nevertheless, the follow-up studies suggested that there were several limitations that caused attenuation in the correlation coefficients. These included: the problem of locating and stabilizing criterion variables, (in some studies the criterion variable was college GPA in the freshman year, in others it was the cumulative GPA beyond the freshman year, etc.); the variation in the different instructors' instructional and grading procedures; the difference in institutional programs and standards; and the time interval between the occurrence of the predictor variable and the criterion measurement (the greater the time interval, the greater the likelihood of the occurrence of extraneous factors which may confound the validity).

Thus far, this review has been concerned with studies

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[10]Hunter M. Breland, Population Validity and College Entrance Measures (Princeton: College Board Publication, 1976), 48.

which demonstrate the effectiveness of the traditional/ cognitive variables as predictors of college success among predominantly white populations. Other recent studies suggest that these cognitive variables derived from the standardized tests and high school GPA are less predictive of future college success for black students.[11] Terrence J. Tracey and William E. Sedlacek of the University of Maryland in College Park, Maryland, conducted research on the "Prediction of College Graduation Using Noncognitive Variables by Race."[12] Stepwise discriminant analysis was utilized. Although this was a follow-up validity study of the Noncognitive Questionnaire in predicting graduation after five and six years, some rather interesting conclusions were reached. The graduation rates for black and white students were found to be different, with black students showing lower graduation rates. A trend was found for black students to take a slightly longer time to be graduated than Whites. The noncognitive variables were found to be significantly related to graduation of the black students, while the traditional measures of academic ability

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[11]A. Farver, H. Sedlacek and G. Brooks, "Longitudinal Prediction of Black and White University Student Grades," Measurement and Evaluation in Guidance 7 (1974): 246; Marcus Pfeifer and H. Sedlacek, Cross-Cultural Scaling Studies in the Development of Probabalistic Teaching Performance Criteria Anchored to Utility and Time Scales (Philadelphia: La Salle College, 1974), 1:49.

[12]Tracey and Sedlacek, "Prediction of College Graduation Using Noncognitive Variables by Race" (Bethesda, MD: ERIC Document Reproduction Service, ED 271 513, 1986), 7.

(i.e., SAT) scores were not. For Blacks, the most predictive variables were self-assessed academic motivation, perseverance, having strong support for college plans, and demonstrated community service. Further, Tracey and Sedlacek found that different noncognitive variables related more strongly to academic success for Blacks at different points in their college careers.[13] Black students' early persistence was found to be related to having strong support for educational plans, preference for long-range goals, positive self-concept, and realistic self-appraisal. These factors were also found to relate to persistence throughout the college years. After two or three years, persistence was found to be related to an ability to understand and deal with racism, and to demonstrated community service.

Along that same line, Kenneth Clark and Lawrence Plotkin discovered that for black students entering predominantly white universities, success in college was dependent on their motivation and goals regardless of their precollegiate performance or entrance examination indices.[14]

On the other hand, studies by Thomas and Stanley suggested on the basis of correlational analyses that aptitude tests are better predictors of college performance

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[13]Ibid.

[14]Kenneth B. Clark and Lawrence Plotkin, The Negro Student at Integrated Colleges (New York: National Scholarship Service and Fund for Negro Students, 1984), 201.

of black students than high school grades.[15]

Evidently, it may be said, based on the findings cited above, that although cognitive variables are used as admission criteria for both black and white students, these variables do better in predicting the college success for the Whites than for the Blacks.

## Nontraditional/Noncognitive Preadmission Measures and College Performance

It is worthy of note that many recent studies tend to support the idea that factors other than the traditional standardized tests may be more valid variables to use in admission selection. For example, Terrence Tracey and William Sedlacek of the University of Maryland in College Park, rather succinctly stated:

> In reaction to focusing on these demographic variables, or on traditional ability measures (e.g., SAT or ACT scores and high school grades), many practitioners and researchers are examining more individual, noncognitive variables that might be related to academic success in higher education. Increasingly, the relationship of noncognitive dimensions to academic success (both with respect to grade point average and persistence) has been substantiated in the literature.[16]

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[15]Allen Thomas and M. Stanley, Community Colleges, 1986. A National Seminar on the Community College in Canada (Toronto: Canadian Association for Adult Education, 1966), 34.

[16]Terrence J. Tracey and William E. Sedlacek, Predicting College Graduation Using Noncognitive Variables by Race (College Park, MD: ERIC Document Reproduction Service, ED 259 493, 1984), 6.

W. E. Sedlacek and G. C. Brooks hypothesized that noncognitive variables would be more relevant in the prediction of academic success for the Blacks than for the Whites in predominantly white colleges.[17] The following noncognitive variables were used in their study:

1. positive self-concept
2. realistic self-appraisal
3. understanding of and ability to deal with racism
4. preference of long-term goals over the more immediate short-term needs
5. availability of a strong support person
6. successful leadership experience
7. demonstrated community service

Sedlacek and Brooks found that the above variables correlated with academic success for the black students in a predominantly white school.

Lewis Beasely and William Sease, in turn, discovered that students' biographical characteristics and their extra-curricular participation in student government, science, mathematics, art and music organizations, as well as their reasons for attending college, were all valid in predicting black students' college GPA and persistence.[18] Further-

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[17] W. E. Sedlacek and G. C. Brooks, Jr., Racism in American Education: A Model for Change (Chicago: Nelson-Hall, 1976).

[18] Lewis S. Beasely and William A. Sease, "Using Biographical Data as a Predictor of Academic Success for Black University Students," Journal of College Student Personnel 15 (1974): 204.

more, the results of Beasely and Sease's study were supportive of the findings of earlier studies carried out by Anastasi,[19] Aiken,[20] Sedlacek and Brooks,[21] and Pruitt.[22] These studies suggested that such measures as educational aspirations, motivation, precollegiate preparation and experiences, and social and academic support be used as alternative admissions criteria to traditional standardized tests, high school rank, and high school GPA for black students' college admission. On the other hand, Michael Nettles et al.[23] used thirty-one academic, personal, and attitudinal/behavior variables with black and white students in a study utilizing a regression model. While most significant predictors were equally effective for both black and white students, the first four of the following listed variables had differential predictive

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[19]Anne Anastasi, The Validation of Biographical Inventory as a Predictor of College Success, Development and Validation of the Scoring Key (New York: College Entrance Examination Board, 1960), 1:74.

[20]Ray L. Aiken, "The Prediction of Academic Success and Early Attrition by Means of a Multiple-choice Biographical Inventory," American Education Research Journal 1 (1964): 132.

[21]Sedlacek and Brooks, Racism in American Education, pp. 50-62.

[22]A. S. Pruitt, "Minority Admissions to Large Universities: A Response," Journal of College Student Personnel 14 (1973): 22-4.

[23]Michael Nettles et al., A Comparative Analysis of the Predictors of Black and White Students' Academic Achievement in College: A Case for Expanding Admissions Policies to Include Quality of the College Experience (Chicago, IL: ERIC Document Reproduction Service, ED 259 625, 1985).

validities for the two races. The rest of the variables only helped to explain racial differences in college performance.

1. Scholastic Aptitude Test scores
2. Students' satisfaction with university
3. Peer relationships
4. Interfering problems
5. High school attended and college preparation
6. Majority/minority status in college
7. Where students live while attending college
8. Feeling that the university is discriminatory

Although their studies were based mostly on high school subjects, a few researchers have delved into the more specific areas of mathematics and computer science and used nontraditional preadmission measures. For instance, Susan De Phillis of the University of California looked into the factors correlating with student enrollment patterns in elective computer science coursework and found that sex is relatively a minor variable.[24]

Finally, in a study which used the Noncognitive Questionnaire (NCQ) developed by Sedlacek and Brooks in 1976,[25] some noncognitive variables were found to be more

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[24]Susan E. De Phillis, "Factors Correlating with Student Enrollment Patterns in Elective Computer Science Coursework" (Doctoral Dissertation, University of California, Riverside, 1985), 140-160.

[25]Brenda H. Rogers and D. Hughes, "The Use of Noncognitive Variables in the Prediction of Fall GPA for Black Freshman." ([Unpublished paper], May, 1984), 9.

predictive of college success among black students at North Carolina State University.

From the foregoing studies, noncognitive variables are suggested as better predictors of college success for the Blacks than for the Whites.

## Nigeria-based Studies

Although a number of studies have been carried out in the area of college success prediction, studies in the area of computer science success prediction based on admission and student background (noncognitive) criteria have been scanty. Furthermore, no published work has been done in this area involving the JAMB Test and the Nigerian universities or students. Thus, this study becomes a necessary one, especially at a time when the validity of the admissions selection criteria of the JAMB is being questioned in the Nigerian community,[26] and the computer science programs in the Nigerian universities are being harnessed to provide an effective base for the nation's technological objectives.

## Conclusions/Implications of Literature

Evidently, the literature is supportive of the fact that traditional (cognitive) preadmission measures enable

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[26]Kenneth O. Dike, 20 Years of University Education in Nigeria (Lagos: Academy Press Limited, 1983), 46-47.

differential predictions of college performance, depending on the major area of study and the race of the student. According to the literature, cognitive variables are better predictors of college performance for Whites than for Blacks. Among students in the computer science programs, while the total college cumulative GPA is better predicted with the high school GPA, the cumulative GPA in the major is more effectively predicted using the Mathematics Achievement Test score. Furthermore, the nontraditional (noncognitive) preadmission measures tend to predict more successfully the college performance of Blacks than Whites.

After careful consideration of these implications, the major question remains unanswered: Are these trends different in Nigeria, specifically with respect to the students' JAMB Test scores, cognitive and noncognitive preadmission measures, and their university performance in the computer science programs?

Undoubtedly, the previously cited studies, although based mainly in the USA, have, in no small measure, given an in-depth elucidation of the cognitive and noncognitive predictor factors of college success, and thus, have greatly enhanced the focus of the problem addressed in this study as well as its solution process.

# CHAPTER 3

# METHODOLOGY

This chapter presents the methodology used in the study. The categories in the chapter include: selected characteristics of the population of universities in Nigeria, sampling procedure, sample of universities, programs in the sample of universities, record systems, method of data gathering, and statistical analysis.

