EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Gender-based comparison of students' academic performance using regression models

Aderibigbe Israel Adekitan*[1)] and Olamilekan Shobayo[2)]

[1)]Department of Electrical Engineering and Information Technology, Technische Universität Ilmenau, Germany
[2)]Department of Electrical and Information Engineering, Covenant University, Ota, Ogun State, Nigeria

Received 25 September 2019
Revised 2 January 2020
Accepted 24 January 2020

Abstract

The process required to gain admission into tertiary institutions is challenging for Nigerian students. This is due to the various examinations and requirements that must be met to be qualified for admission among innumerable applicants. It is therefore imperative that after admission, students must pursue academic excellence to justify the opportunity given to them, and this will also improve their chances of success after graduation. In a university, some first-year students struggle because of cultural disadvantages, as well as their economic and social backgrounds. This has resulted in poor performance by some students and inevitably led to bad grades at graduation and some drop out of the university without graduating. Female students are often said to perform a bit poorer in terms of academic performance. This study is a comparative performance analysis of male and female students in Science, Technology, Engineering and Mathematics (STEM), conducted using regression models. Trend analysis shows that in this case study, female students have a tendency to improve on their academic performance from their first to their final year. The highest R-squared value of 0.7069 was achieved based on a regression analysis of the performance of 1,093 female students.

Keywords: Teaching and learning strategies, Data mining algorithms, Educational data mining, Machine learning, Knowledge discovery, Performance evaluation methodologies

1. Introduction

When discussing the education system in Nigeria, the first things that strike our minds are the general promotion of students, examination malpractice, poor facilities, and the fall in educational standards [1]. Formal education in Nigeria was introduced by the British during colonial times, and as such, the structure of the education system is modelled after them. It starts with the primary education in which children of about six years of age are eligible to enrol and this last for six years. It is immediately followed by secondary education which runs for another six years. At the sixth year, students take the Senior Secondary Certificate Examination (SSCE), an examination administered by two bodies in the education system, the West African Examinations Council (WAEC), and the National Examination Council (NECO). These examinations form the basic requirements for admission into tertiary institutions in the country [2].

According to WDI (World Development Indicators), Nigeria is responsible for up to 10% of children that are out of school in the world. This number is higher in the North than the southern part of the country. The reason for this disparity can be attributed to incessant violence in the North. Many children in the North struggle to enrol and complete even their primary education. Nigeria is doing better than countries in the sub-Saharan region but falls short when benchmarked against the world's emerging economies. This can be attributed to poor funding, chronic shortages of teachers [3-4], and poor policy implementation [5]. Foreign bodies have tried to help Nigeria abate the issues surrounding her education system. Some of these include the United Nations (UN), the Mainstream Environment and Sustainability in Africa Universities Partnership (MESA), and some others created by local bodies such as Universal Basic Education (UBE) [2]. The UN, through the Decade of Education for Sustainable Development (UNDESD), pinpointed that there are numerous hurdles to sustaining the Nigerian education system [6].

The role of Science, Technology, Engineering and Mathematics (STEM) education in the economy of a nation is very vital [7]. This has been necessitated by the development of emerging technologies that shape the way the world does its business. In many developing countries, the teaching of STEM subjects to undergraduates has become important [8], as this is the only viable option for these countries to enjoy sustainable economic progress in the presence of academic [9] and non-academic challenges. The adoption of a scientific mindset, as research has shown, is needed to achieve economic prosperity [10-11]. Investments in STEM education helps to improve a country's standard of living, and also better the quality of lives in numerous areas

*Corresponding author.
Email address: ade_kitan@yahoo.com
doi: 10.14456/easr.2020.27

such as transportation, medical engineering, agriculture, efficient energy production and industrial progress.

Research has shown that the students who drop out the most from university are the first-year students [12]. Obtaining a degree has been said to benefit individuals through increased cognitive abilities, socialisation and economic enhancement. So, it is proper to identify the challenges new students face in a university to help them to adjust to the academic rigours of the university environment. This is because starting well is critical to finishing well [12].

Overtime and even up till now, there is some contention in views regarding female students out-performing their male counterparts in higher educational institutions. The gender of a student, particularly in an African country, greatly influences the academic and non-academic challenges faced by the student. Does the gender composition of a university affect overall student performance? [13]. Is there a significant difference between the performance of female and male students in a university? These are salient questions worthy of investigation. In the current study, the performance of 1,093 females and 1,953 male students of Covenant University in Nigeria was evaluated using regression models. The study identified the differences between the performances of both genders, and also compared the regression models for the performance prediction of final-year results of the male and female students in terms of the coefficient of determination (R^2). This coefficient was used as a measure of how well students settled into the university system, and their likelihood to graduate with good grades, based on established performance trends.

