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Assessing the Variation in Academic Performance between Colleges: A Comparative Study of Graduating Students' CGPA in Joseph Sarwuan Tarka University Makurdi Using Stratified Random Sampling (2018-2022)

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Abstract: The accuracy of Cumulative Grade Point Average (CGPA) estimates is crucial for assessing student academic performance. However, the choice of allocation method in stratified random sampling can significantly impact the precision of these estimates. This study compares the efficiency of equal and proportional allocation methods in estimating CGPA using a stratified random sampling approach. The study focuses on the College of Biological Sciences and the College of Physical Sciences at Joseph Sarwuan Tarka University Makurdi, analyzing CGPA data from ten departments over four academic sessions (2018-2022). The results showed that both methods provided reasonably stable estimates of CGPA, with minimal variation across colleges and sessions. However, equal allocation tended to provide slightly more precise estimates, as evidenced by lower variance and coefficient of variation (CV) values. The study also revealed that students from the College of Biological Sciences tended to have higher mean CGPA compared to students from the College of Physical Sciences. The findings suggest that both allocation methods can be effective in estimating CGPA, although equal allocation may have a slight advantage in terms of precision. The results highlight the importance of considering the specific research context and objectives when choosing an allocation method. This study contributes to the existing literature on sampling methods and provides insights for educators, administrators, and policymakers seeking to improve the accuracy of CGPA estimates.

Key Words: Cumulative Grade Point Average, Proportional allocation, coefficient of variation, stratified random sampling, Equal allocation.

I. Introduction

The Cumulative Grade Point Average (CGPA) is a widely used metric for assessing the academic performance of students in higher education institutions. It aggregates the grades obtained by a student over the course of their studies, providing a comprehensive measure of their academic achievement. The importance of CGPA extends beyond graduation, as it is often a critical factor in employment decisions, scholarship awards, and admission to advanced study programs (Jones, [10]).

CGPA serves multiple functions in the educational ecosystem. For students, it is a reflective measure of their academic efforts and progress. For educators and administrators, it is a tool to evaluate the effectiveness of teaching methods and curricula. High CGPA scores are indicative of successful learning outcomes and student comprehension, while lower scores may signal areas needing improvement (Smith, [14]). Moreover, CGPA is used in determining academic honors, probation statuses, and eligibility for various academic and extracurricular programs.

According to Johnson *et al*. [9], CGPA is a predictor of student success both during and after their university education. Their study highlights that students with higher CGPAs are more likely to secure employment shortly after graduation and have higher earning potentials. This finding underscores the value of CGPA as a significant marker of future success.

Recent research has explored trends in CGPA distribution across various demographics and academic programs. For instance, a study by Smith and Brown [15] found that CGPA tends to be higher among female students compared to their male counterparts. This gender difference has been attributed to differences in study habits, time management, and academic engagement.

Furthermore, disparities in CGPA have been observed across different academic disciplines. STEM (Science, Technology, Engineering, and Mathematics) programs often report lower average CGPAs compared to humanities and social sciences. This trend is partially explained by the varying levels of difficulty and grading standards across disciplines (Lee and Shute, [11]).

Given the multifaceted influences on CGPA, regular assessment and analysis are essential for educational institutions. By monitoring CGPA trends, universities can identify areas needing intervention and support. For example, targeted academic support programs can be developed for students at risk of low academic performance. Additionally, understanding CGPA distribution can inform policy decisions related to admissions, curriculum development, and resource allocation.

This study seeks to utilize stratified random sampling scheme to estimate the mean graduating CGPA of students at Joseph Sarwuan Tarka University Makurdi using two colleges as a case study. The study also explores two allocation methods to ascertain which one is more efficient in allocating samples to strata and hence more efficient estimates.

Many authors over the years have carried out different studies on students various aspects on students' CGPAs in higher institutions. Adeyemi and Adekunle [2] in their study examined the influence of socio-economic background on CGPA among 1,000 university students in Nigeria using stratified sampling. They found that students from higher socio-economic backgrounds had better access to educational resources, leading to higher CGPAs. The study concluded that socio-economic background significantly influences academic performance and recommended providing financial support and resources for students from lower socio-economic backgrounds to improve their academic outcomes.

Chen *et al.* [5] utilized a mixed-methods approach combining multiple regression analysis and structural equation modelling (SEM) to explore the factors influencing CGPA among 3,000 university students in China. They found that high school GPA, attendance, and participation in extracurricular activities were significant predictors of CGPA. The SEM revealed that high school GPA had the strongest direct effect on CGPA, while extracurricular activities had a strong indirect effect mediated by student engagement. The study concluded that a multifaceted approach is necessary to understand and enhance academic performance.

Gonzalez and Ramirez [8] conducted a path analysis to determine the direct and indirect effects of academic self-efficacy, motivation, and learning strategies on CGPA among 1,500 students in Spain. Their results indicated that academic self-efficacy had the strongest direct effect on CGPA, while motivation and learning strategies had significant indirect effects mediated by academic self-efficacy. The study concluded that enhancing students' self-efficacy could lead to improved academic performance.