## Selected Characteristics of the Population of Universities

There are over thirty universities which have long enjoyed an international reputation for high academic quality, excluding a greater number of two-year and four-year colleges, are spread across the nation to cater more effectively to the country's educational and developmental needs.

With an average university enrollment of about 8,000 students, many Nigerian universities have student bodies which cut across state, tribal, ethnic, and linguistic barriers, although some universities draw most of their students from the home state or locality. Curricula, in general, are diversified and include degree and nondegree as well as liberal arts and professional programs. The computer science programs, in particular, are relatively new and have fewer students.

For a decade, the discipline of engineering and technology (which includes computer science) in the 30 operating Nigerian universities had a growth rate of 363 students per year.[27] This growth rate yielded a total of 2430 majors in the area of engineering and technology in the nine universities involved in this study. It was estimated that majors in engineering would comprise 50 percent of the 2430 students. Other areas outside of engineering, such as food technology, agriculture technology, mineral science and technology, medical technology, environmental pollution science and technology, fisheries technology, etc., would comprise 32 percent. Computer science, a relatively new discipline which is just being established in some of the institutions, was estimated to comprise 16 percent of the 2430 students. This 16 percent yielded an estimated target population of 400 computer science majors in the nine universities with a computer science program.

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[27] Chizea, <u>20 Years of University Education in Nigeria</u>, 86-87.

## Sampling Procedure

Although some undergraduate computer science programs are being created in many of the nation's educational and professional institutions, it was necessary to indicate that the population for this study included only those Nigerian universities that have already started undergraduate computer science programs. These nine universities, spread across the country, were representative of the entire Nigerian university system, in the sense that they included (a) both institutions with large student enrollment and those with small enrollment, (b) both older institutions (with twenty years or more of existence) and newer institutions (with fewer than twenty years), and (c) both federal and state institutions. Figure 2 describes graphically the stratification of the universities by age of establishment.

It was necessary to adopt a stratified sampling procedure because of the differences relating to the age of the establishment and the professional orientation of the universities which might affect the program. For example, the older universities were more likely to have better organized and stable programs, greater number of students, and more infrastructural and instructional facilities than the newer universities. The newer universities, on the other hand, were likely to have greater flexibility (less bureaucratic inhibitions) in the introduction of new ideas

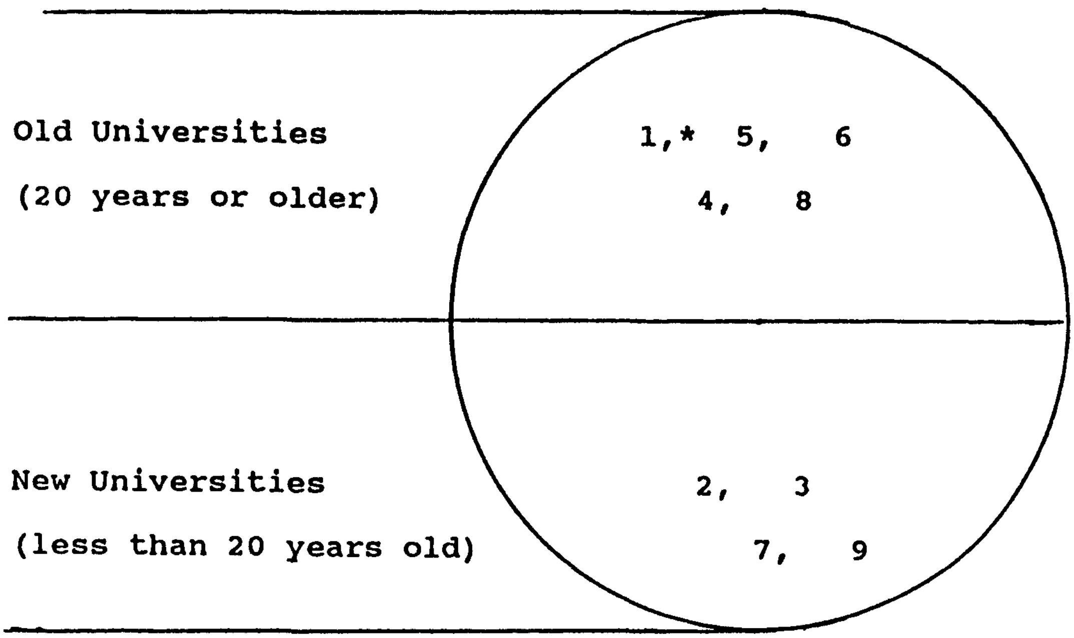


Fig. 2. Stratification of the population of universities by age.

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*Number indicates the sequential position of the university on the list (Appendix 4).

and in spending for them. Furthermore, the professional universities in their curricula place more emphasis on the mathematical and engineering skills than the liberal arts institutions. Thus, the population of universities was stratified into three categories: five older liberal arts universities; two newer liberal arts universities; and two newer professional universities. Note that there is no older professional university. See Table 1 for the strata.

## The Sample Universities

In this section certain characteristics of the sample of universities are presented.

According to F. N. Kerlinger and E. J. Pedhazur although methods to compute the sample size in a general sense do exist, there is no method of determining the exact sample size that reflects the number of independent variables involved in a design utilizing the multiple regression analysis.[28] However, they did recommend a sample of at least 100 subjects for a multiple regression analysis utilizing several independent variables. Thus, in this study involving a maximum of 7 independent variables in a single multiple regression analysis, a sample size of 100 subjects would be adequate. According to A. J. Wilburn, the

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[28]Fred N. Kerlinger and Elazer J. Pedhazur, Multiple Regression in Behavioral Research (New York: Holt, Rinehart and Winston, Inc., 1973), 446-447.

TABLE 1

STRATIFICATION OF THE POPULATION OF UNIVERSITIES
BY AGE AND PROFESSIONAL ORIENTATION

| Classification | | Number of Population Universities | Number of Sample Universities |
|---|---|---|---|
| Old | Liberal Arts | 5 | 3 |
| | Professional | 0 | 0 |
| New | Liberal Arts | 2 | 1 |
| | Professional | 2 | 1 |
| Total | | 9 | 5 |

use of a sample size of a least 100 subjects from a population of 400-1000 subjects will provide the investigator with 99.58 percent confidence that the population error rate is less than 5 percent.[29] Since the target population is 400 students, averaging approximately 35 students per university, by selecting at random one half of the universities in each of the strata, a sample size of 175 students could be obtained. Consequently, the sample size for this study was determined using this procedure.

Of the nine universities, five were selected--three from the five older universities and two from the four newer universities. Among the two professional/technological universities, one was selected. Out of the seven liberal arts universities, four were selected (see Table 1). From a regional perspective, one university was selected from the North, three from the East, and one from the West. The procedure for selecting institutions in the sample was aimed at ensuring adequate representation of the population in the sample. These five universities were:

| | | | |
|---|---|---|---|
| 1. | Ahmadu Bello University | Zaria | Federal (old) |
| 2. | Federal University of Technology | Owerri | Federal (prof/new) |
| 3. | University of Ife | Ile-Ife | Federal (old) |
| 4. | University of Nigeria | Nsukka | Federal (old) |
| 5. | Univ. of Port Harcourt | P.H. | Federal (new) |

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[29]Arthur J. Wilburn, Practical Statistical Sampling for Auditors (New York: Marcel Dekker, Inc., 1984), 192-194, 379.

## Computer Science Programs in the Sample Universities

Although the universities in Nigeria have many nearly identical computer science programs, program objectives, and content, the implementation and evaluation procedures and data storage systems, nevertheless, appeared to differ considerably. Only one institution in the sample admitted into its computer science program students who did not have the Advanced General Certificate of Education (GCE) in relevant subject areas from high school. Most admissions were done through the JAMB. In most of the institutions visited, students selected majors after at least one year of general studies, about 43% of which consisted of mathematics courses. Indeed, in two of the sample of universities, students were allowed to choose majors after two years of general curriculum studies. On the average, mathematics comprised about 40% of the core courses in the computer science programs. A substantial proportion of the content of most of the nonmathematics courses in computer science, physics, chemistry, and engineering involve mathematical skills. The student rating standards were similar, with the grade ratings of A, B, C, D, E, and F translating to the quality points 5, 4, 3, 2, 1, and 0, respectively.

## Record Systems

Each Nigerian university in the sample used a different student record system. This necessitated initial tutorial and familiarization sessions for the investigator on the institutions' systems. Each of the data items was carefully extracted from various parts and sections of each student's file. In some instances, it took three days to locate some files. Worse still, about four (1.6% of 250) files were never located at all.

## Instrumentation

In this section, the data-gathering instruments utilized in this study are discussed. These instruments were: the noncognitive questionnaire (Appendix 1) and the data sheets I, II, and III (Appendix 2).

The variables used in this study and their symbolic names and numbers are listed in Table 2. The noncognitive questionnaire was designed to gather data for the following noncognitive variables: Instr-supt (10), Goal-rel (11), Interv-prob (12), and Prv-cs-exp (13). In order to measure effectively some of these variables, certain attributes were identified. For instance, Instr-supt (10) had four attributes: the number of teacher-student conferences measured by items #4 and #5 on the questionnaire, the number of tutor-student conferences measured by items #6 and #7 on the questionnaire, the frequency of the laboratory attendant's help measured by items #3 and #11, and the number of available computer terminals in working

TABLE 2

DESCRIPTION OF THE VARIABLES USED IN THE STUDY

| ID# | Name | Description |
|---|---|---|
| 1 | CS-1 | First year college GPA in computer science program core courses |
| 2 | CS-2 | Second year college GPA in computer science program core courses |
| 3 | CS-3 | Third year college GPA in computer science program core courses |
| 4 | CS-MAT1 | First-year college GPA in the mathematics component of the computer science program |
| 5 | CS-MAT2 | Second-year college GPA in the mathematics component of the computer science program |
| 6 | CS-MAT3 | Third-year college GPA in the mathematics component of the computer science program |
| 7 | CS-NONMAT1 | First-year college GPA in the nonmathematics component of the computer science program |
| 8 | CS-NONMAT2 | Second-year college GPA in the nonmathematics component of the computer science program |
| 9 | CS-NONMAT3 | Third-year college GPA in the nonmathematics component of the computer science program |
| 10 | INSTR-SUPT | Amount of instructional support a student received while in the college computer science program |
| 11 | GOAL-REL | The degree of relationship of the computer science program to the goals and aspirations of the student |
| 12 | INTERV-PROB | Intervening emotionally and mentally destabilizing problems |
| 13 | PRV-CS-EXP | Number of times a student had previously used the computers |
| 14 | JAMB-MAT | JAMB test score in the mathematics subsection |
| 15 | JAMB-TOTL | JAMB total test score (in all subjects taken) |
| 16 | HS-TOTL | High school GPA in all courses/subjects |
| 17 | HS-MAT | High school GPA in the mathematics courses/subjects |

order measured by items #8, #9, and #10. These responses were weighted in the following manner: items #1 through #7, #12, and #13 were weighted with the numbers indicated on the questionnaire; in items #8 through #10, Yes = 1 and No = 0; and in item #11, SA = 3, A = 2, D = 1, and SD = 0. The frequencies of occurrence of these attributes or the values indicated on the questionnaire were summed to obtain the data for that variable. Furthermore, Interv-prob (12) was measured by item #12 on the questionnaire. Prv-cs-exp (13) was measured by items #1 and #2. Finally, Goal-rel (11) was measured by item #13.

