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Investigating the Interplay between Students Entering Age and Grades: the Gibbs Sampling Approach

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Keywords

Academic Performance, Tertiary institution, Bayesian Regression, Gibbs Sampling

Abstract

Although periodic reviews of the requirements for admission into universities in Nigeria are essential for quality education and enhanced academic performance, however, they at times have negative consequences, such as inconsistent policies resulting in unstable benchmark standards. This paper appraises students' academic performance using the Bayesian Linear Regression Model in comparison with the classical linear regression model. A sample of 146 graduating students from the Faculty of Physical Sciences, Modibbo Adama University, Yola in Nigeria was used. The study reveals that the final Cumulative Grade Point Average (CGPA) of students does not depend on their entry age but on their first-year CGPA. Based on the standard error of the parameter estimates as well as the Bayesian Credible Interval and Confident Interval, the Bayesian approach performed better than the classical Linear Regression Model. Against the backdrop of pegging the entry age for Nigerian tertiary institutions, the work recommends that Age should not be considered a barrier to intending students while admonishing them to take their academic activities seriously right from the first year.

Mathematical Subject Classification: 62J02, 62F15, 62J05, 65C05

1. Introduction

Over the years, the Nigerian tertiary education admission body, the Joint Admissions and Matriculation Board (JAMB) has relaxed the uniform cut-off mark for admission, allowing every tertiary institution to fix its cut-off mark but with minimum benchmark. However, instead of relaxing the age limit as well, there has been strict adherence to the minimum of sixteen (16) years age requirement for any candidate to obtain admission to any university in Nigeria. In so doing, emphasis is placed on age rather than performance.

Recently, the minister of education at the policy meeting of the JAMB made an attempt to bar students under 18 years from enrolling in higher education institutions in the country (Bolaji, 2024), lending

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weight to the emphasis on age and not performance or character. The Minister's advocacy to review the minimum age requirement upward to eighteen (18) years generated serious argument and counterargument from parents and other stakeholders in the university education. On the contrary, similar argument followed the policy on the reduction for elementary school enrolment age from the traditional 7 years to 3 or 4 years in Zimbabwe (Sibanda, 2023). Striking a balance between the divergent entering age policies in the two countries (Nigeria and Zimbabwe), Pellizzari and Billari (2011) investigated students of different ages within the same cohorts at Bocconi University. Controlling for potential selection effects as well as differences in cognitive ability in the data, Pellizzari & Billari, (2011) and Billari & Pellizzari (2008) establish that, at the undergraduate level, youngest students perform better compared with their oldest peers especially, in technically oriented subjects. While age and performance are requirements for job placement, most employers, especially financial institutions, prefer very young employees. Graduates face a lot of challenges as a result of age specification during recruitment especially, by organizations like the banking sector in Nigeria as studied by Adedeji & Olekanma, (2024). Abdullahi (2023) observes that the government's parastatals in most cases fix the age limit for job recruitment at 25 years of age.

In so doing, the emphasis is on performance and minimum age. Achugbu, (2024)stated that most graduates hardly turn out from the university within the age required by these institutions due to the restriction placed on entering age, prolonged incessant strikes by the university-based unions, and inconsistent academic calendar. Strike actions for instance, usually cause instability in the academic calendar, and consequently prolong students' number of years in school as explored by Egwu, (2021). By and large, the reality on the ground is opposed to the intended policies and practices of the admission body.

The admission-age and workplace-age requirement often place candidates between opposing situations. This paradox calls for investigation into the relationship between age and performance grades of university students, and this is the target of this paper. Using the Bayesian Linear Regression Model, this paper empirically investigates the interplay between students entering age, starting grade, and final grade. We investigated the dependency of final-year CGPA on first-year GPA and entry age using data from the Faculty of Physical Sciences, Modibbo Adama University, Yola.

2. Literature Review

Education is a powerful tool capable of producing qualified man-power, improving health and livelihoods, accelerating economic development, and solving the real problems of a community as noted by Tadese, et al., (2022). The extent to which the livelihood can improve, and economic development is accelerated depends on the performance or outcome of student engagement. Performance is an act of doing a task in a bit to attract commendation or reward. This may depend to a large extent on factors like experience, age, environment, motivations, and the availability of needed resources as investigated by Nahshon, (2023). Reliable academic appraisal, as in the Unified Tertiary Matriculation Examination (UTME) administered by JAMB helps admission officials to differentiate between suitable and unsuitable candidates for a particular academic program.