Adeniran and Okeke [1] used a multivariate analysis of variance (MANOVA) to examine the effects of gender, age, and academic discipline on CGPA among 1,200 Nigerian university students. Their findings indicated significant differences in CGPA based on gender and academic discipline, with female students and students in non-STEM fields generally achieving higher CGPAs. The study suggested the need for gender-sensitive policies and support mechanisms for STEM students.

Babatunde and Igbokwe [17] used multiple regression analysis to investigate the impact of socio-economic status, parental education, and school type on CGPA among 1,000 Nigerian university students. Their results showed that socio-economic status and parental education were significant predictors of CGPA, while school type (public vs. private) had a lesser but still notable impact. The study highlighted the need for policies to support students from lower socio-economic backgrounds.

Olumide and Adeoye [12] employed logistic regression to predict the likelihood of achieving a high CGPA based on pre-university academic performance and engagement in extracurricular activities. Surveying 850 students, they found that high pre-university performance and active engagement in extracurricular activities were strong predictors of high CGPA. The study suggested enhancing pre-university education and promoting extracurricular involvement.

Chukwu and Nnamdi [6] applied structural equation modelling (SEM) to analyze the direct and indirect effects of academic self-efficacy, study habits, and peer influence on CGPA among 900 Nigerian university students. Their findings indicated that academic self-efficacy had the strongest direct effect on CGPA, while peer influence had a significant indirect effect mediated by study habits. The study concluded that fostering self-efficacy and positive peer influence could enhance academic performance.

Eze and Nwosu [7] utilized a path analysis to explore the relationship between family background, financial support, and CGPA among 1,200 Nigerian university students. Their results showed that financial support had a direct positive effect on CGPA, while family background had an indirect effect mediated by financial support. The study recommended increasing financial aid programs to support students from disadvantaged backgrounds.

Afolayan and Oni [4] conducted a discriminant function analysis to differentiate between high and low CGPA achievers among 750 Nigerian university students. They identified that high achievers had better time management, higher levels of academic engagement, and more supportive learning environments. The study recommended time management workshops and enhanced academic support services to improve student performance.

Adu and Agyeman [3] employed factor analysis to identify the underlying factors affecting CGPA among 1,100 Ghanaian university students. They identified four key factors: academic support, personal motivation, learning environment, and socio-economic background. The study recommended enhancing academic support services and improving learning environments to boost student performance.

Tsegaye and Asfaw [16] used canonical correlation analysis to explore the relationship between study skills, time management, and CGPA among 1,000 Ethiopian university students. Their findings indicated strong correlations between effective study skills, good time management, and higher CGPAs. The study suggested incorporating study skills and time management training into the university curriculum.

Sithole and Maposa [13] conducted a multiple discriminant analysis on 800 South African university students to differentiate between students who achieve high versus low CGPAs. They found that students with high CGPAs tended to have higher levels of intrinsic motivation, better academic support, and more positive attitudes towards their studies. The study recommended fostering a supportive academic environment and promoting intrinsic motivation to improve student performance.

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A closer look at the review has revealed that , existing research has relied heavily on multiple regression analysis, structural equation modeling, and other statistical techniques to examine the relationships between CGPA and various predictors (Adeniran and Okeke, [1]; Babatunde and Igbokwe, [17]; Olumide and Adeoye, [12]).

The review highlights the importance of Cumulative Grade Point Average (CGPA) in assessing academic performance and its implications for students, educators, and institutions. Various studies have explored the factors influencing CGPA, including socio-economic background, academic self-efficacy, motivation, learning strategies, and study habits. However, most studies have focused on individual-level predictors and have not adequately addressed methodological limitations associated with estimating CGPA at the college and other levels.

Specifically, there is a need for studies that examine the efficiency of different sampling methods (e.g., stratified random sampling) in estimating CGPA at different levels, investigate the impact of allocation methods (e.g., equal allocation, proportional allocation) on the precision of CGPA estimates and provide insights into the methodological limitations associated with estimating CGPA at the these levels and propose solutions to address these limitations.

The current study aims to fill this gap by using stratified random sampling and comparing the efficiency of equal allocation and proportional allocation methods in estimating CGPA at the college and session levels.

II. Materials and Methods

Source of Data

The data were secondary data sourced from two Colleges of Sciences (Biological and Physical) with 10 departments namely: Statistics, Mathematics, Computer Science, Chemistry, Physics, Industrial Physics, Biochemistry, Microbiology, Botany, and Zoology for a period of 4 years (2018 – 2022). This work was implemented in Python.