The Data Sheet I, made up of three sections, was used to gather data for the following:

1. The cognitive variables--the GPA (Grade Average) in all high school subjects attempted and the GPA (Grade Average) in the high school mathematics courses attempted (see Appendix 3 for common high school subjects).

2. The JAMB aptitude test scores--both the total score and the score in the mathematics section.

3. The student's yearly cumulative GPAs in the college computer science program, the mathematics subsection, and the nonmathematics subsection.

Note that no computer science courses were attempted in the high schools.

The Data Sheet II was used to gather data relating to the number of students admitted into the programs, the number of these students who dropped out of the programs, the number of the students who changed their majors, etc.

Finally, Data Sheet III was used to list the computer science program core courses and the mathematics component at each university for the determination of the interinstitution course equivalents.

## Method of Data Gathering

Having secured the authorization for data collection from the appropriate offices of the sample of universities, the investigator proceeded first to each of the sample universities, where he administered the questionnaires to the students in groups of ten to thirty. The questionnaires were completed in 10 to 15 minutes (see Appendix 1 for a copy of the questionnaire). These questionnaires, with the students' names on them, were taken to the registrar's office where copies of students' transcripts were attached to the corresponding (or matching) questionnaires. Before the investigator left the registrar's office, he saw to it that all the names and other forms of identification were blotted out. Where confidentiality of records was a problem, the registrar had the data sheets (I, II, and III--see Appendix 2 for copies) completed. Thus, the students' lists of computer science and mathematics courses taken, their letter grades, and their yearly/cumulative GPA in the program were obtained. Finally, because the investigator obtained the JAMB test scores of the computer science majors at the sample institutions, a visit to the JAMB office was unnecessary.

This data-gathering project was completed in one month, after which the investigator returned to the United States where he commenced the analysis of the data.

Data were evaluated in three cohorts, namely, (1) the first year records of the students who had completed one, two, or three years in the computer science program (those who entered the program in 1986, 1985, and 1984, respectively), (2) the second year records of the students who had completed two or three years in the program (those who entered the program in 1985 and 1984, respectively), and (3) third year records of the students who had completed three years in the program (those who entered the program in 1984). (See Figure 3.)

## Statistical Analysis

This section presents the statistical procedures used to test each of the hypotheses of this study.

While the JAMB test score was the independent variable in hypotheses 1(a), 1(b), and 1(c), the GPAs in the mathematics and nonmathematics components, and the cumulative GPA in the computer science program were the respective dependent variables. Also, while the score in the mathematics section of the JAMB test was the independent variable for hypothesis 2, and the college GPA in the mathematics courses taken in the program was the independent variable in hypothesis 8, college GPA in the computer

| Year of Entry into the Computer Science Program | Number in Cohort I | Number in Cohort II | Number in Cohort III |
|---|---|---|---|
| 1986 (first year students | 44 | | |
| 1985 (second year students | 62 (150) | 62 | |
| 1984 (third year students | 44 | 44 (106) | 44 (44) |

Fig. 3. A three-cohort data classification.

science program was the dependent variable in these two cases. Therefore, these hypotheses (1(a), 1(b), 1(c), 2, 8, and 9) were tested using the Pearson product-moment correlation. Since these hypotheses postulated a simple test of the degree of a relationship, Pearson product-moment correlation was an appropriate statistical test instrument.

In hypotheses 3 and 4, the predictability of performance in computer science based on the selected independent variables (cognitive and noncognitive, respectively) was testing using multiple regression analysis ($Y' = A + B_1X_1 + B_2X_2 + \ldots + B_kX_k$--fundamental prediction equation). In order to test hypotheses 5 and 6, stepwise regression analysis was used first to determine the predictive powers of each predictor variable in the three cohorts (i.e., freshman, sophomore, and junior years). While the criterion variables were the college GPAs at the various levels, the independent variables were the cognitive predictor variables (for hypothesis 5) and the noncognitive predictor variables (for hypothesis 6). Similarly, hypothesis 7 was tested using stepwise regression analysis, where college GPA in the program was the dependent variable. It may be noteworthy that all tests were made at the significance (alpha) level $p < .05$.

# CHAPTER 4

# DATA ANALYSIS AND INTERPRETATION

This study was designed to (1) identify among computer science majors in Nigerian universities with computer science programs, those cognitive and noncognitive variables with the greatest magnitude of prediction of achievement in the computer science program and the mathematics and the nonmathematics component from a selected set of possible predictor variables; (2) determine the relative predictive power of each cognitive and noncognitive variable; (3) find the levels (of student classification in the program) at which the effects of these predictor variables are maximized; and (4) evaluate the extent to which achievement in the computer science program is affected by achievement in the mathematics component.

## Data Description

Records were obtained on 250 students. These 250 records included the following: 37 records of students who dropped out of the programs, 30 records of students who changed their majors and/or transferred out of their institutions, and 33 inconsistent records which either were not completed for the most part or could not be matched with any corresponding questionnaire. Only 150 records were complete or matchable to an appropriate questionnaire. Thus the analysis was performed with records of 150 students. The 150 records in Cohort I were made up of 44 first-year records of the students who had completed three years in the programs, 62 first-year records of the students who had completed two years in the programs, and 44 first-year records of the students who just completed one year in the programs. The 106 records in Cohort II were made up of 44 second-year records of the students who had completed three years in the programs and 62 second-year records of the students who had completed two years in the programs. Finally, the 44 records in Cohort III were made up of 44 third-year records of the students who had completed three years in the programs.

For the purposes of analysis, these data were grouped into three cohorts: all GPAs obtained by students at the end of the first year in the program (Year I GPAs), all GPAs obtained by students at the end of the second year in the program (Year II GPAs), and finally, all GPAs obtained by students at the end of the third year in the program (Year III GPAs).

Table 3 shows the data distribution for each variable. Note that for variables 11 and 13, the skewness was 1.4573 and 1.0945, respectively, indicating in both cases that fewer people had goal-related ambition in the program and

TABLE 3

DESCRIPTIVE STATISTICS

| Variable | Mean | S.D. | N | S.E. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| 1 | 2.6318 | 0.6347 | 147 | 0.0570 | 0.0806 | 0.6177 |
| 2 | 2.7843 | 0.5856 | 105 | 0.0571 | 0.7879 | 0.0830 |
| 3 | 2.9154 | 0.5472 | 39 | 0.0844 | 0.5952 | -0.4431 |
| 4 | 2.6377 | 0.72323 | 146 | 0.0497 | 0.0547 | 0.3455 |
| 5 | 2.7119 | 0.6818 | 104 | 0.0669 | 0.1440 | 0.1972 |
| 6 | 2.6441 | 0.8883 | 37 | 0.1460 | 0.0582 | 0.2980 |
| 7 | 2.6675 | 0.8297 | 144 | 0.0791 | 0.3347 | 0.0825 |
| 8 | 2.8532 | 0.8775 | 104 | 0.0860 | 0.2283 | 0.1434 |
| 9 | 2.5613 | 1.6013 | 39 | 0.2564 | -5.7728 | 34.0264 |
| 10 | 9.7643 | 4.9773 | 140 | 0.4223 | 0.5887 | -0.3299 |
| 11 | 0.6071 | 0.7642 | 140 | 0.0574 | 1.4573 | 1.2296 |
| 12 | 0.7427 | 0.7032 | 140 | 0.1140 | 0.8916 | 0.8843 |
| 13 | 1.3786 | 1.3470 | 140 | 0.1140 | 1.0945 | 0.8843 |
| 14 | 58.7519 | 10.4631 | 133 | 0.9073 | 0.0196 | -0.0026 |
| 15 | 222.4790 | 31.0528 | 133 | 2.6926 | -0.0685 | 5.7829 |
| 16 | 27.6338 | 7.9274 | 142 | 0.6653 | -0.0981 | -0.0127 |
| 17 | 4.1056 | 1.8011 | 142 | 0.1511 | 0.2047 | -0.7871 |

previous computer experience before entry into the program. Also observe that most students had high scores on the JAMB (total) test, variable 15 (skewness being -0.0685), concentrating around the mean of 222.479 in a range of 0 to 300 points for 3 subject areas (kurtosis being 5.7829--leptokurtic). At the same time, kurtosis for variable 16 was -0.0127 (platykurtic), indicating that students' high school GPAs were almost evenly distributed.

Further description of the data is furnished in Table 4, which highlights the correlations of variables one with another. Note the individual correlations of the cognitive and noncognitive variables with the first-year achievement in computer science (highlighted at the top row). Also notice the correlations among the noncognitive variables (highlighted at the center). Similarly, the correlations among the cognitive variables are highlighted at the bottom right hand corner. Furthermore, Figure 4 is a histogram showing the distribution of the main dependent variable, the first year achievement in the computer science program (for all the sample). This distribution exhibits normality, as was expected.