2. Related studies

A disparity in the presence and participation of females in certain STEM programmes, e.g., technology and engineering, has been observed in some regions of the world [14]. This gender gap in the number of graduates, and achievements in STEM fields [15] may be due to socio-cultural background [16], religious views, societal expectations of women, and lack of female mentors to inspire female interest in STEM fields. Even in a developed country like America, it has been reported that female workforce accounts for less than 25% of the total STEM-related jobs [17]. Interestingly, the study by Stoet and Geary (2018) [15] discovered that countries with a high level of STEM gaps also had a high level of gender equality, which seems quite a paradox.

Numerous academic researchers did studies to predict the academic performance of students in higher educational institutions [18]. Some of the developed prediction models were used to guide the students' performance throughout their stay in the university [19-20]. Using different metrics such as Grade-Point Average (GPA) and Scholastic Assessment Test (SAT) scores, faculty members have been able to guide students. Oladokun et al. (2008) [21] used predictions to analyse how students that are considering a career in industrial engineering will perform when they are admitted into the program using a dataset of the past five cohorts at the University of Ibadan, Nigeria. Arsad et al. (2013) [22] used prediction algorithms to forecast the results of matriculating and diploma students to help mentor them before their final semesters in engineering courses.

Educational data mining was applied by Hussain et al. (2019) [23] to a student dataset having 666 samples and 11 features. Various clustering and classification analyses (Neural Network MLP, Naïve Bayes, Decision Tree) were carried out using Weka, Orange, and R Studio. A minimum accuracy of 57.81% was achieved. In the study by Sarra et al. (2019) [24], student drop-out tendency was investigated to enable early identification of at-risk students by evaluating their motivation, performance, and resilience using data mining techniques. The impact of ethnicity on the performance of students in higher educational institutions was investigated using data mining analysis [18]. According to Ramaswam (2019) [25], the accuracy of student performance prediction can be further enhanced through data mining techniques.

Huang and Fang (2013) [26] described the use of prediction models as a tool to encourage students with low performance to improve their grades through new learning strategies. According to these researchers, generally, student performance prediction models help students to:

a) Gain insight into how they are faring, well or poorly, in a course.
b) They give students an opportunity to evaluate the effectiveness of their learning strategies.
c) Instructors use the results to proactively help students to improve their learning experience when they are deemed to have low performance. Such proactive steps include:
    - Making the students do extra technical work in the course.
    - Face-to-face teaching and revision of important notes in the class.
    - Providing extra classes.
    - Encouraging students to revisit what they learnt before in a course, which they would still encounter in the future.

3. Methodology

A dataset in this study was used to analyse the academic performance of both female and male students of Covenant University in Nigeria that graduated between the years 2010 and 2014. The dataset comprises the performance records of 1,093 female, and 1,953 male students, totally 3,046 students, across seventeen Science, Technology, Engineering and Mathematics programs at Covenant University. The dataset was sourced from a study by John et al. (2018) [27]. It covers the following academic programs: Building Technology, Industrial Chemistry, Microbiology, Industrial Physics, Electronics and IT Applications, Information and Communication Engineering, Computer Engineering, Electrical and Electronics Engineering, Mathematics, Petroleum Engineering, Chemical Engineering, Industrial Physics-Renewable Energy, Applied Geophysics, Management and Information Systems, Mechanical Engineering, Biochemistry and Civil Engineering.

The student data variables analysed included their secondary school cumulative grade point average (SGPA), gender, the program of study, first-year (100L) cumulative grade point average (CGPA), and final year CGPA. Three regression models were developed to separately fit the academic performance records to graduation for males, females, and both groups (males and females) combined. The programs were coded as 1 to 17, while gender was coded as 1 for females and 2 for males. The regression models for