In most Nigerian universities, performance criteria start from day one on campus, and it extend and accumulates to the end of the student's study (Balogun, et al., 2020). The main objective of appraisal in academic performance is to determine the likelihood of a particular student excelling or failing at a particular grade level. This appraisal of Academic performance at the tertiary institution is mostly through cumulative grade point average (CGPA). Nahshon (2023) further opined that results obtained from such appraisal may be used in categorizing students: the intelligent, average, poor, or weak. Such categories are likely to be based on age group; Sibanda (2023) for instance, shows a significant difference in the academic performance of three different age groups for Zimbabwean high school students. On the other hand, students can be informed from the appraised results about the likelihood of either failure or passing and then adjust accordingly.

Using academic records from seven Engineering departments, School of Engineering, Covenant University, Nigeria, Balogun, et al., (2020), shows a strong positive correlation between the first-year and final-year results. The investigation of factors related to the academic performance of university students has become a topic of growing interest in higher education. Many studies were carried out to explore factors affecting university students' academic performance. Factors such as learning abilities, gender and race (Hanson, 2000), family income level, attending full-time study, receiving grant aid, and completing advanced-level classes (Simmons, et al., 2005), as well as individual's previous academic performance (Mckenzie and Schweitzer, 2001) are identified as the most significant predictors of university performances. Other factors include attitude towards attendance in classes, time allocation for studies, mother's age and mother's education (Hijazi and Naqvi, 2006), study skills, and learning approaches also included. Others are: time management, using information resources, taking class notes, communicating with teachers, preparing for and taking examinations, and several other learning strategies. The enumerated factors can be largely dependent on age. Hence, more needs to be done on the influence of entering age on students' academic performance.

3. Methodology

Data on the first-year CGPA, age, and Final CGPA of 146 graduating students for the 2022/2023 academic session from the Department of Computer Science, Statistics, Operations Research, Geology, Physics, Industrial Mathematics, Chemistry, Industrial Chemistry and Mathematics with Economics in the Faculty of Physical Sciences was used. The relationship between the final grades (CGPA), age, and first-year grade (FYGPA) is expressed by:

$$Y = X\beta + \varepsilon \tag{1}$$

Y is a $(n \times 1)$ vector of the dependent variable (CGPA), X is a $(n \times 2)$ matrix of independent variables age and (FYGPA), β is a vector of regression parameters and ε is a $(n \times 1)$vector of error term with the assumption $\boldsymbol{\varepsilon} \sim N(0_N, h^{-1}I_N)$. Since the error is assumed to be normally distributed, the variables $(Y|X,\beta,h)$ are also normally distributed. Thus, the variables $(Y|X,\beta,h) \sim N(X\beta, h^{-1})$with the probability density function.

$$P(Y|X,\beta,h) = \frac{1}{\sqrt{2\pi h^{-1}}} exp\, \{-\frac{h}{2}(y - X\beta)'\,(y - X\beta)\} \tag{2}$$

The multivariate normal likelihood is:

$$L(Y \mid X,\beta,h) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi h^{-1}}} exp\, \{-\frac{h}{2}(y - X\beta)'\,(y - X\beta)\}$$

$$\propto (h)^{n/2} exp\{-\frac{h}{2}(y - X\beta)'(y - X\beta\}\tag{3}$$

The data information and the desire for an analytical solution is a good guide for the selection of prior distribution. Therefore, the conjugate prior is suitable in this case, resulting in a posterior distribution in the same family as the prior distribution. The Normal-Gamma is a conjugate prior for the parameters β and h^{-1} respectively.

With both β and h^{-1} unknown, the conjugate prior is specified as:

$$P(\beta) = \frac{1}{(2\pi)^{\frac{T}{2}}} |\underline{V}|^{-\frac{1}{2}} exp\left[-\frac{1}{2}(\beta - \underline{\beta})'\underline{V}^{-1}(\beta - \underline{\beta})\right] \tag{4}$$

$$P(h) = C_G^{-1} h^{\frac{\underline{u}-2}{2}} exp\left(-\frac{h\underline{u}}{2\underline{s}^{-2}}\right) \tag{5}$$

Like in other Bayesian literature, we use an underscore to indicate prior parameters and a bar for posterior parameters.$C_G^{-1}$is the integrating constant for gamma distribution.