## Analysis

In the earlier sections, the hypotheses were stated in the substantive form. For the purpose of analysis those hypotheses are, in this section, restated in the null form

TABLE 4

INTERVARIABLE CORRELATION MATRIX (UPPER TRIANGLE)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) | 1.00 | .88 | .81 | .84 | .75 | .60 | .72 | .52 | .04 | .00 | .05 | .04 | .07 | .08 | .18 | .19 | .17 |
| (2) | - | 1.00 | .94 | .78 | .85 | .64 | .72 | .72 | .83 | -.02 | -.13 | .06 | .07 | .02 | .21 | -.33 | -.25 |
| (3) | - | - | 1.00 | .77 | .86 | .70 | .73 | .80 | .83 | .22 | .11 | -.01 | -.01 | -.07 | .21 | -.30 | -.16 |
| (4) | - | - | - | 1.00 | .68 | .56 | .51 | .50 | -.07 | -.02 | -.01 | .06 | -.05 | .10 | .30 | -.29 | -.36 |
| (5) | - | - | - | - | 1.00 | .52 | .58 | .61 | .70 | .03 | -.17 | .00 | -.06 | .06 | .22 | -.31 | -.28 |
| (6) | - | - | - | - | - | 1.00 | .46 | .68 | .60 | .33 | .24 | .03 | -.14 | -.16 | .27 | -.37 | -.06 |
| (7) | - | - | - | - | - | - | 1.00 | .61 | .03 | .07 | .07 | -.06 | -.08 | .06 | .17 | -.26 | -.22 |
| (8) | - | - | - | - | - | - | - | 1.00 | .73 | .06 | -.05 | -.00 | -.12 | -.04 | .11 | -.22 | -.14 |
| (9) | - | - | - | - | - | - | - | - | 1.00 | .13 | .15 | -.05 | .17 | .32 | .15 | .03 | .06 |
| (10) | - | - | - | - | - | - | - | - | - | 1.00 | .06 | .05 | .14 | .01 | -.01 | -.00 | -.04 |
| (11) | - | - | - | - | - | - | - | - | - | - | 1.00 | -.11 | .08 | .08 | .03 | .00 | .05 |
| (12) | - | - | - | - | - | - | - | - | - | - | - | 1.00 | -.01 | .03 | .06 | .06 | -.05 |
| (13) | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | .04 | -.15 | .03 | .01 |
| (14) | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | .56 | -.35 | -.41 |
| (15) | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | -.50 | -.55 |
| (16) | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 | .59 |
| (17) | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | - | 1.00 |

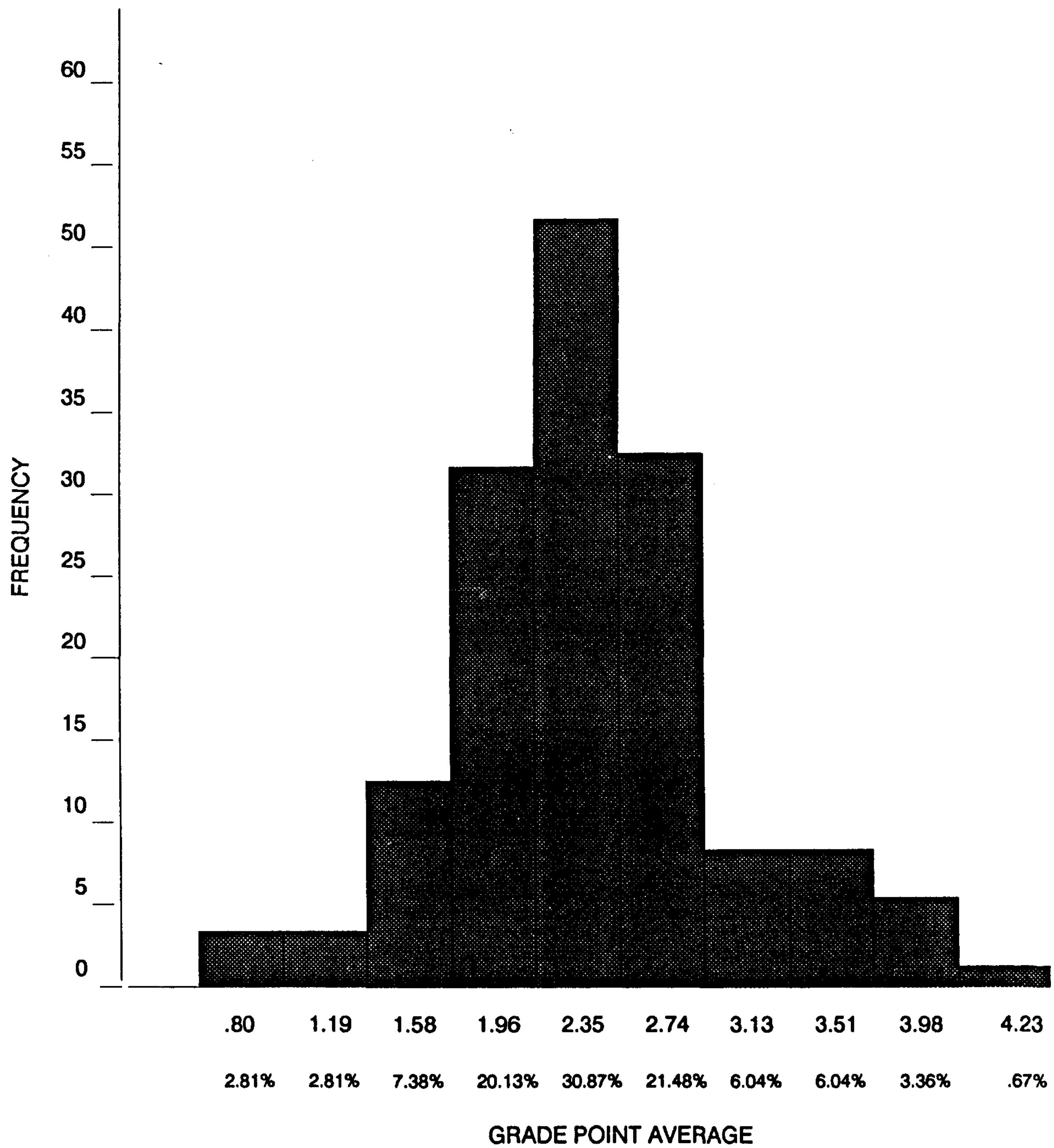


Fig. 4. Histogram of first year achievement in computer science.

and the analyses performed according to the "natural" categories of the hypotheses.

Hypothesis 1

a. There is no relationship between the JAMB test score and achievement in the computer science programs for the three cohorts--first year, second year, and third year students.

The Pearson product-moment correlation was used to test this hypothesis in each cohort, and the following were the results:

Cohort-1

In cohort 1, the correlation $r(130^{*}) = 0.1759$, with a t-value of 2.037 was found to be statistically significant at $p < .05$.

Cohort-2

An $r(97)$ of 0.2063, with a t-value of 2.076 was found significant at $p < .05$.

Cohort-3

At this level, $r(33)$ was 0.2134, $t = 1.255$. Nevertheless, this correlation was not found significant at $p < .05$.

Thus, while there was significant correlation between JAMB(total) and Achievement in the computer science program at the first-year and second-year levels, this correlation

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*Number in parentheses indicates the degrees of freedom.

was not significant at the third-year level. The null hypothesis was rejected in cohorts 1 and 2 but not 3.

b. There is no relationship between the JAMB test scores and achievement in the mathematics courses of the program as measured by the GPA in the mathematics courses taken by students from the university listed computer science program core courses in the three cohorts.

This hypothesis was tested using the Pearson product-moment correlation, with the following statistical results:

Cohort-1

In cohort 1, the correlation was at 0.2923 (df being 129), with a t-value of 3.472, this correlation was significant at $p < .05$ level.

Cohort-2

In cohort 2, the correlation was 0.2219 (with $t = 2.241$, $df = 97$) and this was significant at $p < .05$.

Cohort-3

In cohort 3, $r(32) = 0.2683$ and t equaled 1.575. This correlation was not statistically significant at $p < .05$.

JAMB(total) also correlated significantly with achievement in the mathematics component of the computer science program at the first- and second-year levels, but did not at the third-year level. Thus, the null hypothesis was rejected in cohorts 1 and 2 but not 3.

c. There is no relationship between the JAMB test score and achievement in the nonmathematics courses of the program as measured by the GPA in the nonmathematics courses taken by students from university-listed computer science program core courses for the three cohorts.

This hypothesis was also tested with the Pearson product-moment correlation with the following results:

Cohort-1

In cohort 1, the r(126), 0.1718, was found significant at $p < .05$ level ($t = 1.957$).

Cohort-2

In cohort 2, the correlation was at 4(97) = 0.1137, t-value being 1.127, and was statistically not significant at $p < .05$.

Cohort-3

In cohort 3, an r(34) of 0.1506, with a t-value of 0.888, was found not significant at $p < .05$.

Thus, the correlation between JAMB(total) and achievement in the nonmathematics component of the program was significant only at the first year level. Therefore the null hypothesis was rejected only in cohort 1.

Notably, the difference in the degrees of freedom for the correlation coefficients at the three cohort levels was due to the following: (1) because of some missing data and (2) because there were 150 first-year cases, 106 second-year cases, and 49 third-year cases.

## Hypothesis 2

There is no relationship between the score in the mathematics component of the JAMB test and achievement in the computer science program, for the three cohorts.

Similarly, this hypothesis was tested with the Pearson product-moment correlation with the following results:

<u>Cohort-1</u>

The correlation $r(130) = 0.0832$, yielding a t-value of 0.952, was not found statistically significant at $p < .05$.

<u>Cohort-2</u>

In evaluating this relationship, a correlation of $r(97) = -0.0179$ with a t-value of 0.176 was found not statistically significant.

<u>Cohort-3</u>

An $r(33)$ of 0.0682 with a t-value of 0.392 was found. This was not significant at $p < .05$. Thus, there was no significant relationship between the score in the mathematics component of the JAMB test and computer science GPA for any of the three cohorts.

The null hypothesis was not rejected.

## Hypothesis 3

There is no relationship between the achievement in the computer science program and the joint effect of the following cognitive variables:

a. High school GPA

b. High school GPA in mathematics courses

The multiple regression analysis and the stepwise multiple regression analysis were used to test this hypothesis. In the determination of the various unique contributive abilities of the independent variables (cognitive or noncognitive), the backward selection procedure of the stepwise multiple regression analysis was used.