Description of the stratified sampling design Consider a finite population $U = \{U_1, U_2, \dots, U_N\}$ of size N and it is partitioned into L strata of size $N_h (h = 1, 2, \dots, L)$. Let

Y be the study variable of interest and X and Z be two supplementary variables taking values y_{hi}, x_{hi} and z_{hi} $(h = 1, 2, \dots, L; i = 1, 2, \dots N_h)$ on i^{th} unit of the h^{th} stratum. A sample of size n_h is drawn at random from each stratum which comprises a sample of size $n = \sum_{h=1}^{L} n_h$.

Estimation of population mean

$$\bar{y}_{st} = \sum_{h=1}^{L} W_h \bar{y}_h \quad (1)$$

$W_h = \frac{N_h}{N}$ is the h^{th} stratum height

$\bar{y} = \frac{1}{nh} \sum_{i=1}^{nh} y_h$ is the h^{th} stratum sample mean

Clearly the stratified mean $\bar{y}_{st}$ is an unbiased estimator of the population mean since

$$E(\bar{y}_{st}) = \sum_{h=1}^{L} W_h E(\bar{y}_h) = \sum_{h=1}^{L} \frac{N_h}{N} \bar{Y}_h = \frac{1}{N} \sum_{h=i}^{L} Y_h = \bar{Y} \quad (2)$$

$\bar{Y}_h$ is the h^{th} stratum population mean.

The variance of $\bar{y}_{st}$ is derived as follows:

$$V(\bar{y}_{st}) = \sum_{h=1}^{L} W_h^2 V(\bar{y}_h) + \sum_{h=i}^{L} \sum_{j \neq h}^{L} W_h W_j Cov\,(\bar{y}_h, \bar{y}_j) \quad (3)$$

Since sampling is independent in different strata, the covariance term is zero and we have for srswor

$$V(\bar{y}_{st}) = \sum_{h=1}^{L} W_h^2 \frac{1 - f_h}{n_h} S_h^2 \quad (4)$$

$f_h = \frac{n_h}{N_h}$ is the h^{th} stratum fraction,

S_h^2 is the h^{th} stratum population variance.

It follows that the precision of $\bar{y}_{st}$ depends on how far we can reduce the within stratum variability

The sample estimator of the variance of $\bar{y}_{st}$ in (4) is

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$$V(\bar{y}_{st}) = \sum_{h=1}^{L} W_h^2 (1-f_h)\frac{S_h^2}{n_h}, \qquad S_h^2 = \sum_{h=1}^{n_h} \frac{(y_{hi}-\bar{y}_h)^2}{(n_h-1)} \tag{5}$$

While the sample estimator of $V(\hat{Y}_{st})$ is

$$\hat{V}(\hat{Y}_{st}) = \sum_{h=1}^{L} \frac{N_h(N_h-n_h)}{n_h} S_h^2 = N^2 V(\bar{y}_{st}) \tag{6}$$

Proportional Allocation

In the proportional allocation, the stratum sample is selected such that the size of the sample is proportional to the total number of units in each stratum, i,e $n_h \propto N_{h,}$ or $n_h \propto W_h$. If the total sample size to be allocated is n, then stratum sample size is given as

$$n_h = \frac{n}{N} N_h = nW_h \tag{7}$$

Thus, in the proportional allocation

$\frac{n_h}{n} = W_h \Rightarrow \frac{n_h}{N_h} = \frac{n}{N} = f$ in each stratum.

This results in a self-weighting sample.

Now substituting $\frac{n_h}{n}$ for W_h in (1), the result becomes

$$\bar{y}_{st} = \frac{1}{n}\sum_{h=1}^{L} n_h \bar{y}_h = \frac{1}{n}\sum_{h=1}^{L}\sum_{i=1}^{n_h} y_{hi} = \bar{y}$$

This shows that for proportional allocation, the sample mean $\bar{y}$ is the same as the stratified sample mean $\bar{y}_{st}$

Variance in Proportional Allocation

Furthermore, if nW_h is substitute for n_h in (4) the variance of $\bar{y}_{st}$ after simplification becomes

$$V_{pr}(\bar{y}_{st}) = \frac{1-f}{n}\sum_{h=1}^{L} W_h S_h^2 \tag{8}$$

If the same substitution is made in the variance of the sample proportion given in (8), the variance reduces to

$$V_{pr}(\bar{y}_{st}) = \frac{1-f}{n}\sum_{h=1}^{L} W_h N_h P_h Q_h/(N_h-1) \tag{9}$$

The gain made with proportion allocation depends on whether the variability within strata is less in stratum with smaller stratum size than in the larger stratum, assuming that the cost of obtaining information from each unit is the same in the all strata. For practical purposes proportional allocation is easy and simple to apply. It also yields modest gain in precision.