3.1 The Posterior Density Function

The joint posterior then takes the form

$$p(\beta, h\,|y, X) \propto (h)^{n/2} \exp\{-\frac{h}{2}(y - X\,\beta)'(y - X\,\beta\}$$

$$\times\, exp\,\{-\frac{1}{2}(\beta - \underline{\beta})'\underline{V}^{-1}(\beta - \underline{\beta})\}$$

$$\times\, h^{\frac{\underline{u}-1}{2}}\, exp\left(-\frac{h\underline{u}}{2\underline{s}^{-2}}\right) \tag{6}$$

$$P(\beta, h|y, x) \propto exp[-\frac{1}{2}\{h(y - X\,\beta)'(y - X\,\beta)\}$$

$$+\{(\beta - \underline{\beta})'\underline{V}^{-1}(\beta - \underline{\beta})\}].h^{\frac{n+\underline{u}-2}{2}}\, exp\left(-\frac{h\underline{u}}{2\underline{s}^{-2}}\right) \tag{7}$$

Since

$S^2 = \frac{(y - x\hat{\beta})(y - x\hat{\beta})}{u}$, it can be shown that $uS^2 - y'y + 2\hat{\beta}'x'y - \hat{\beta}'x'x\hat{\beta} = 0$

The first part of the kernel of (7) can is seen to be (Koop, 2023):

$\{h(y - X\,\beta)'(y - X\,\beta + 0\}= h\{(\beta - \hat{\beta})'x'x(\beta - \hat{\beta}) + uS^2\}$

Hence,

$$P(\beta, h|y, x) \propto \exp\{-\frac{1}{2}\left[(\beta - \hat{\beta})'x'x(\beta - \hat{\beta})\right] + \left[(\beta - \underline{\beta})'\underline{U}^{-1}\left(\beta - \underline{\beta}\right)\right]\}$$

$$\times \exp\left\{-\frac{1}{2}h(uS^2)\right\} h^{\frac{n+\underline{u}-2}{2}} \exp\{-\frac{1}{2}h(\underline{uS}^2)\} \tag{8}$$

Where $U^{-1} = h^{-1}\underline{V}^{-1}$. Under-bar and over-bar indicate prior and posterior parameters, respectively. The joint posterior density of the parameters can, therefore, be given as

$$P(\beta, h|y, x) \propto \exp\{-\frac{1}{2}\left[\left(\beta - \overline{\beta}\right)'\overline{U}^{-1}\left(\beta - \overline{\beta}\right)\right]\}h^{\frac{\overline{u}}{2}-1}\exp\{-\frac{1}{2}h(\overline{uS}^2)\} \quad (9)$$

From (9), the kernel of the posterior density is normal-gamma density. The conditional posterior for β is

$$\beta|y, x, h \sim N_p(\overline{\beta}, \overline{U}) \quad (10)$$

$$\overline{\beta} = \overline{U}(\underline{U}^{-1}h^{-1}\underline{\beta} + x'x\hat{\beta}) \quad (11)$$

$$\overline{U} = (x'x + \underline{U}^{-1}h^{-1})^{-1} \quad (12)$$

And that of h is

$$h|y, x, \beta \sim G(\overline{S}^2, \overline{u}) \quad (13)$$

Where $\overline{u} = n + \underline{u}$, and $\overline{S}^2 = \frac{uS^2 + uS^2}{\overline{u}}$

3.2 Sampling Technique

The Gibbs sampler is an MCMC technique for posterior simulation when the conditional distribution is known. The strategy involves sequentially drawing samples from the full conditional posterior of the distributions of interest $\beta|y, x, h \sim N_p(\overline{\beta}, \overline{U})$ and $h|y, x, \beta \sim G(\overline{S}^2, \overline{u})$. Blocking the vector of the parameter $(\beta_0, \beta_1, \beta_2, h)' = \theta$, since it is not easy to draw from the joint distribution, $P(\theta|y)$ directly, we instead draw from $P(\beta_0|y, \beta_1, \beta_2, h)$, $P(\beta_1|y, \beta_0, \beta_2, h)$, $P(\beta_2|y, \beta_0, \beta_1, h)$, $P(h|y, \beta_0, \beta_1, \beta_2)$. The steps involved are outlined in Koop (2003) and Albert (2009) involve the following:

Initialize the stated values: $\beta^{(0)} = (\beta_0^{(0)}, \beta_1^{(0)}, \beta_2^{(0)})$

Step 1. Draw $\pi(\beta_0|\beta_1^{(i)}, \beta_2^{(i)}, data)$
Step 2. Draw $\pi(\beta_1|\beta_0^{(i+1)}, \beta_2^{(i)}, data)$
Step 2. Draw $\pi(\beta_2|\beta_0^{(i+1)}, \beta_1^{(i+1)}, data)$
Step 4. Return to step 1 and repeat the process s times
Step 5. Take the average of $(s - n)$ draws $g\left(\beta^{(n+1)}\right), \ldots, g(\beta^{(s)})$ Where n is burn-in.