The basic logic of this method was to remove variables (Table 5) systematically from the regression equation and to evaluate the statistical significance of their unique contributions to the explanation of the variance of the dependent variable. Based on the Beta values, the weakest variable was removed. The F-test was then conducted for significance on the unique contribution of each independent variable (now having been partialed out). Each subsequent equation was checked for changes in the Sums of Squares due to regression resulting from the removal of the independent variable(s). This was because the variable removed from the equation might have been the best single predictor, but of significantly less predictive value once others, with which it overlapped, were also in the equation. Thus, once in the equation, variables did not necessarily remain in it as progressive evaluations and comparisons were made. In this way, not only was the best set of statistically significant

TABLE 5

MULTIPLE REGRESSION ANALYSIS ON FIRST-YEAR ACHIEVEMENT IN COMPUTER SCIENCE AND COGNITIVE AND NONCOGNITIVE VARIABLES

Multiple correlation: .3422 $F(8,123) = 2.039$ $p = .047$
$R^2$: .1171
Adjusted $R^2$: .0597

| Independent Variable | Beta | B | Standard Error of B | t(123) | p |
|---|---|---|---|---|---|
| 10 | -.030062860 | -.003407 | .009747 | -.34955 | .7255 |
| 11 | .073988903 | .053584 | .062789 | .85340 | .3996 |
| 12 | .078763344 | .063054 | .068917 | .91492 | .3651 |
| 13 | -.069884318 | -.028935 | .036347 | -.79606 | .4333 |
| 14 | -.065492205 | -.003541 | .005640 | -.62786 | .5384 |
| 15 | -.014746033 | -.000270 | .002166 | -.12443 | .8688 |
| 16 | -.125450037 | -.009029 | .007835 | -1.15242 | .2500 |
| 17 | -.264358204 | -.083601 | .036437 | -2.29440 | .0221 |

Intercept = 3.471486394

predictors of the criterion variable detected, but the combined and relative contributions of the independent variables were determined as well.

Cohort-1

In cohort 1, the multiple regression coefficient R between achievement in the computer science program and the combination of High School GPA(total) and High School GPA(mathematics courses only) was found to be 0.3319, $R^2$ = 0.1102, while the adjusted $R^2$ was found to be 0.0925. This was found significant at $p < .05$.

The Beta values (-0.223, -0.151, respectively) of both independent variables were negative because the lower the high school GPA(total), the better the student's performance (according to the West African Examinations Council [WAEC] evaluation procedures). That is, while better performance in computer science programs is indicated by a high score, in the high school GPA it is indicated by a low score. Also, the High School GPA/average, with a partial correlation of $Pr^2 = 0.489$, significant at $p < .05$, was the greater single contributor to the variability of first-year achievement in the computer science program.

Cohort-2

In cohort 2, the multiple regression analysis using high school GPA(total) and high school GPA(mathematics courses only) as independent variables yielded an R of

0.3410, $R^2$ of 0.1163, and adjusted $R^2$ of 0.0988. This was found significant at $p < .05$. Also, the partial correlation coefficient, 0.1267, of high school GPA/average with the achievement in the computer science program was statistically significant.

Cohort-3

In cohort 3, an R-value of 0.4202 was found significant at $p < .05$. Similarly, the partial r (out of the two cognitive variables) influencing ability, 0.1074, of High School GPA(total) was found to be significant at $p < .05$. For the individual unique predictive abilities of all cognitive and noncognitive variables, see Table 6. The r's in Table 5 are the correlations of the individual independent variables with the dependent variables (the yearly computer science program achievement). The $Pr^2$ is the individual independent variable contribute ability (in the regression model) to the prediction of the dependent variables. The F-values (for significance) were computed for the $Pr^2$ values. Evidently, the cognitive variables jointly correlated highly with achievement in the computer science program in all cohorts.

## Hypothesis 4

There is no relationship between achievement in the computer science program, the mathematics courses, and the

TABLE 6

THREE-LEVEL UNIQUE PREDICTIVE ABILITIES
OF INDEPENDENT VARIABLES

| | | 1st Yr. Prog. Achievement | | | 2nd Yr. Prog. Achievement | | | 3rd Yr. Prog. Achievement | | |
|---|---|---|---|---|---|---|---|---|---|---|
| No. | Independent Variable | r[a] | $[Pr_i^2]$[b] | F-value[c] | r | $Pr_i^2$ | F-value | r | $Pr_i^2$ | F-value |
| 10 | INSTR-SUPT | .00 | .01 | 0.16 | -.02 | .01 | 0.06 | .22 | .00 | 0.99 |
| 11 | GOAL-REL | .05 | .01 | 0.06 | -.13 | .00 | 1.30 | .11 | .03 | 0.03 |
| 12 | INTERV-PROB | .04 | .01 | 0.12 | -.06 | .01 | 2.41 | .01 | .03 | 0.13 |
| 13 | PREV-CS-EXP | -.07 | .04 | 4.49[d] | .07 | .01 | 0.45 | .01 | .03 | 0.12 |
| 14 | JAMB-MAT | .08 | .02 | 2.42 | -.02 | .04 | 4.71[d] | .07 | .05 | 2.53 |
| 15 | JAMB-TOTAL | .18[d] | .00 | 0.80 | .21[d] | .00 | 0.77 | .21 | .03 | 0.03 |
| 16 | HS-TOTAL | -.19[d] | .03 | 4.11 | -.33[e] | .13 | 15.22[e] | -.30 | .11 | 5.21[d] |
| 16 | HS-MAT | -.17[d] | .18 | 20.75[e] | -.25[d] | .11 | 4.39[d] | -.16 | .03 | 0.01 |

[a]Individual variable product-moment correlation with dependent variable
[b]Independent variable's unique contribution (in the regression equation) to the explanation of the variance of the dependent variable
[c]F-value of the partial contribution
[d]Significant at $p < .05$ [e]Significant at $p < .01$

nonmathematics courses of the program, and the joint effect of the following noncognitive variables:

a. Amount of instructional support available to the students. This support is measured by the number of the following attributes:
   - teacher-student conferences
   - tutor-student conferences
   - lab attendant's help
   - computer terminals in working order

b. Number of mentally or emotionally destabilizing problems which include:
   - death of family member/close friend
   - accident/injury leading to the loss of any body part
   - loss of job
   - unforeseen financial setback

c. Number of times subject has previously used the computers

d. Having computer-related goals, such as aspiration to become a computer scientist, computer software/ hardware design engineer, computer programmer/ analyst, etc.

Testing this hypothesis with the multiple regression analysis and the stepwise multiple regression analysis yielded the following results for each cohort:

<u>Cohort-1</u>

1. In cohort 1, the multiple correlation coefficient R = 0.156 was obtained, yielding an F-value(4,98) = 0.607, between achievement in computer science program and the set of noncognitive variables was not significant.

2. With the achievement in the mathematics component of the computer science program, the noncognitive variables jointly correlated at 0.3061 and yielding a coefficient of determination 0.09 and F-value(4,30) = 0.775. This was not significant either.

3. In the case of performance in the nonmathematics portion of the computer science program, the noncognitive variables, with a coefficient of determination 0.09 and R of 0.3047, did not exert a significant joint influence. Thus, in the first year, the noncognitive variables jointly did not correlate significantly with achievement in the computer science program.

<u>Cohort-2</u>

1. In cohort 2, the R was found to be 0.1538 with adjusted $R^2$ = 0.02. This R value was not significant.

2. The noncognitive variables jointly correlated with achievement in the mathematics component of the computer science program at 0.2813. This did not reach statistical significance.

3. Similarly, R = 0.2843 was found not significant for the multiple correlation between the achievement in the

nonmathematics part of the computer science program and the noncognitive variables at the second year-level.

Evidently there was no significant correlation between the combination of noncognitive variables and achievement in the computer science program at the second-year level.

<u>Cohort-3</u>

1. For the seniors, the $R = 0.2297$ with adjusted $R^2 = 0.0656$ and degrees of freedom = (4,32), was not significant at $p < .05$ level.

2. An R of 0.4611 (df being 4,30), with a coefficient of determination as high as 0.21 and F-value = 2.025, was not significant for the noncognitive variables and achievement in the mathematics part of the computer science program.

3. The noncognitive variables jointly correlated with achievement in the nonmathematics component of the computer science program with an R, 0.4344 and p-value of 0.166, yielding a joint explanatory power of only 19%. Also this joint correlation was not statistically significant at $p < .05$ level.

Again, it was found that there was no significant joint correlation between these noncognitive variables and achievement in the computer science program in the third year. The null hypothesis was not rejected.

## Hypothesis 5

The strength of the relationship between the joint effect of the listed cognitive predictor variables and achievement in the computer science program is not greatest in the freshman year.

The results of the multiple regression analysis indicate that all the cognitive variables were significant (at $p < .05$). However, considering the Rs of 0.3319, 0.3410, and 0.4202 for years I, II, and III, respectively, the F-values were $F(2,101) = 6.25$, $F(2,101) = 6.64$, and $F(2,32) = 3.43$; these yielded corresponding coefficients of determination of 0.0925, 0.0988, and 0.1251. From these results it appeared that the strength of the relationship increased with length of time in the computer science program. The null hypothesis was not rejected.

## Hypothesis 6

The strength of the relationship between the joint effect of the listed noncognitive variables and achievement in the computer science programs is not greater in the sophomore and junior years than in the freshman year.

With the regression test, none of the noncognitive variables was found significant at the sophomore and junior levels. At the freshman level, only Previous Use/Experience in computers was significant at $p < .05$. The Rs were .156,

.154, and .230; and the F-values were $F(4,98) = .66$, $F(4,98) = .59$, and $F(4,32) = .45$. The $R^2$s were found to be .024, .024, and .053, respectively.

## Hypothesis 7

The noncognitive variables do not have greater joint strength of prediction of the achievement in the computer science program and the mathematics and nonmathematics courses of the program than the cognitive variables.