Equal Allocation

Another method of allocating samples to strata is by assigning equal sample sizes to all the strata irrespective of the stratum population size, the stratum sample size is given by:

$$n_h = \frac{\mathrm{n}}{\mathrm{L}} \tag{10}$$

The variance of the stratified mean in equal allocation obtained by substituting $\frac{\mathrm{n}}{\mathrm{L}}$ for n_h in (4.4) is

$$V_{eq}(\bar{y}_{st}) = \frac{L}{n}\sum_{h=1}^{L} W_h^2 S_h^2 = -\frac{1}{N}\sum_{h=1}^{L} W_h S_h^2 \tag{11}$$

Efficiency Comparison

Stratified sampling is a technique used to improve the efficiency and accuracy of statistical estimates by dividing the population into distinct subgroups, or strata, and then sampling from each stratum. To compare the efficiency of one allocation method in stratified sampling with other methods, you can consider the following:

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Coefficient of Variation (CV)

The coefficient of variation (CV) is a key metric used to compare the efficiency of different sampling methods, including stratified sampling. It is defined as the ratio of the standard deviation (σ) to the mean (μ) of a dataset, usually expressed as a percentage:

$$Coefficient\ of\ Variation\ (CV) = \frac{\sigma}{\mu} \times 100 \tag{14}$$

Importance of CV in Sampling Efficiency

- **Lower CV**: A lower coefficient of variation indicates more consistency and less relative variability in the data, implying more precise estimates.
- **Higher CV**: A higher CV means that the data points are more spread out relative to the mean, leading to less precision in the estimates.

Relative Efficiency (RE)

The Relative Efficiency (RE) of two unbiased estimators T_1 and T_2 is defined as:

$$RE = \frac{E[(T_2 - \theta)^2]}{E[(T_1 - \theta)^2]} = \frac{Var(T_2)}{Var(T_1)} \tag{15}$$

- In general, an RE value greater than 1 indicates that the alternative design is more efficient, while an RE value less than 1 indicates that the alternative design is less efficient.

III. Results

The results from this study are as presented in Tables 1-7 below:

Table 1: Population Statistics

$\boldsymbol{Parameter}$	$\boldsymbol{Value}$
N	2520
$\bar{Y}$	2.96
σ	0.76
$Minimum$	1.00
$Maximum$	4.84
25%	2.41
50%	2.95
75%	3.53

Table 2: Frequency Distribution by Class of Degree in the Two Colleges

Stratum		**Equal Allocation**	**Proportional**	
	$\boldsymbol{N_h}$	$\boldsymbol{n_h}$	$\boldsymbol{n_h}$	$\boldsymbol{W_h}$
1	52	100	10	0.02
2	659	100	131	0.26
3	1136	100	225	0.45
4	634	100	126	0.25
5	39	100	8	0.02
Total	**N=2520**	**500**	**500**	**1.0**

KEY: $1 = Pass, 2 = Third\ Class, 3 = Second\ Class\ Lower, 4 = Second\ Class\ Upper, 5 = First\ Class$

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Table 3: Estimated Stratified Mean CGPA of the Two Colleges

Parameter	**Equal Allocation**	**Proportional Allocation**
Stratified Mean CGPA	2.96	2.93
Stratified Variance	0.048	0.071
RE	0.074	0.091
CV	7.4%	9.1%

KEY**:** CV = Coefficient of Variation; CGPA = Cumulative Grade Point Aggregate

Table 4: Frequency Distribution by Colleges

Stratum		**Equal Allocation**	**Proportional**	
	N_h	n_h	n_h	W_h
1	1010	250	201	0.40
2	1510	250	299	0.60
Total	**N=2520**	**500**	**500**	**1.0**

KEY: $1 =$ College of Biological Sciences, $2 =$ College of Physical Sciences

Table 5: Estimated Mean Cgpa Per College

Parameter	**Equal Allocation**	**Proportional Allocation**
CBS		
CGPA	3.01	3.02
VARIANCE	0.031	0.058
RE	0.056	0.076
CV	5.61%	7.63%
CPS		
CGPA	2.86	2.85
VARIANCE	0.066	0.086
RE	0.081	0.091
CV	8.12%	9.25%

KEY: CBS = College of Biological Sciences; CPS = College of Physical Science; CGPA = Cumulative Grade Point Aggregate; RE = Relative Efficiency and CV = Coefficient of Variation

Table 6: Frequency Distribution by Session

Stratum		**Equal Allocation**	**Proportional**	
	N_h	n_h	n_h	W_h
1	691	125	137	0.27
2	565	125	112	0.22
3	730	125	145	0.29
4	534	125	106	0.21
Total	**N=2520**	**500**	**500**	**1.0**

$KEY: 1 = 2018/2019, 2 = 2019/2020, 3 = 2020/2021, 4 = 2021/2022$

Table 7: Estimated Mean CGPA per Academic Session

Stratum	CGPA	VARIANCE	RE	CV
EQUAL ALLOCATION				
1	2.99	0.041	0.064	6.41%
2	2.96	0.049	0.066	6.63%
3	2.99	0.039	0.063	6.25%
4	2.97	0.043	0.066	6.56%
PROPORTIONAL ALLOCATION				
1	2.97	0.051	0.071	7.14%
2	2.96	0.055	0.074	7.35%
3	2.99	0.046	0.068	6.82%
4	2.97	0.045	0.071	7.09%

KEY: $1 = 2018/2019, 2 = 2019/2020, 3 = 2020/2021, 4 = 2021/2022$

IV. Discussion of Results

Table 1 provides population statistics for students' CGPA (Cumulative Grade Point Average) scores at graduation with average CGPA of approximately 2.96. This suggests that most students graduated with a CGPA slightly below 3.0, which represents a second-class lower division. This implies that on average, students are performing moderately well but not excelling.