A sample of 20000 draws was generated with a burn-in of 5000 and a thinning space of 2 using the above steps. The choice of the hyperparameter was based on their sensitivity to the parameter estimates, hence, $\underline{\beta}_0 \sim N(0, 0.76244991)$, $\underline{\beta}_1 \sim N(0, 0.001335922)$, $\underline{\beta}_2 \sim N(0, 0.017573706)$ and $\underline{h} \sim G(0.08921072, 0.001)$ were found suitable. The underbar, _, indicates a prior parameter.

4. Results and Discussion

The following is the summary table of the data of the students.

Table 1. Summary Statistics of the Data

Variable	N	Minimum	Maximum	Mean	SD
CGPA	146	2.550	4.880	3.682	0.52445
Age	146	16.00	26.00	22.00	2.14237
FYGPA	146	2.110	4.800	3.495	0.61175

Table 1 is the summary of the data used for the study. N is the number of observations for each variable, 2.55 and 4.88 are the minimum and maximum CGPA respectively, while the average is 3.68 with a standard deviation of 0.52445. The minimum and maximum ages are 16 and 26 years respectively. The wide age gap is common in northern Nigeria and can be attributed to factors such as socio-economic, level of education of the parents, religious background, and more. For instance, some parents will send their ward to religious school first, before formal education. 22.00 is the average age with a standard deviation of 2.14237. For the first FYGPA, 2.11 is the lowest value, while 4.80 is the maximum. The mean and the standard deviation are 3.495 and 0.61175, respectively. The following is the histogram of the three (3) variables; Age, Final Year Grade Point Average (FYGPA), and Cumulative Grade Point Average (CGPA) overlaid by the density plot respectively.

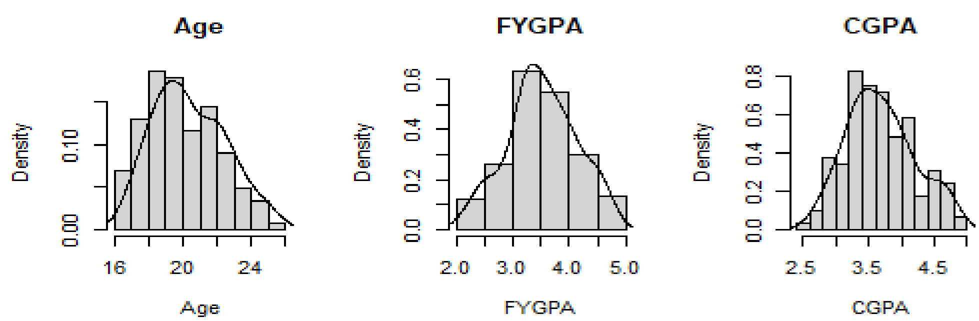

Figure 1. The Density Plot of the Data Sets (Age, FYGPA, and CGPA) Overlaid with the Density Plot.

The density plots suggest the appropriateness of normal linear regression whether from the Bayesian or classical point of view. Table 2 shows the parameter estimates for both the Bayesian and classical linear regression models for the three (3) variables.

Table 2 Bayesian Posterior and OLS Regression Parameter Estimates

Parameters	OLS Estimate	Bayesian Estimate	95% OLS CI	95% BCI	PSRF
Intercept	1.548 (0.281)	1.46 (0.001)	[0.993, 2.101]	[0.913, 1.273]	1
Age	-0.017 (0.012)	-0.0138 (0.000)	[-0.040, 0.006]	[-0.035, 0.021]	1
FYGPA	0.705 (0.040)	0.712 (0.000)	[0.626, 0.785]	[0.633, 0.686]	1
Variability(h)	0.296 (0.025)	0.297 (0.000)		[0.265, 0.285]	1

*Values in the parenthesis attached to parameter estimates are the standard error and naïve standard error for OLS and Bayesian estimates respectively.
*BCI= Bayesian Credible Interval.
*OLS CI= Ordinary Least Squares Confidence Interval.
*PSRF= Potential Scale Reduction Factor.