Using the same regression test, the joint strength of prediction of the noncognitive variables was found statistically not significant at $p < .05$. At the same time, this strength (ranging from 0.0237 to 0.2126) was found to be less than that of the cognitive variables (ranging from 0.1163 to 0.2565) in all the cohorts. Thus, the null hypothesis (with respect to all cohorts) was not rejected. For details of the individual unique predictive powers and the joint correlational strengths of these variables, see Tables 6 and 7, respectively.

## Hypothesis 8

There is no relationship between achievement in the computer science program and achievement in the mathematics component for the three cohorts.

To test hypothesis 8, the Pearson product-moment

TABLE 7

JOINT PREDICTIVE ABILITIES OF COGNITIVE AND NONCOGNITIVE VARIABLES ON ACHIEVEMENT IN THE COMPUTER SCIENCE PROGRAM

| Level | Dependent Variable | Independent Variables | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cognitive Variables | | | Noncognitive Variables | | |
| | | R | $R^2$ | Signif. | R | $R^2$ | Signif. |
| I (Yr.1) | CS Total | .33 | .11 | * | .16 | .02 | |
| | CS Math | .42 | .17 | * | .31 | .09 | |
| | CS Nonmath | .51 | .26 | * | .31 | .09 | |
| II (Yr.2) | CS Total | .34 | .12 | * | .15 | .02 | |
| | CS Math | .39 | .15 | | .28 | .08 | |
| | CS Nonmath | .42 | .18 | * | .28 | .08 | |
| III (Yr.3) | CS Total | .47 | .22 | * | .23 | .05 | |
| | CS Math | .41 | .16 | | .46 | .21 | |
| | CS Nonmath | .43 | .13 | * | .43 | .19 | |

*Significant at $p < .05$.

correlation was used.

Cohort-1

In year I, an r(144) of 0.8415 was found, a t-value of 18.687 and a correlation coefficient $r^2$ of 0.708. This showed a strong correlation, significant at $p < .05$.

Cohort-2

Among the juniors, r(102) was 0.8475, $r^2$ being 0.72, and the t-value was 16.128, also indicating significance at $p < .05$.

Cohort-3

At the senior level, the relationship was found to be slightly lower than at the sophomore and junior levels, but still yielding a high correlation $r(35) = 0.7130$, $r^2$ being 0.51, and t-value being 6.02, which was significant at $p < .05$.

Thus, achievement in the computer science program correlated highly with achievement in the mathematics component at all three levels.

## Hypothesis 9

There is no relationship between achievement in the computer science program and achievement in the nonmathematics component for the three cohorts.

The Pearson product-moment correlation is utilized in testing this hypothesis. Again, each cohort was tested separately.

Cohort-1

Among the sophomores, r(142) was found to be 0.7177, while the $r^2$ and the t-value were 0.5151 and 12.281, respectively. This was significant at $p < .05$.

Cohort-2

For the juniors, an r(102) of 0.7235, with t-value being 10.58 and $r^2$ being 0.52, significant at $p < .05$, was found.

This indicated a high correlation between achievement in the computer science program and achievement in the nonmathematics subsection at all three levels.

Cohort-3

In the case of the seniors, r(36) was 0.8334 and the t-value was 9.046, $r^2$ being 0.69, indicating a strong correlation. This was also significant at $p < .05$. For a summary of the findings with more exact computer-generated confidence intervals, see Table 8.

## Interpretation

Based on the results of the data analysis in this

TABLE 8

SUMMARY OF TEST RESULTS

| Hypotheses Tested | Results: Cohort I | Cohort II | Cohort III | Remark |
|---|---|---|---|---|
| 1a. JAMB score positively related to achievement in CS | $H_0$-R $p<.05$ | $H_0$-R $p<.05$ | $H_0$-NR | |
| 1b. JAMB score positively related to achievement in CS-math | $H_0$-R $p<.05$ | $H_0$-R $p<.05$ | $H_0$-NR | |
| 1c. JAMB score positively related to CS-nonmath achievement | $H_0$-R $p<.05$ | $H_0$-NR | $H_0$-NR | |
| 2. JAMB-math positively related to achievement in CS | $H_0$-NR | $H_0$-NR | $H_0$-NR | |
| 3. Cognitive variables are related to achievement in CS | $H_0$-R $p\leq.005$ | $H_0$-R $p<.005$ | $H_0$-R $p<.05$ | See Table 7 |
| 4a. Noncognitive variables are related to achievement in CS | $H_0$-NR | $H_0$-NR | $H_0$-NR | See Table 7 |
| 4b. Noncognitive variables are related to achievement in CS-math | $H_0$-NR | $H_0$-NR | $H_0$-NR | See Table 7 |

TABLE 8
(continued)

| Hypotheses Tested | Results | | | Remark |
|---|---|---|---|---|
| | Cohort I | Cohort II | Cohort III | |
| 4c. Noncognitive variables are related to achievement in CS-nonmath | $H_0$-NR | $H_0$-NR | $H_0$-NR | See Table 7 |
| 5. Effect of cognitive variables on achievement in CS is strongest in freshman year | $H_0$-R Predict better $p<.001$/ $p<.05$ | Predict better $p<.001$/ $p<.05$ | * | Yr1: $R^2=.09$, $p<.005$ Yr2: $R^2=.10$, $p<.005$ Yr3: $R^2=.13$, $p<.05$ |
| 6. Effect of noncognitive variables on achievement in CS is strongest in sophomore and junior years | $H_0$-NR Only Prev. Exp. was signif. | $H_0$-NR None was signif. | $H_0$-NR | Yr1: $R^2=.02$ Yr2: $R^2=.02$ Yr3: $R^2=.07$ |
| 7. Noncognitive variables have stronger relationship with CS, CS-math, and CS-nonmath than cognitive variables | $H_0$-NR (Weaker) | $H_0$-NR (Weaker) | $H_0$-NR (Weaker) | See table 7 |
| 8. Achievement in CS is positively related to achievement in CS-math | $H_0$-R $p<.0001$ | $H_0$-R $p<.0001$ | $H_0$-R $p<.0001$ | |

**TABLE 8**
**(continued)**

| Hypotheses Tested | Results | | | Remark |
|---|---|---|---|---|
| | Cohort I | Cohort II | Cohort III | |
| 9. Achievement in CS is positively related to achievement in CS-nonmath | $H_0$-R $p<.0001$ | $H_0$-R $p<.0001$ | $H_0$-R $p<.0001$ | |

CS - Achievement in the computer science program
$H_0$-R - Null hypothesis ($H_0$) is rejected
$H_0$-NR - Null hypothesis ($H_0$) is not rejected
* - Only High School total score significant at $p < .05$

research, the following interpretations were made.

There was a positive relationship between achievement in the computer science program and the JAMB test score at the sophomore and junior levels (hypothesis 1(a)). However, a careful comparative look at the r-values (0.1759, 0.2063, and 0.2134) at the first, second, and third year levels, respectively, indicated a consistent increase. The insignificance of the correlation at the third year level may be attributable to the fact that there were only 44 cases in this cohort.

The implication of the results of this hypothesis is that achievement in a computer science program can be predicted based on aptitude tests (e.g., JAMB). This obviously is contrary to the literature, which seems to suggest that for Blacks this predictor is not effective.

In hypothesis 1(b), the positive relationship between achievement in the mathematics component of the computer science program and the JAMB test score was even stronger (0.2923, 0.2219, and 0.2683 for years I, II, and III, respectively) than that between achievement in the computer science program and JAMB score (0.1759, 0.2063, and 0.2134 for years I, II, and III, respectively).

In hypothesis 1(c), a positive relationship between the JAMB test score and the nonmathematics part of the computer science program existed only in the first year, although only 3% of the changes in the achievement in this part of the program was accounted for by the changes in JAMB test score.

For hypothesis 2, there was no relationship between the score in the mathematics part of the JAMB test and achievement in the computer science program at the three levels considered in this study. Note that in cohort II, there was a negative correlation (-0.0179) between the mathematics subset of the JAMB test and the second year achievement in the computer science program. This negative relationship seemed to disconfirm the postulate that the commonalities of mathematics and computer science were responsible for the ability of the JAMB(total) score in predicting achievement in the computer science program. However, it is possible that the JAMB(math) part of the test was not effectively testing the relevant skills which related to achievement in the computer science program. For instance, the mathematics section of the JAMB test may not have been sensitive to the nonalgorithmic skills and/or the data structural control skills in computer science.

As for hypothesis 3, achievement in the computer science program could be predicted based on both high school GPA(total) and high school GPA(mathematics courses only) with the chances of error of 5 in 1000 cases at the first and second year levels, and 5 in 100 at the third year level of the program.

Individually, high school GPA(total) and high school GPA(mathematics courses only) were significantly correlated with achievement in the computer science program at the first and second year levels but were not at the third year level (see Table 6). But note that although high school GPA(total) had a higher correlation with achievement in the computer science program in the third year than in the first year, it did not reach the significant level due to a smaller number of degrees of freedom. Additionally, the individual unique contributions to the variability of the computer science program achievement were significant at all levels for high school GPA(total), and at the first and second year levels for high school GPA(mathematics).

Interestingly enough, while high school GPA(mathematics) alone accounted for about 18% of the variability in the computer science program in the first year, better than 3% by high school GPA(total), it accounted for only 3% of the changes in the third year achievement in computer science compared to about 11% by the high school GPA(total). Thus, cognitive variables are effective predictors of college achievement in the computer science program for the Blacks in Nigeria just as the literature suggested them to be in predicting college success for the Whites in the U.S.

Examining hypothesis 4, achievement in the computer science program might not be effectively predicted (for the three cohorts) based on the joint effect of the listed noncognitive variables. Only about 2% of the variance in achievement in the computer science program at the first year level is accounted for by the variance in the joint effect of the noncognitive variables (amount of instructional support, number of mentally and emotionally destabilizing problems, previous experience with computers, and having a computer-related goal). Note that achievement in computer science might be predicted based on some individual noncognitive variables. The joint correlation of the noncognitive variables with achievement in the mathematics component, indicating the power to account for 8% of the variance in it, did not reach significance. For example, with an r of 0.333 (found significant at $p < .05$), availability of instructional support correlated with third year achievement in the mathematics component of the computer science program. Also, with a partial correlation coefficient $pr^2 = 0.037$, previous computer use/experience was found to make a significant unique contribution (nearly 4%) to the explanation of the variance of achievement in the computer science program in the first year.