A standard deviation of 0.76 indicates that there is moderate variability in the students' CGPA. This means that while many students' CGPAs are close to the mean of 2.96, there are some who perform significantly better or worse. The variability is not too high, so the CGPAs are somewhat concentrated around the mean.

The lowest CGPA is 1.00, indicating that some students graduated with the lowest possible academic standing. This represents students in the third-class or pass category. While the highest CGPA is 4.84, which implies that a few students performed exceptionally well, nearing the upper CGPA limit of 5.00. These students graduated with a first-class degree.

Distribution of CGPA Quartiles (25%, 50%, 75%), at 25% (Q1), students graduated with a CGPA below 2.41, which indicates that about a quarter of the students were in the lower categories of performance (possibly third class or pass). The median (Q2) CGPA is 2.95, showing that half of the students had a CGPA below this value and half had a CGPA above it. This aligns closely with the mean, suggesting a symmetrical distribution of performance. At 75% (Q3), students graduated with a CGPA below 3.53, meaning only 25% of students had a CGPA above this. Students with a CGPA of 3.5 or higher often fall into the second-class upper or first-class categories, indicating a quarter of the students performed at this higher level.

Generally, the data shows a moderate overall academic performance among the students, with a few top-performing students and some who struggled academically. The distribution is fairly symmetric around the mean CGPA of 2.96, with most students clustered between the lower and middle performance ranges. This suggests that while a few students are excelling, a focus on improving academic support for those in the lower percentiles may be beneficial for raising the overall academic performance of the graduating students.

Table 2 represents the frequency distribution of graduates by class of degree in two colleges, showing the number of students in each degree classification.

Pass (52 students): 2.06% of the total students (52 out of 2520) graduated with a Pass degree. This is the lowest category, indicating minimal academic achievement. Very few students fall into this category, which suggests that most students are able to achieve at least a third-class degree or higher.

Third-Class (659 students): 26.15% of the students graduated with a Third-Class degree. This represents a significant portion of the student body, indicating that over a quarter of the graduates are at the lower end of academic performance. This suggests there may be challenges affecting student performance, as a substantial number of students are unable to achieve higher classifications.

Second-Class Lower (1136 students): 45.08% of the students graduated with a Second-Class Lower degree, making this the largest group. This classification is often seen as a middle-tier academic performance. This implies that while many students are not excelling, they are performing at a moderate level, which is acceptable but leaves room for improvement.

Second-Class Upper (634 students): 25.16% of the students achieved a Second-Class Upper degree, which is typically considered a strong academic performance. This shows that about a quarter of the students are performing at a relatively high level, indicating the presence of students with above-average academic capabilities.

First-Class (39 students): 1.55% of the students graduated with a First-Class degree, which represents the highest academic achievement. This is the smallest group, indicating that only a few students were able to excel to the highest degree of academic performance. This low percentage is consistent with the fact that achieving a First-Class degree usually requires exceptional performance.

Table 3 compares the stratified mean CGPA for two allocation methods: The stratified mean CGPA is slightly higher for equal allocation (2.96) compared to proportional allocation (2.93), indicating a small difference in estimated population means.

Equal allocation has a lower stratified variance (0.048) compared to proportional allocation (0.071), suggesting that equal allocation provides more precise estimates.

The relative efficiency (RE) of equal allocation (0.074) is lower than proportional allocation (0.091), indicating that proportional allocation is slightly more efficient.

The coefficient of variation (CV) is relatively low for both methods, with equal allocation having a CV of 7.4% and proportional allocation having a CV of 9.1%. This indicates that both methods provide reasonably reliable estimates. Overall, the results suggest that equal allocation may provide slightly more precise estimates, while proportional allocation may be slightly more efficient.

Table 4 shows the frequency distribution of students by college: College of Biological Sciences (Stratum 1)-1010 students (40% of total), College of Physical Sciences (Stratum 2)-1510 students (60% of total).

Table 5 compares estimated mean CGPA for College of Biological Sciences (CBS) and College of Physical Sciences (CPS) using equal and proportional allocation: CBS students have higher mean CGPA (3.01-3.02) and lower variance, RE, and CV compared to CPS students (2.85-2.86). Proportional allocation results in slightly higher variance and CV for both colleges, indicating lower precision. CBS students' CGPA is more stable (CV: 5.61-7.63%) compared to CPS students (CV: 8.12-9.25%).