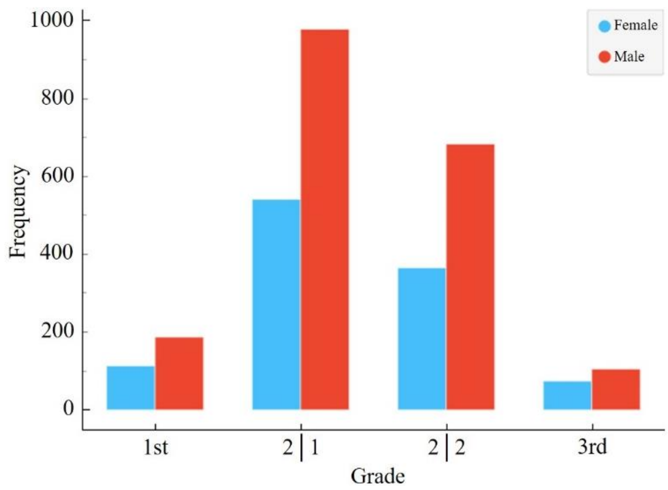

Figure 1 First-year class of grade comparison

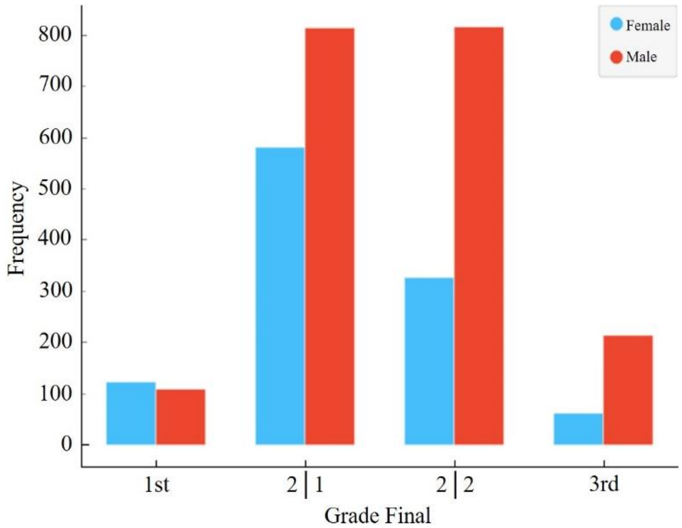

Figure 2 Final year class of grade comparison

predicting the graduation results of the 1,093 female students and 1,953 male students separately had three independent variables, the coded program of study (Prog Code), the secondary school cumulative grade point average (SGPA), and the first year (100L) cumulative grade point average (CGPA) of the student, while the final year CGPA was the dependent variable. The regression model developed for the total 3,046 had four independent variables, the coded program of study, coded gender, secondary school cumulative grade point average, and the first year (100L) cumulative grade point average (CGPA) of the students, while the final year CGPA was the dependent variable. The SGPA is the overall academic score of the student at the point of admission determined as the average of the scored West African Examinations Council (WAEC) grade [28], Joint Admissions and Matriculation Board (JAMB) Score, and the university-based post-JAMB examination score [29]. JAMB is the Nigerian authority to conduct examinations for admission into higher educational institutions in Nigeria [30].

For this case study, the null hypothesis H_0 was proposed as: Gender has no effect on the prediction of the academic performance of students at Covenant University. The study seeks to determine the validity of the hypothesis (H_0: $\beta_G = 0$), where β_G is the regression weight of the gender variable.

4. Results

The dataset for male and female students was analysed, and the statistical trends observed are presented comparatively in Figures 1-5. The diagrams shown in Figures 1 and 2 contrast the class performance of male and female students in their first and final years respectively. From the first to the final year, the performance of the female students improved significantly. More female students moved into the first-class group. However, their numbers in the second-class upper group remained fairly constant in the final year compared with their first-year performance. Concurrently, more male students slipped from the second class upper to the second class lower group, demonstrating a decline in academic performance. Figures 3-5 show box plots of the SGPA, the 100L CGPA, and the final year CGPA of the students. The average CGPA for the male and female students are reasonably close for both the SGPA (3.109 and 3.139) and 100L CGPA (3.644 and 3.621) results. However, in the final year, there is a significant difference in the average CGPA (3.391 and 3.680). This indicates that between the period of admission and the first year, up to the final year, significant changes occurred in the performance of both the male and female students.