Contrary to the literature which indicated that the noncognitive variables are better predictors of college success for the Blacks in the United States, the results of the analysis in this hypothesis suggested that the noncognitive variables are not effective predictors of college achievement in the computer science program for the Blacks in Nigeria. However, a possible explanation for this insignificant combined effect is the interaction effect among the noncognitive variables. Even with this in mind, the individual contribution effects of most of these variables were not significant. Additionally, the fact that the noncognitive variables used in this study are not exactly the same as those used in previous studies may account for some differences in the findings in this study and those of the previous studies.

The results of the analysis for hypothesis 5 indicated that the strength of this relationship between the cognitive variables and achievement in the computer science program increased with length of time in the program, rather than decreased, as was postulated. However with $R^2$ of 0.1935, 0.1461, and 0.1251 in the years I, II, and III, respectively, their joint power to explain the variance of achievement in the computer science program was greatest in the first year.

For hypothesis 6, although the multiple regression coefficient R between the noncognitive variables and achievement in computer science was statistically insignificant at all three levels, a careful look at the adjusted $R^2$ (0.0156, 0.0162, and 0.0656 in cohorts I, II, and III, respectively) revealed that the strength of the relationship increased steadily with length of time in the program.

Looking at hypothesis 7, the noncognitive variables in this study did not have greater joint predictive power than cognitive ones. Instead, the cognitive variables consistently appeared to have greater predictive power at all levels in this study. However, a systematic removal of the individual noncognitive variables from the regression model revealed a great deal of interaction among these variables. This multicolinearity offered a possible explanation to this unexpected result.

In hypothesis 8, there was a strong positive relationship between achievement in computer science and achievement in the mathematics component at all three levels. With one, the other might be predicted with an error chance of 1 in 10,000, at all three levels. At least 70% of the variance in achievement in the computer science program is attributable to variance in achievement in the mathematics component of it. This strong relationship might have been caused by the fact that a substantial portion of the program curriculum was mathematics. Additionally, the one or more years of general studies with emphasis in mathematics preceding a choice of major might have given further support to this degree of strength in the relationship. This result implies that with improvements in the achievement in the mathematics subunit of the program, achievement in the computer science program could be improved.

Finally, for hypothesis 9, as was expected, there was a strong positive relationship between achievement in computer science and achievement in the nonmathematics component at all three levels. This indicated an agreement of performances in all components of the program. Given one, the other might be predicted, and the improvement of one will bring about the improvement of the other.

Additionally, with an $r$ of 0.8115, significant at $p <$

0.05, the first year achievement in the computer science program correlated with the third year computer science achievement (accounting for 66% of its variance). It then might be concluded that a student who does well in the first year of admission into the program is very likely to do well in the senior year. Note that first year achievement in the computer science program correlated even more strongly (r = 0.8756) with second year achievement in the computer science program. Thus graduation can be effectively predicted based on achievement in the program after one year in it.

For further illustration of these relationships, see the scatterplots in Figs. 5 and 6.

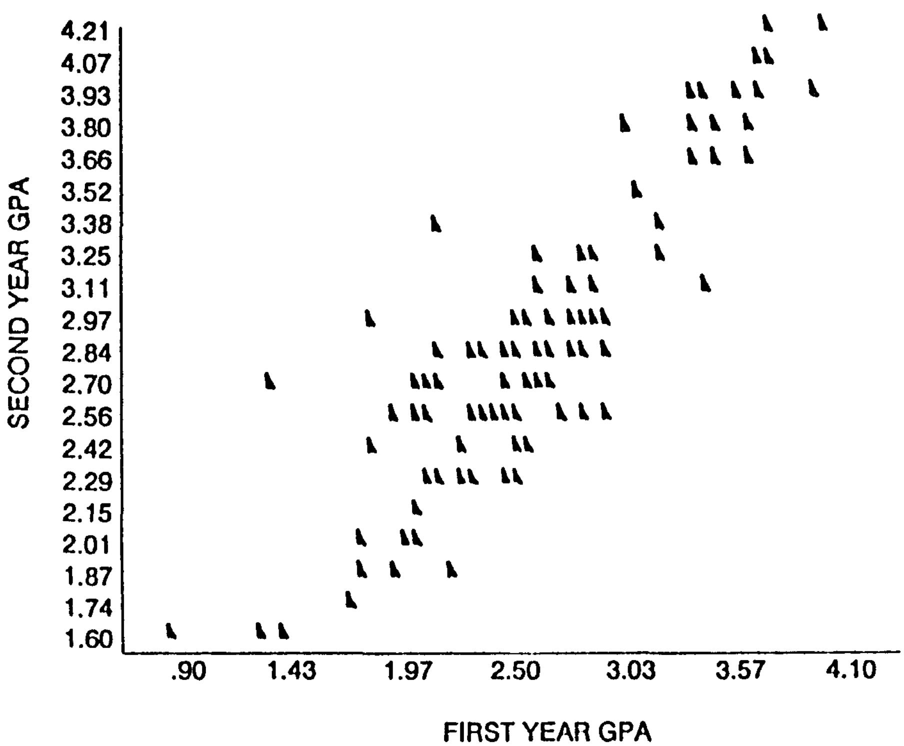


Fig. 5. Scatterplot of first and second year GPAs in computer science.

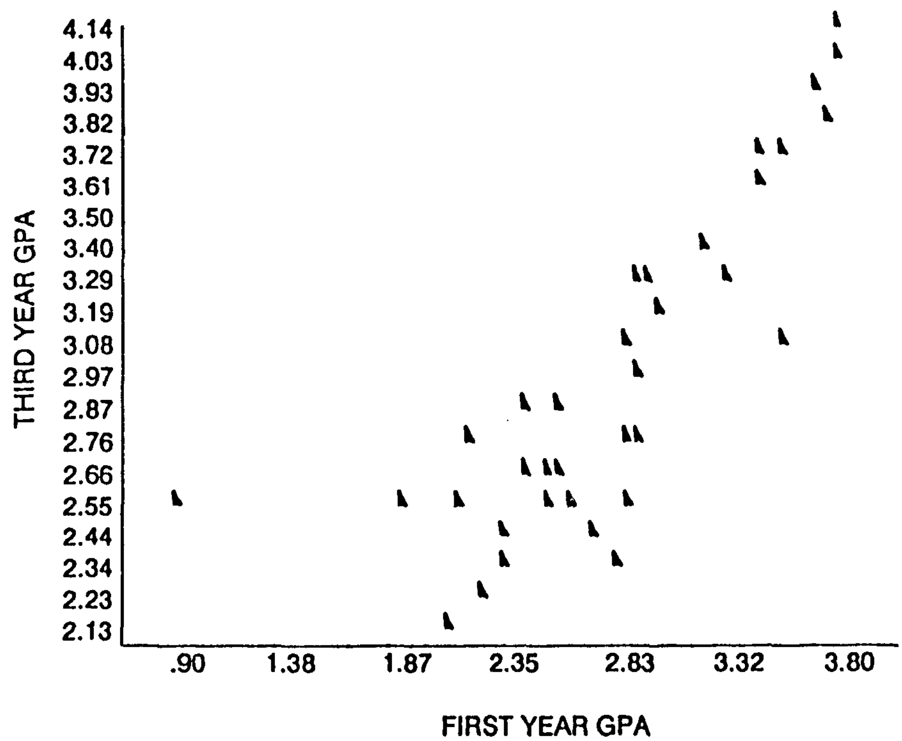


Fig. 6. Scatterplot of first and third year GPAs in computer science.

# CHAPTER 5

# SUMMARY AND CONCLUSIONS

This chapter embodies the summary of the study--involving brief statements of the problem, the hypotheses, and principal findings; the conclusion--covering the major conclusions from the findings; the implications--indicating the major inferences; and recommendations--highlighting some of the major recommendations.

## Summary

The purpose of this study was to (1) identify among computer science majors in Nigerian universities with computer science programs, those cognitive and noncognitive variables with the greatest magnitude of prediction of achievement in the total computer science program, in the mathematics component of the program, and in the nonmathematics components of the program, from a selected set of possible predictor variables; (2) determine the relative predictive power of each cognitive and noncognitive variable; (3) find the levels (of student classification in the program) at which the effects of these predictor variables are maximized; and (4) evaluate the extent to which achievement in the computer science program is related to achievement in the mathematics component. The following major hypotheses tested in this study were:

1. There is a positive relationship between the JAMB test score and achievement in the computer science program for the three cohorts: freshman, sophomores, and juniors.

2. There is a positive relationship between the score in the mathematics component of the JAMB test and achievement in the computer science program, for the three cohorts.

3. Achievement in the computer science program can be predicted (for the three cohorts) based on the cognitive variables listed in the study.

4. Achievement in the computer science program, the mathematics courses, and the monmathematics courses of the program can be predicted (for the three cohorts) based on the noncognitive variables listed in the study.

5. The noncognitive variables have greater strength of prediction of the achievement in the computer science program, the mathematics, and the nonmathematics courses of the program than the cognitive variables.

6. There is a positive relationship between achievement in the computer science program and achievement in the mathematics component for the three cohorts.

The major findings of this study included the following:

1. There was a positive relationship between the JAMB test and the achievement in the computer science program.

2. There was a positive relationship between the cognitive variables in high school GPA (total) and high school GPA (mathematics).

3. There was no relationship between achievement in the computer science program and the noncognitive variables listed in the study.

4. A strong positive relationship existed between the achievement in the computer science program and each of the components, mathematics and nonmathematics, of the program.

## Conclusions

The principal conclusions in this study include the following:

1. Aptitude tests such as the JAMB test can predict college achievement in the computer science program among Nigerian students. Similarly, the cognitive variables such as the high school GPA (or high school scholastic achievement) can predict achievement in computer science in Nigeria.
2. The noncognitive variables may not effectively predict achievement in the computer science program in Nigeria.
3. There is a strong relationship between the mathematics and nonmathematics subunits of the computer science program and the whole program.

## Implications

The major implications of the results of this study include the following.