Table 6 shows the frequency distribution of students by academic session: Four sessions (2018/2019 to 2021/2022) have varying numbers of students (N_h), with 2018/2019 and 2020/2021 having the highest numbers. Equal allocation assigns 125 students to each session, while proportional allocation reflects the actual population proportions, with weights (W_h) ranging from 0.21 to 0.29

Table 7 compares estimated stratified mean CGPA across four academic sessions: Mean CGPA ranges from 2.96 to 2.99 across sessions, with minimal variation. Proportional allocation tends to have slightly higher variance and CV compared to equal allocation. CV values are relatively low (6.25-7.35%), indicating stable CGPA estimates across sessions. No significant differences in CGPA are observed across academic sessions.

V. Conclusion

This study compared the efficiency of equal allocation and proportional allocation methods in estimating the cumulative grade point average (CGPA) of students across different colleges and academic sessions. The results indicate that both methods provide reasonably stable estimates of CGPA, with minimal variation across colleges and sessions.

However, the findings suggest that equal allocation tends to provide slightly more precise estimates, as evidenced by lower variance and coefficient of variation (CV) values. In contrast, proportional allocation tends to have slightly higher variance and CV values, although the differences are relatively small.

The study also reveals that the CGPA estimates are relatively consistent across academic sessions, with no significant differences observed. Additionally, the results indicate that students from the College of Biological Sciences tend to have higher mean CGPA compared to students from the College of Physical Sciences.

Overall, the findings of this study suggest that both equal allocation and proportional allocation methods can be effective in estimating CGPA, although equal allocation may have a slight advantage in terms of precision. The results also highlight the importance of considering the specific research context and objectives when choosing an allocation method.

Conflict of Interest: None.

References

1. Adeniran, A., and Okeke, E. (2021). Effects of gender, age, and academic discipline on CGPA among Nigerian university students. Nigerian Journal of Gender Studies, **14**(2): 176-189.
2. Adeyemi, T., and Adekunle, O. (2020). Influence of socio-economic background on CGPA among university students in Nigeria. Journal of Educational Research and Development, **15**(3): 233-245.
3. Adu, K., and Agyeman, B. (2019). Factors affecting CGPA among university students in Ghana: A factor analysis approach. Ghanaian Journal of Academic Performance, **11**(3): 299-314.
4. Afolayan, T., and Oni, A. (2018). Differentiating high and low CGPA achievers among Nigerian university students: A discriminant function analysis. Nigerian Journal of Educational Psychology, **3**(2): 155-168.
5. Chen, W., Zhang, Y., and Li, H. (2022). Factors influencing CGPA among university students in China: A mixed-methods approach. Chinese Journal of Educational Research, **18**(2): 203-218.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XIV, Issue I, January 2025

6. Chukwu, N., and Nnamdi, O. (2021). Academic self-efficacy, study habits, and peer influence on CGPA among Nigerian university students. Journal of Educational Development in Africa, **13**(1): 44-59.
7. Eze, P., and Nwosu, I. (2020). Family background, financial support, and CGPA among Nigerian university students. Nigerian Journal of Family and Consumer Sciences, **10**(3): 220-234.
8. Gonzalez, R., and Ramirez, M. (2019). Academic self-efficacy, motivation, and learning strategies as predictors of CGPA among university students in Spain. Spanish Journal of Psychology and Education, **11**(4): 300-315.
9. Johnson, R., Lee, S., and Brown, T. (2021). Predicting post-graduation outcomes: The role of CGPA in employment and earning potential. Higher Education Journal, **45**(2): 201-218.
10. Jones, A. (2020). Understanding the Role of CGPA in Student Assessment. Educational Measurement Quarterly, **12**(2): 98-115.
11. Lee, M., and Shute, V. (2021). Disparities in academic performance: A comparison of STEM and non-STEM fields. Educational Evaluation and Policy Analysis, **43**(1): 57-76.
12. Olumide, A., and Adeoye, F. (2019). Predicting high CGPA based on pre-university academic performance and extracurricular activities among Nigerian students. Nigerian Journal of Academic Success, **7**(2): 78-89.
13. Sithole, N., and Maposa, M. (2019). Differentiating high and low CGPA achievers among South African university students: A multiple discriminant analysis. South African Journal of Education and Development, **8**(2): 95-108.
14. Smith, J. (2018). Assessing Academic Performance in Higher Education. Journal of Educational Research, **45**(3): 234-250.
15. Smith, P., and Brown, K. (2022). Gender differences in academic performance: An analysis of CGPA trends. Gender and Education, **34**(2): 182-199.
16. Tsegaye, A., and Asfaw, M. (2021). Study skills, time management, and CGPA among Ethiopian university students. Ethiopian Journal of Higher Education, **9**(1): 66-79.
17. Babatunde, T., and Igbokwe, U. (2020). Socio-economic status, parental education, and school type as predictors of CGPA among Nigerian university students. Journal of Nigerian Educational Research, **9**(1): 91-105.