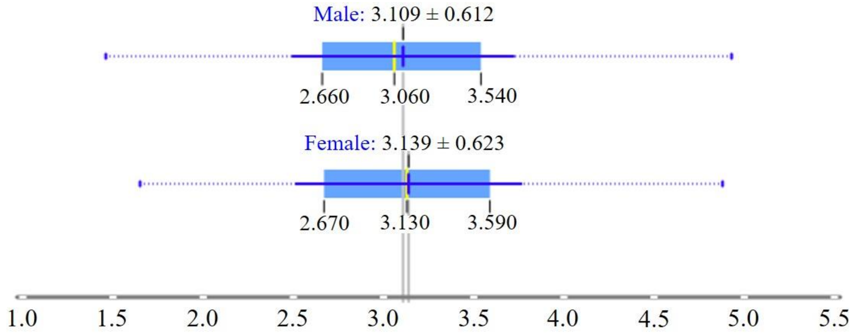

Figure 3 Box plot of the SGPA of male and female students

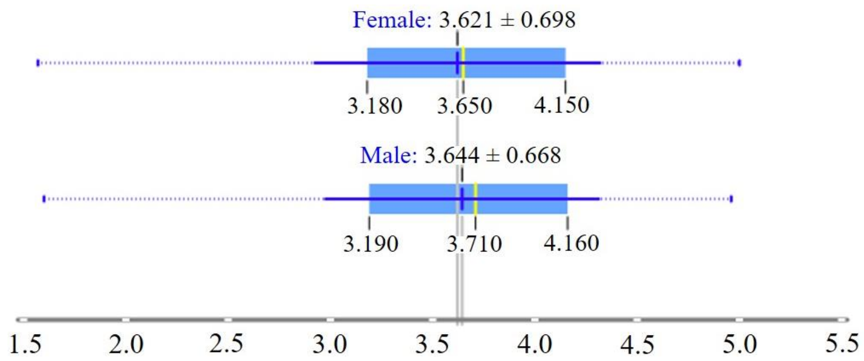

Figure 4 Box plot of the 100L CGPA of male and female students

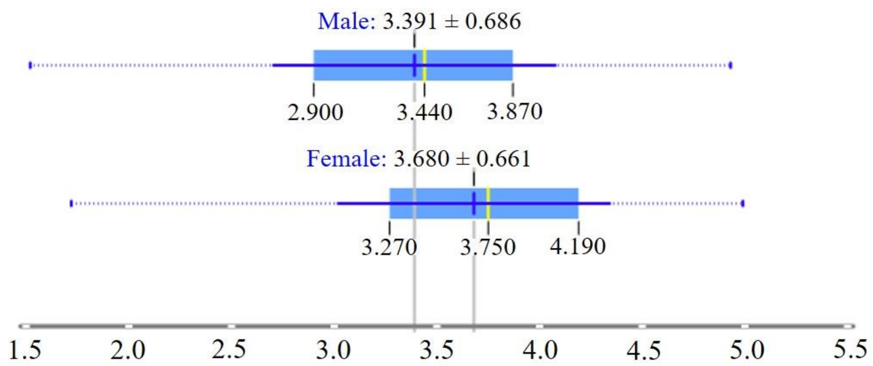

Figure 5 Box plot of the final-year CGPA of male and female students

Table 1 Regression statistics of male student data

Multiple R	0.7984
R Square	0.6374
Adjusted R Square	0.6368
Standard Error	0.4138
Observations	1953

4.1 Multiple linear regression model for the performance of the male students

The result of the regression analysis for the 1,953 male-student datasets is presented in this section. Table 1 shows the regression statistics. Table 2 shows the Analysis of Variance (ANOVA) for the regression model, while Table 3 presents a summary of the regression model. An overall R^2 value of 0.6374 was achieved. From Table 3, it can be seen that the program of study has a p-value of 0.4257 (> 0.05). As such, the variable is not significant in the prediction of the final CGPA of male students. The equation of the regression model in terms of the three independent variables is given by Equation 1.

$$\textit{Final CGPA} = 0.3554 + (0.0408 \times \textit{SGPA}) + (0.8025 \times 100\textit{L CGPA}) \quad (1)$$

4.2 Multiple linear regression model for the performance of the female students

The result of the regression analysis for the 1,093 female students is presented in this section. Table 4 shows the regression statistics. Table 5 shows the ANOVA, and Table 6 presents a summary of the regression model. An overall R^2 value of 0.7069 was achieved. From Table 6, the program of study has a p-value of 0.1950 (> 0.05), which implies that it is not significant in the prediction of the final CGPA of the female students. Also, the SGPA with a p-value of 0.0546 (> 0.05) is slightly weak in the prediction model. This means that the academic standing of the female students at the point of admission is not a very strong indication of their future university performance.