The finding that the cognitive variables are more reliable than the noncognitive ones in the prediction of college success for Nigerian students is comparable to the findings of A. Farver, W. Sedlacek, and G. Brooks (1975); Marcus Pfeifer and William Sedlacek (1974); B. H. Rogers and D. Hughes (1984); and Kenneth Clark and Lawrence Plotkin

(1984); which indicated that cognitive variables are reliable in predicting college success for the Whites and not the Blacks.

A major implication of the findings (in hypotheses 1, 3, 4, and 5) on the literature deserves attention. While the literature appeared to suggest that cognitive variables such as high school GPA or academic achievement are not good predictors of college success for the Blacks in the United States, this study strongly suggested otherwise for the Blacks in Nigeria. The findings in this study seemed to suggest that just as the cognitive variables (such as high school GPA or high school scholastic achievements) and aptitude tests (such as the JAMB or SAT) are good predictors of college success for the Whites, so are they for the Blacks in Nigeria.

Note that in this study the noncognitive variables are not good predictors of achievement in the computer science program. This was true in this study despite the suggestions in the pertinent literature that the reverse would occur.

The results of this study suggest that the differential predictive weights of the cognitive and noncognitive variables for the Whites and Blacks in the U.S., and the power of the cognitive variables or the aptitude tests to predict effectively the college success for the Blacks in the United States may not be attributable to race, intelligence (or lack of it), or innate characteristics, but rather may be attributable to cultural, socioeconomic, stereotypic, or environmental variables. Additionally, this discrepancy (in the finding, relative to the literature) may be due to the following factors:

1. Difference in cultural/educational background/ preparation.
2. Difference in the actual composition of the noncognitive variables.
3. The fact that this study was focused on achievement in the computer science program and not on college GPA.

One implication for the computer science program includes that performance in the program could be improved with appropriate reinforcements in the mathematics subunit of the program. The reverse may also be true.

The study has several implications for the college admissions policies. According to the regression model, the three best predictors appear to be High School GPA(mathematics), followed by Previous Computer Experience and High School GPA(total). On the other hand, the three best predictors, according to the Pearson's product-moment correlation (for the dependent variable and each of the independent variables) appear to be High School GPA(total), followed by JAMB(total) and High School GPA(mathematics). Thus, High School GPA(mathematics) and High School GPA(total) may be listed as the two best predictors (based simply on their occurrence in both cases).

Incontrovertibly, the use of the best predictors would enable the early detection of the potentially high-achieving (and low-achieving) computer science majors at admission level. In the same manner, this would reduce the "float" of students with undecided majors and as a consequence the number of students admitted could be adjusted to meet limited openings in the program. Obviously, the positive effects of an admission process guided by an effective predictive model on cost reduction (national or institutional) and quality enhancement of the educational experience at the universities, cannot be overemphasized.

## Recommendations

The following recommendations were made based on the results of the data evaluation performed in this study.

1. The computer science programs, especially the new ones, should include at least one year of general studies with strong emphasis in mathematics. This will give the students the necessary background enhancement for better achievement in computer science once an entry into the program is made.

2. Further studies are recommended to identify the technological needs of the nation, as well as the adequacy of the human and technical equipment of the Nigerian universities to meet these needs.

3. A model computer science program for these universities should be designed in line with the national needs/priorities as identified in #2 above. This may, no doubt, enhance the national program(s) coordination and control, thus eliminating program redundancy.

4. A review of the JAMB test materials, aimed at improving its effectiveness in predicting either overall college success or achievement in the major discipline. This can be done through "fine tuning" of the test materials to reflect the relevant skills in the major disciplines.

5. A national accreditation body should be instituted to articulate, inter alia, a set of accreditation criteria (for these computer science programs) pertinent to the national objectives, thus creating quality standards and maintaining them.

6. Furthermore, the results of a comparative study of the computer science program effectiveness and productivity in Nigeria and the United States will be revealing.

7. A replication of this study in Nigeria or in other African countries is recommended.

8. A replication of this study in the United States detailing college performances of the Blacks and Whites (in both white and black environments) and showing the effects of their social/economic status or class is recommended.

APPENDIX 1

QUESTIONNAIRE

RESEARCH QUESTIONNAIRE
TO THE
COMPUTER SCIENCE MAJORS IN NIGERIAN UNIVERSITIES

PLEASE ANSWER EACH QUESTION WITH YOUR FIRST REACTION

Circle the option that most closely resembles your response using the following guideline:

0 = none    1 = about 1 hr.    2 = about 2 hrs.    3 = 3 hrs. or more

01. In the last 2 years before you were admitted into the computer science program, how many hours did you spend studying/using computers? [0] [1] [2] [3]

Circle the option that most closely resembles your response using the following guideline:

0 = never    1 = seldom    2 = sometimes    3 = often

02. Before you were admitted into the computer science program in this university, how many times did you attend a computer-oriented conference/meeting/fair? [0] [1] [2] [3]

03. Since you were admitted into the computer science program in this university, how frequently do you obtain help from the computer lab attendant? [0] [1] [2] [3]

04. How frequently do you have conferences with your math instructor? [0] [1] [2] [3]

05. How frequently do you have conferences with your computer science instructor? [0] [1] [2] [3]

06. How frequently do you have conferences with a math tutor? [0] [1] [2] [3]

07. How frequently do you have conferences with a computer science tutor? [0] [1] [2] [3]

08. Does your university have a computer laboratory that you can use? [Yes] [No]

If you answered Yes to item #08, then complete the rest of the items; otherwise, skip to item #12 below.

09. Do you have a sufficient number of computer terminals in the laboratory? [Yes] [No]

10. Is your computer in working order? [Yes] [No]

<u>Circle the option that most closely resembles your response using the following guideline</u>:

SA = <u>strongly agree</u> A = <u>agree</u> D = <u>disagree</u> SD = <u>strongly disagree</u>

11. The lab attendants have been helpful to me in this program. [SA] [A] [D] [SD]

Consider the following examples of problems/events:

** death of family member or loss of a close friend
** traffic-related or other accidental injury(ies) that led to the loss of body part/parts
** loss of job
** divorce of spouse
** unplanned financial incapacitation adversely affecting your continuation in college or family livelihood

<u>Circle the option that most closely resembles your candid response using the following guideline</u>:

0 = none has happened to me
1 = two or fewer have happened to me
2 = four or fewer have happened to me
3 = all five or probably more have happened to me

12. How many of the above problems/events or the like have happened to you in the last five years? [0] [1] [2] [3]

<u>Circle the option that most closely resembles your candid response using the following guideline</u>:

0 = <u>different field</u> 1 = <u>not sure</u> 2 = <u>related field</u> 3 = <u>same field</u>

13. How closely related is this computer science program to your personal future career/job goal(s)? [0] [1] [2] [3]

APPENDIX 2

DATA SHEETS

# DATA SHEET I

(to be completed for each student)

________________________________________

(Name of the University)

## SECTION A

1. GPA (Grade Average) in all secondary school subjects attempted. ______

2. Sec. sch. GPA (Grade Average) in mathematics courses. ______

3. Number of semesters (terms) of sec. school computer courses. ______

4. Sec. sch. GPA (Grade Average) in computer courses. ______

## SECTION B

1. JAMB Test score (in math part) ______

2. JAMB Test score (in computer part) ______

3. JAMB Test score (for all test parts) ______

## SECTION C

1. Classification (# yrs. in the computer science program). ______

| | Yr. 1 | Yr. 2 | Yr. 3 |
|---|---|---|---|
| 2. GPA in nonmathematics component of the computer science program core courses attempted (in the university). | | | |
| 3. GPA in math. component of computer science program core courses attempted. | | | |
| 4. GPA in all computer science program core courses attempted. | | | |

# DATA SHEET II

(to be completed for each university)

________________________________________
(Name of the University)

SECTION D

| | 83/84 | 84/85 | 85/86 | 86/87 | TOTAL |
|---|---|---|---|---|---|
| 1. Number of prospective students offered admission into the Computer Science Program in the academic years | | | | | |
| 2. Number who actually started in the Computer Science Program in the years | | | | | |
| 3. Number who changed their major from Computer Science to other majors | | | | | |
| 4. Number who dropped from the Computer Science program and out of the university | | | | | |
| 5. Number not originally admitted into the program who switched their majors to Computer Science | | | | | |

DATA SHEET III

(to be completed for each university)

______________________________________

(Name of the University)

SECTION E

List of computer science program core courses

List of mathematics courses required for the computer science program

# APPENDIX 3

## COMMON HIGH SCHOOL SUBJECTS IN NIGERIA

## SOME COMMON HIGH SCHOOL SUBJECTS IN NIGERIA

It is worthy of note that there exists a very wide range of subjects offered in Nigerian high schools, depending on whether the school is private or public, Christian or non-Christian, grammar school or vocational, etc. Nevertheless, the following list (in particular order) includes the more common high school subjects* in Nigeria.

1. Mathematics (additional, modern or nonmodern)
2. Biology
3. Chemistry
4. Physics
5. English Language
6. English Literature
7. Scripture (Christian or non-Christian)
8. Languages (Vernacular, Latin, French, Spanish, etc.)
9. History
10. Geography
11. Agricultural Science
12. Art
13. Economics
14. Commerce
15. Government
16. Music

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*<u>JAMB Brochure 1987-88: Guidelines for Admission to First Degree Courses in Nigeria Universities</u> (Lagos: Jeromelaiho and Associates Limited, 1987), p. 231.

17. Principles of Accounting
18. Shorthand
19. Statistics
20. Typewriting

APPENDIX 4

LIST OF THE POPULATION OF UNIVERSITIES

UNIVERSITIES WITH UNDERGRADUATE COMPUTER SCIENCE PROGRAM

| Name | Location | Status |
|---|---|---|
| Ahmadu Bello University | Zaria | federal |
| Anambara State Univ. of Tech. | Enugu | state |
| Federal Univ. of Tech. | Owerri | federal |
| Ibadan University | Ibadan | federal |
| Ife University | Ile-Ife | federal |
| Lagos University | Lagos | federal |
| University of Maiduguri | Maiduguri | federal |
| University of Nigeria | Nsukka | federal |
| University of Port Harcourt | Port Harcourt | federal |

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