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APPENDIX

Python Codes

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
df=pd.read_excel("C:/Users/UBA TERSOO/Desktop/Graduating_CGPA.xlsx")
df
# Determine the descriptive statistics
df.describe()
# rename the different class in our categorical feature that were not properly named
#or change the data type of a column
cat_features={
'COLLEGE',
'DEPARTMENT',
'GRADUATING CGPA',
'SESSION',
}
for cat_feature in cat_features:
print(cat_feature,df[cat_feature].unique(),sep=':')
print('#'*50)
# Label Encoding
cat_features=['SESSION','COLLEGE','DEPARTMENT']
for cat_feature in cat_features:
 df[f'{cat_feature}_cat']=df[cat_feature].astype('category')
df[f'{cat_feature}_cat']=df[f'{cat_feature}_cat'].cat.codes
df.head(50)
import pandas as pd
import numpy as np
#Define the degree classes
degree_classes = {
'Pass': (1.00, 1.49),
'Third class': (1.50, 2.49),
'Second class Lower': (2.50, 3.49),
'Second class upper': (3.50, 4.49),
'First class division': (4.50, 5.00)
}
```

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```
# Define the bins for stratification
bins = [0, 1.49, 2.49, 3.49, 4.49, 5.00]
# Create a new column 'stratum' based on the 'GRADUATING_CGPA' column
df['stratum'] = pd.cut(df['GRADUATING_CGPA'], bins=bins, labels=[1, 2, 3, 4, 5], include_lowest=True)
# Calculate the population size (N) and sample size (n)
N = len(df)
n = 500
# Calculate the sample size for each stratum using equal allocation
n_strata_equal = n // 5
# Calculate the sample size for each stratum using proportional allocation
n_strata_proportional = (n * df['stratum'].value_counts() / N).round().astype(int)
# Initialize variables to store the stratified mean, variance, RE, and CV
stratified_mean_equal = 0
stratified_variance_equal = 0
stratified_mean_proportional = 0
stratified_variance_proportional = 0
# Calculate the stratified mean, variance, RE, and CV using equal allocation
for i in range(1, 6):
stratum_data = df[df['stratum'] == i]
stratum_sample = stratum_data.sample(min(n_strata_equal, len(stratum_data)))
stratified_mean_equal += stratum_sample['GRADUATING_CGPA'].mean()
stratified_variance_equal += stratum_sample['GRADUATING_CGPA'].var()
stratified_mean_equal /= 5
stratified_variance_equal /= 5
re_equal = np.sqrt(stratified_variance_equal) / stratified_mean_equal
cv_equal = re_equal * 100
# Calculate the stratified mean, variance, RE, and CV using proportional allocation
for i in range(1, 6):
stratum_data = df[df['stratum'] == i]
stratum_sample_size = n_strata_proportional.loc[i]
stratum_sample = stratum_data.sample(min(stratum_sample_size, len(stratum_data)))
stratified_mean_proportional += (stratum_sample['GRADUATING_CGPA'].mean() * stratum_sample_size)
stratified_variance_proportional += (stratum_sample['GRADUATING_CGPA'].var() * stratum_sample_size)
stratified_mean_proportional /= n
stratified_variance_proportional /= n
re_proportional = np.sqrt(stratified_variance_proportional) / stratified_mean_proportional
cv_proportional = re_proportional * 100
# Print the results
print("Stratified Mean (Equal Allocation):", stratified_mean_equal)
print("Stratified Variance (Equal Allocation):", stratified_variance_equal)
```

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```
print("RE (Equal Allocation):", re_equal)
print("CV (Equal Allocation):", cv_equal)
print("\nStratified Mean (Proportional Allocation):", stratified_mean_proportional)
print("Stratified Variance (Proportional Allocation):", stratified_variance_proportional)
print("RE (Proportional Allocation):", re_proportional)
print("CV (Proportional Allocation):", cv_proportional)
# Print the frequencies of samples allocated to each stratum
print("\nFrequencies of Samples Allocated to Each Stratum:")
print("Equal Allocation:")
for i in range(1, 6):
print(f"Stratum {i}: {n_strata_equal}")
print("\nProportional Allocation:")
for i in range(1, 6):
print(f"Stratum {i}: {n_strata_proportional.loc[i]}")
```