Table 2 ANOVA of male student data

	df	SS	MS	F	Significance F
Regression	3	586.67	195.56	1141.90	0.00
Residual	1949	333.77	0.17		
Total	1952	920.44			

Table 3 Regression model of male student data

	Beta	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-	0.3554	0.0636	5.5883	0.0000	0.2307	0.4801
Prog Code	-0.0109	-0.0019	0.0024	-0.7968	0.4257	-0.0065	0.0028
SGPA	0.0364	0.0408	0.0170	2.3968	0.0166	0.0074	0.0742
CGPA100	0.7812	0.8025	0.0156	51.5153	0.0000	0.7720	0.8331

Table 4 Regression statistics of female student data

Multiple R	0.8408
R Square	0.7069
Adjusted R Square	0.7061
Standard Error	0.3586
Observations	1093

Table 5 ANOVA of female student data

	df	SS	MS	F	Significance F
Regression	3	337.70	112.57	875.33	0.00
Residual	1089	140.05	0.13		
Total	1092	477.75			

Table 6 Regression model of female student data

	Beta	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-	0.7014	0.0716	9.7993	0.0000	0.5610	0.8418
Prog Code	0.0214	0.0033	0.0025	1.2966	0.1950	-0.0017	0.0083
SGPA	0.0351	0.0372	0.0193	1.9242	0.0546	-0.0007	0.0752
CGPA100	0.8268	0.7832	0.0173	45.2533	0.0000	0.7492	0.8171

Table 7 Regression Statistics of all student data

Multiple R	0.8212
R Square	0.6744
Adjusted R Square	0.6740
Standard Error	0.3949
Observations	3046

Table 8 ANOVA of all student data

	df	SS	MS	F	Significance F
Regression	4	982.53	245.63	1574.80	0.00
Residual	3041	474.33	0.16		
Total	3045	1456.86			

The equation of the regression model for predicting the final CGPA of the female students is given by Equation 2.

$$\textit{Final CGPA} = 0.7014 + (0.0372 \times \textit{SGPA}) + (0.7832 \times 100\textit{L CGPA}) \quad (2)$$

4.3 Multiple linear regression model for the performance of all the students

The result of the regression analysis for all the 3,046 students is presented in this section. Table 7 presents the regression statistics. Table 8 shows the ANOVA, while Table 9 presents a summary of the regression model. An overall R^2 value of 0.6744 was achieved.

$$\textit{Final CGPA} = 0.9826 - (0.3065 \times \textit{Gender}) + (0.0397 \times \textit{SGPA}) + (0.7948 \times 100\textit{L CGPA}) \quad (3)$$

From Table 9, it is observed that the program of study has a p-value of 0.9101 (> 0.05) which implies that it is also not significant in the prediction of the final CGPA of the students. The regression model is given by Equation 3. Table 10 presents the correlation matrix of the SGPA, the 100L CGPA, and the final-year CGPA. The result of the correlation matrix shows that there is a moderate positive linear relationship (0.43) between SGPA and the first year CGPA. Additionally, there is a weak positive linear relationship (0.38) between SGPA and the final-year CGPA,

Table 9 Regression model of all student data

	Beta	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
Intercept	-	0.9826	0.0536	18.3477	0.0000	0.8776	1.0876
Prog Code	0.0012	0.0002	0.0018	0.1129	0.9101	-0.0032	0.0036
Gender	-0.2126	-0.3065	0.0150	-20.4915	0.0000	-0.3358	-0.2772
SGPA	0.0353	0.0397	0.0129	3.0706	0.0022	0.0143	0.0650
CGPA100	0.7805	0.7948	0.0117	67.8159	0.0000	0.7718	0.8178