In Table 2, the Bayesian regression intercept, β_0 has a mean of 1.460 while the OLS estimate is 1.548. The measure of the variability of the estimates (standard error) indicates that the Bayesian estimate is closer to the population mean than the OLS estimate. The same thing is applied to Age, β_1 and measure of variability,σ in the data. The Bayesian parameter estimate for Age is -0.0138 with a standard error of 0.000 while the OLS parameter estimate is -0.017 with a standard error of 0.012.

This result suggests that the Bayesian approach produced smaller standard errors, hence is more efficient for the parameter estimation compared to the OLS. The P-value indicates that the students' entering age is not a significant determinant of their CGPA at graduation. This is consistent with the Bayesian Credible Interval, BCI [-0.035, 0.021] with zero inclusive, suggesting that the parameter is insignificant. In general, the BCI for all the parameters are narrower than the OLS CI. Although the Bayesian parameters are seen to be more efficient than the OLS, the point estimates are approximately the same. This indicates that the prior distribution (a conjugate of the distribution function of interest) did not exert much influence on the results. Generally, the existence and use of prior information regarding the parameters will necessarily result in more efficient estimates than otherwise.

The last column in Table 3 is the Potential Scale Reduction Factor (PSRF), a statistic used to compare the variance between chains to variance within multiple chains in Markov chain Monte Carlo simulation. It is used to determine whether the chains have converged to the target distribution. The values are one (1) for each parameter, indicating a good mixing of the chains and convergence to the target distribution achieved. Furthermore, the Effective Sample Size (ESS) for the parameters is shown in Table 3 below. Although, the simulations show good mixing based on the values of the Potential Scale Reduction Factor (PSRF=1), however, the effective sample sizes show considerable variability across the parameter. This sort of variation is expected, as ESS is itself a random variable estimated from simulation draws (Gelman et al, 2021). The parentheses contain the initial values for the parameter for the respective chains; they are crude estimates generated from the data.

Table 3. Effective Sample Size

parameters	Chain 1	Chain 2	Chain 3
β_0	173.6023 (1.54729)	167.7160 (1.4000)	211.0127 (1.6000)
β_1	237.6411 (-0.01691)	217.3865 (-0.00691)	234.3322 (-0.02691)
β_2	610.7889 (0.70504)	579.1979 (0.60504)	588.8032 (0.80504)
σ	18842.5063	14074.2656	17676.4681

Note: Values in parentheses are the initial parameter values for the chains.

By default, an ESS value between 100 and 1000 indicates good mixing and reasonable parameter estimates, suggesting good mixing for the MCMC steps. With ESS ranging from 13596.34 to 15881.59 across the chains, σ shows an excellent mixing. Figure 2 explores the trace plots indicating the MCMC mixing across the chains for the four parameters. Trace plots (Figure 2) show rapid mixing; all PSRF values equal 1.0. ESS values range between 167 and 610 for coefficients and > 14 000 for σ^{-2}, confirming adequate sampling.

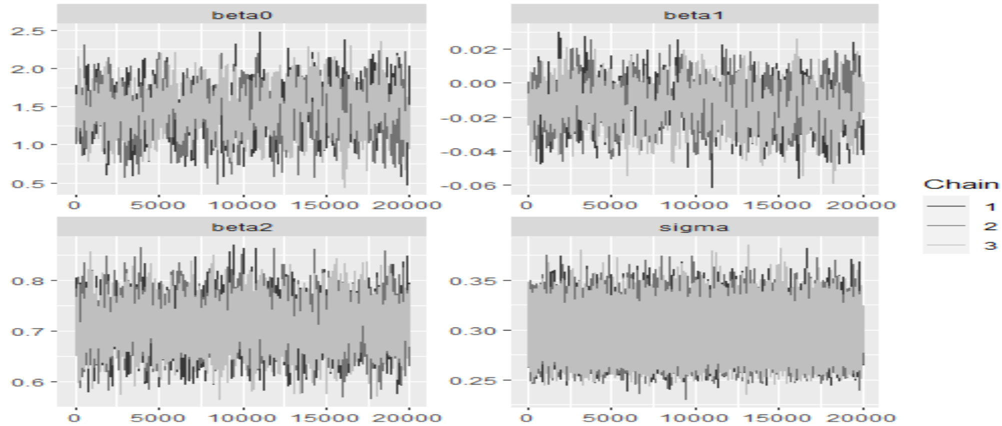

Figure 2. The Trace plot for Three (3) MCMC Chains

The Figure 3 below is the trace plot, QQ plot, density plot, and autocorrelation function diagnosing the error of the fitted Bayesian linear regression.