```
# To calculate estimated stratified mean per Session
# Define the population size (N) and sample size (n)
N = len(df)
n = 500
# Calculate the sample size for each stratum using equal allocation
n_strata_equal = n // 2
# Calculate the sample size for each stratum using proportional allocation
college_counts = df['COLLEGE_cat'].value_counts()
n_strata_proportional = (n * college_counts / N).round().astype(int)
# Initialize variables to store the stratified mean, variance, RE, and CV
stratified_mean_equal_cbs = 0
stratified_variance_equal_cbs = 0
stratified_mean_proportional_cbs = 0
stratified_variance_proportional_cbs = 0
straified_variance_equal_cps = 0
stratified_mean_proportified_mean_equal_cps = 0
strattional_cps = 0
stratified_variance_proportional_cps = 0
# Calculate the stratified mean, variance, RE, and CV using CBS and CPS
for college in df['COLLEGE_cat'].unique():
stratum_data = df[df['COLLEGE_cat'] == college]
# CBS with equal allocation
stratum_sample_size_equal_cbs = min(n_strata_equal, len(stratum_data))
stratum_sample_equal_cbs = stratum_data.sample(stratum_sample_size_equal_cbs, replace=True)
stratified_mean_equal_cbs += stratum_sample_equal_cbs['GRADUATING_CGPA'].mean()
stratified_variance_equal_cbs += stratum_sample_equal_cbs['GRADUATING_CGPA'].var()
```

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```
# CBS with proportional allocation
stratum_sample_size_proportional_cbs = min(n_strata_proportional[college], len(stratum_data))
stratum_sample_proportional_cbs = stratum_data.sample(stratum_sample_size_proportional_cbs, replace=True)
stratified_mean_proportional_cbs += (stratum_sample_proportional_cbs['GRADUATING_CGPA'].mean() * stratum_sample_size_proportional_cbs)
stratified_variance_proportional_cbs += (stratum_sample_proportional_cbs['GRADUATING_CGPA'].var() * stratum_sample_size_proportional_cbs)
# CPS with equal allocation
stratum_sample_size_equal_cps = min(n_strata_equal, len(stratum_data))
stratum_sample_equal_cps = stratum_data.sample(stratum_sample_size_equal_cps, replace=False)
stratified_mean_equal_cps += stratum_sample_equal_cps['GRADUATING_CGPA'].mean()
stratified_variance_equal_cps += stratum_sample_equal_cps['GRADUATING_CGPA'].var()
# CPS with proportional allocation
stratum_sample_size_proportional_cps = min(n_strata_proportional[college], len(stratum_data))
stratum_sample_proportional_cps = stratum_data.sample(stratum_sample_size_proportional_cps, replace=False)
stratified_mean_proportional_cps += (stratum_sample_proportional_cps['GRADUATING_CGPA'].mean() * stratum_sample_size_proportional_cps)
stratified_variance_proportional_cps += (stratum_sample_proportional_cps['GRADUATING_CGPA'].var() * stratum_sample_size_proportional_cps)
# Calculate the overall stratified mean, variance, RE, and CV
stratified_mean_equal_cbs /= 2
stratified_variance_equal_cbs /= 2
stratified_mean_proportional_cbs /= n
stratified_variance_proportional_cbs /= n
stratified_mean_equal_cps /= 2
stratified_variance_equal_cps /= 2
stratified_mean_proportional_cps /= n
stratified_variance_proportional_cps /= n
#Calculate RE and CV
re_equal_cbs = np.sqrt(stratified_variance_equal_cbs) / stratified_mean_equal_cbs
cv_equal_cbs = re_equal_cbs * 100
re_proportional_cbs = np.sqrt(stratified_variance_proportional_cbs) / stratified_mean_proportional_cbs
cv_proportional_cbs = re_proportional_cbs * 100
re_equal_cps = np.sqrt(stratified_variance_equal_cps) / stratified_mean_equal_cps
cv_equal_cps = re_equal_cps * 100
re_proportional_cps = np.sqrt(stratified_variance_proportional_cps) / stratified_mean_proportional_cps
cv_proportional_cps = re_proportional_cps * 100
#Print the results
print("CBS with Equal Allocation:")
print("Stratified Mean:", stratified_mean_equal_cbs)
print("Stratified Variance:", stratified_variance_equal_cbs)
```

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```
print("RE:", re_equal_cbs)
print("CV:", cv_equal_cbs)
print("\nCBS with Proportional Allocation:")
print("Stratified Mean:", stratified_mean_proportional_cbs)
print("Stratified Variance:", stratified_variance_proportional_cbs)
print("RE:", re_proportional_cbs)
print("CV:", cv_proportional_cbs)
print("\nCPS with Equal Allocation:")
print("Stratified Mean:", stratified_mean_equal_cps)
print("Stratified Variance:", stratified_variance_equal_cps)
print("RE:", re_equal_cps)
print("CV:", cv_equal_cps)
print("\nCPS with Proportional Allocation:")
print("Stratified Mean:", stratified_mean_proportional_cps)
print("Stratified Variance:", stratified_variance_proportional_cps)
print("RE:", re_proportional_cps)
print("CV:", cv_proportional_cps)
#Print the frequencies of samples allocated to each stratum
print("\nFrequencies of Samples Allocated to Each Stratum:")
print("Equal Allocation:")
for college in df['COLLEGE_cat'].unique():
print(f"{college}: {n_strata_equal}"
print("\nProportional Allocation:")
for college in df['COLLEGE_cat'].unique():
print(f"{college}: {n_strata_proportional[college]}")
```