Table 10 Correlation matrix of students' grades

	SGPA	CGPA100	FINAL CGPA
SGPA	1		
CGPA100	0.43	1	
FINAL CGPA	0.38	0.79	1

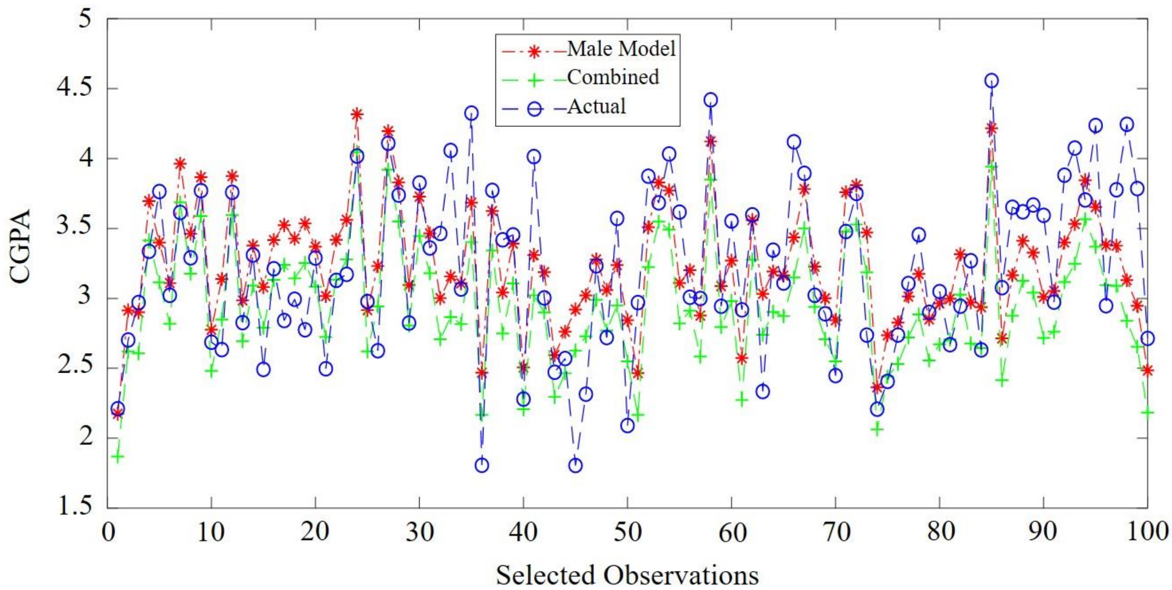

Figure 6 Actual CGPA comparison with the male model and combined model predictions

whereas there is a strong positive linear relationship (0.79) between the 100L CGPA and the final year CGPA. From Table 9, gender as a variable has a p-value of 2.131×10^{-71} (< 0.05), which implies that it is a significant predictor, with a t-value of 20.4915 (>1.96). Also, since the overall significance of the regression model is 0 as shown in Table 8, and the F score is 1574.80 > $F_{(4, 3041, 0.05)}$ 2.3749, i.e., the $F_{critical}$. The null hypothesis H_0 is thereby rejected, and the alternative hypothesis H_1: Gender has an effect on the prediction of the academic performance of students in Covenant University, (H1: $\beta_G \neq 0$), is accepted. The overall model that combines both the male and the female students (i.e., the overall model), with the highest F score, 1574.80, is the recommended model. Figure 6 presents a comparison of the actual CGPA for males and the overall model predictions for a few male samples. Figure 7 shows a comparison of the actual CGPA for females and the overall model predictions for a few female observations.

5. Discussion

The analysis revealed interesting comparisons between the two genders. Most importantly, it indicates that there is a tendency for the academic performance of female students to improve over time, while on the contrary, male students tend to drop in performance. This may be due to lack of concentration as a result of factors such as distractions on the Internet, excessive playing of computer games, and other social activities. There is a lot that goes on in the life of a student after graduation, and the significance of this transition has been largely ignored by stakeholders. Perrone (2003) [31] described this period to be a time of having low self-esteem, depression, uncertainty, loneliness, anxiety, stress, fear, and shock, among other negative feelings. They also assert that this period will affect the quality of life of these students, at least for the short term. Good grades can be related to the spate of opportunities that is available for the students. Espinoza and McGinn (2018) [32] were able to relate good grades to student satisfaction after graduation. Their ability to get good jobs after graduation makes them satisfied with their university attendance. Helping students to achieve success after graduation, demands that universities run programs with good course content together with balanced non-academic social aspects. Early academic performance prediction will provide a platform for providing adequate guidance to students to steer them away from potential failure, and put structures in place to help students achieve their target grades.

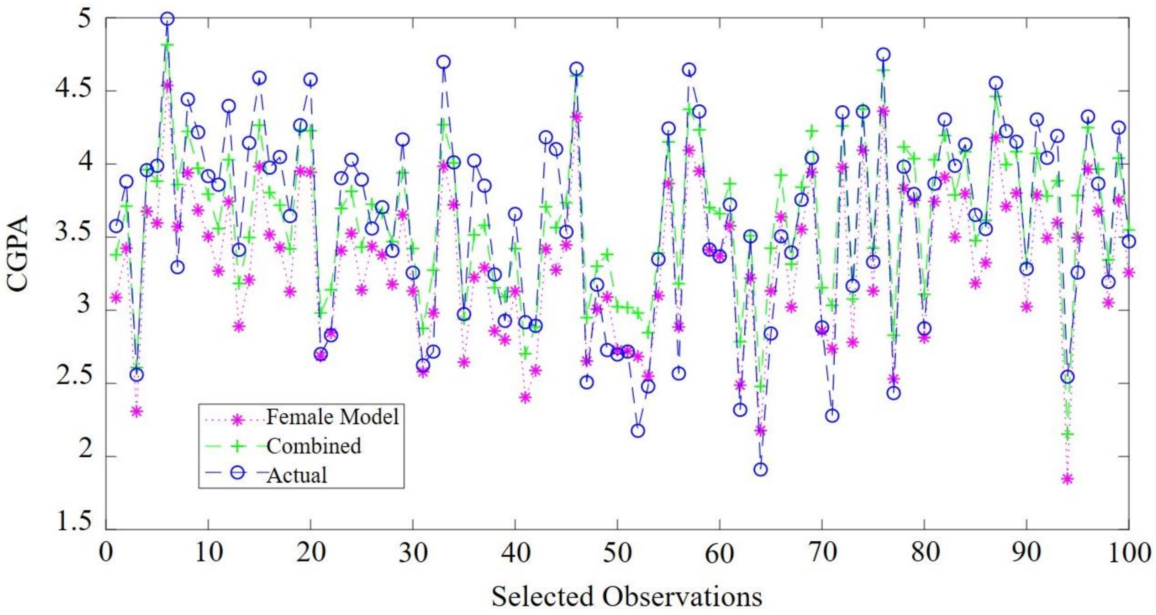

Figure 7 Actual CGPA comparison with female model and combined model predictions

6. Conclusions

The value of education is greatly determined by the quality of the education system to which a student is exposed. To ensure continuous relevance as an institution and to produce graduates that can meaningfully impact society after graduation, a higher education institution must develop quality assurance systems that track institutional efficiencies and practices to identify operational gaps toward proffering improvement. Student performance monitoring is one of the strategies for preventing failures through early identification of students with the potential to fail. This allows for intervention and adequate support to avert such negative outcomes. In this study, regression models were developed to predict the CGPA of both male and female students in the STEM programs in a Nigerian University. An R^2 value of 0.6374 was observed for the male category, while an R^2 value of 0.7069 was observed for the female category. This implies that the model for predicting the final CGPA of the female students is more reliable than that of the male counterparts because 70.69% of the variance in the CGPA of female students is explained by the independent variables. The result also reveals that there is a tendency for the performance of female students to progressively improve from the first to the final year, whereas for male students, a tendency for performance decline is noted. This may be due to peer pressure and the social lifestyle of male students which provide major avenues of distraction from the academic demands of a modern-day university.

7. References

[1] Odia LO, Omofonmwan SI. Educational system in Nigeria problems and prospects. J Soc Sci. 2007;14(1):86-5.

[2] Labo-Popoola SO, Bello AA, Atanda F. Universal basic education in Nigeria: challenges and way forward. Soc Sci. 2009;4(6):636-43.

[3] Bertoni E, Di M, Molini V, Nisticò R. Education is forbidden: the effect of the Boko Haram conflict on education in North-East Nigeria. J Dev Econ. 2018:1-19.

[4] Barnes AE, Boyle H, Simmons S. Reforming teacher education in Nigeria: laying a foundation for the future. Teach Teach Educ. 2019;79:153-63.

[5] Odukoya JA, Bowale EI, Okunlola S. Formulation and implementation of educational policies in Nigeria. Afr Educ Res J. 2018;6(1):1-4.

[6] Akeel U, Bell S, Mitchell JE. Assessing the sustainability literacy of the Nigerian engineering community. J Clean Prod. 2019;212:666-76.

[7] Prainetr S, Yotmongkol K, Prainetr N. Development of teaching electrical technology integrating PBL and CBL and supporting STEM education. Eng Appl Sci Res. 2018;45(1):65-9.

[8] Pornsurat P, Changsri N, Inprasitha M. STEM education in mathematics education: focusing on students' argumentation in primary school. Eng Appl Sci Res. 2018;45(4):316-9.

[9] Massagram W, Prapanitisatian S, Kesorn K. A novel technique for Thai document plagiarism detection using syntactic parse trees. Eng Appl Sci Res. 2018;45(4):290-300.

[10] Akinsowon OA, Osisanwo FY. Enhancing interest in sciences, technology and mathematics (STEM) for the Nigerian Female Folk. Int J Inform Sci. 2014;4(1):8-12.

[11] Akpan BB. Innovations in science and technology education through science teacher associations. Sci Educ Int. 2010;21(2):67-79.

[12] Zanden PJACVD, Denessen E, Cillessen AHN, Meijer PC. Domains and predictors of first-year student success: A systematic review. Educ Res Rev. 2018;23:57-77.

[13] Hu F. Do girl peers improve your academic performance?. Econ Lett. 2015;137:54-8.

[14] Goy SC, Wong YL, Low WY, Noor SNM, Fazli-Khalaf Z, Onyeneho N, et al. Swimming against the tide in STEM education and gender equality: a problem of recruitment or retention in Malaysia. Stud High Educ. 2018;43(11):1793-809.

[15] Stoet G, Geary DC. The gender-equality paradox in science, technology, engineering, and mathematics education. Psychol Sci. 2018;29(4):581-93.

[16] El Nagdi M, Roehrig GH. Gender equity in STEM education: the case of an Egyptian girls' school. In: Fomunyam KG, editor. Theorizing STEM Education in the 21st Century. London: IntechOpen; 2019.

[17] Beede DN, Julian TA, Langdon D, McKittrick G, Khan B, Doms ME. Women in STEM: a gender gap to innovation. USA: US Department of Commerce, Economics and Statistics Administration; 2011.

[18] Adekitan AI, Salau O. Toward an improved learning process: the relevance of ethnicity to data mining prediction of students' performance. SN Appl Sci. 2020;2(1):1-15.

[19] Pelumi O, Hilary O, Omoleye AO, Opanuga A. Analysis of the inter-relationship between students' first year results and their final graduating grades. Int J Adv Appl Sci. 2018;5(10):1-6.

[20] Adekitan AI, Salau O. The impact of engineering students' performance in the first three years on their graduation result using educational data mining. Heliyon. 2019;5(2):e01250.

[21] Oladokun V, Adebanjo A, Sc B, Charles-Owaba O. Predicting students academic performance using artificial neural network: a case study of an engineering course. Pac J Sci Tech. 2008;9:72-9.

[22] Arsad PM, Buniyamin N, Manan JA. Prediction of engineering students' academic performance using artificial neural network and linear regression: a comparison. 2013 IEEE 5th Conference on Engineering Education (ICEED); 2013 Dec 4-5; Kuala Lumpur, Malaysia. USA: IEEE; 2013. p. 1-6.

[23] Hussain S, Atallah R, Kamsin A, Hazarika J. Classification, clustering and association rule mining in educational datasets using data mining tools: a case study. In: Silhavy R, editor. Cybernetics and Algorithms in Intelligent Systems. Cham: Springer; 2019. p. 196-211.

[24] Sarra A, Fontanella L, Di Zio S. Identifying students at risk of academic failure within the educational data mining framework. Soc Indicat Res. 2019;146(1):41-60.

[25] Ramaswami G. Using educational data mining techniques to increase the prediction accuracy of student academic performance. Inform Learn Sci. 2019;120(7/8):451-67.

[26] Huang S, Fang N. Predicting student academic performance in an engineering dynamics course: a comparison of four types of predictive mathematical models. Comput Educ. 2013;61:133-45.

[27] John TM, Badejo JA, Popoola SI, Omole DO, Odukoya JA, Ajayi PO, et al. The role of gender on academic performance in STEM-related disciplines: Data from a tertiary institution. Data Brief. 2018;18:360-74.

[28] Oladele OM, Hou L. Students perspective comparison of higher education entrance examination: a tale of two countries; China and Nigeria education system. Acad Educ Leader J. 2019;23(2):1-16.

[29] Aribisala BS, Dosunmu OA, Akanbi MA, Shittu IO. Comparative analysis of university matriculation examination and post university matriculation examination admission models in Lagos State University. Ethiop J Sci Technol. 2018;11(2):129-43.

[30] Odukoya JA, Adekeye OA, Atayero AA, Omole DO, Badejo JA, John TM, et al. The predictive validity of university admission examinations: case study of Nigerian unified tertiary matriculation examination. Covenant Int J Psychol. 2018;3(1):1-10.

[31] Perrone L. Life after graduation as a "very uncomfortable world": an Australian case study. Educ Train. 2003;45(2):69-78.

[32] Espinoza O, McGinn N. Graduates' satisfaction as a measure of quality: Evidence from two programs in three Chilean universities. Int J Educ Res. 2018;90:133-43.