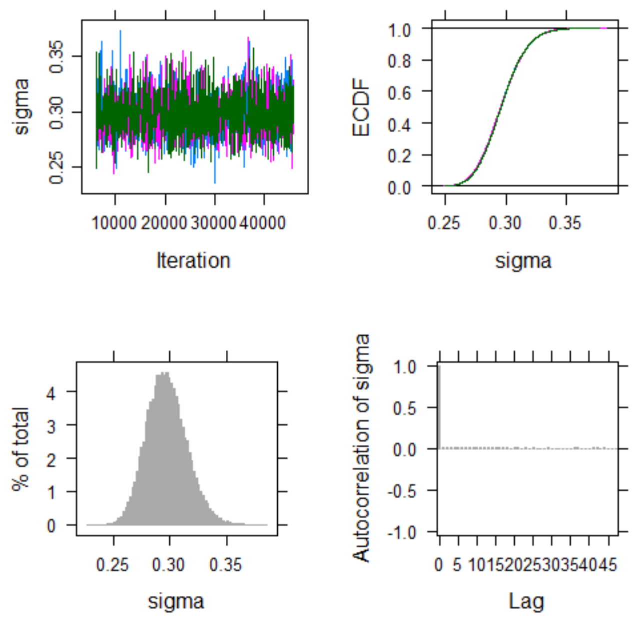

Figure 3. Posterior Distribution Residuals Plot.

The residuals plot indicated above suggests a good fit for the parameters of the Bayesian linear regression. The convergence to the target distribution of each parameter is shown in Figure 4 using a density plot.

From the histogram of the MCMC samples in Figure 4, It can be seen that there is convergence to a great extent to the target distribution. The figure shows a good mixing for the specified number of iterations. The empirical cumulative distribution function, the density plot, and the autocorrelation plot all attest to the convergence of the Bayesian linear regression model. Figure 5 is the Density plot of the MCMC sample for three (3) different chains.

The initial values for the chains are: β_0 = (1.6, 0, -1.6); β_1 = (-0.01, 0, 0.01); and β_2 = (0.71, 0, -0.71) respectively. The measure of skewness is consistent for the chains across the parameter, however the peak is not. Chain 2 seems to produce a platykurtic posterior density, especially for β_0 and β_1.

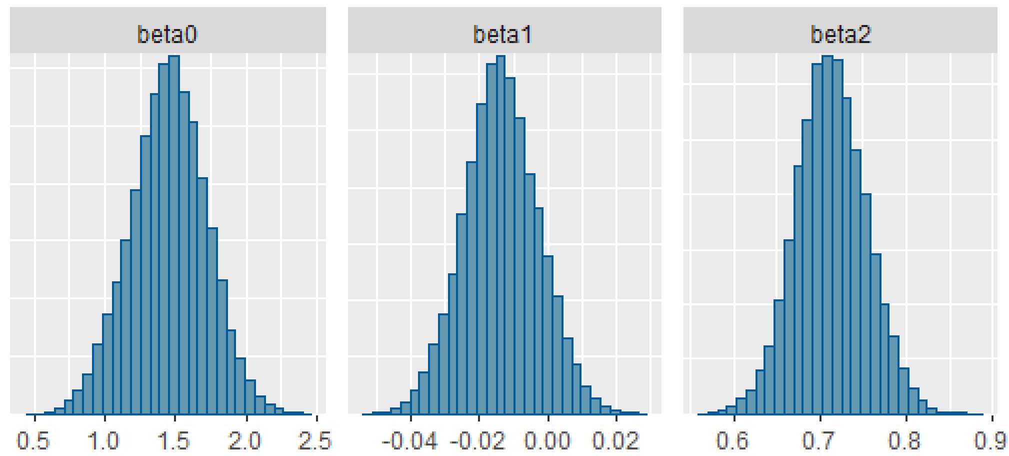

Figure 4. Histogram of the MCMC samples

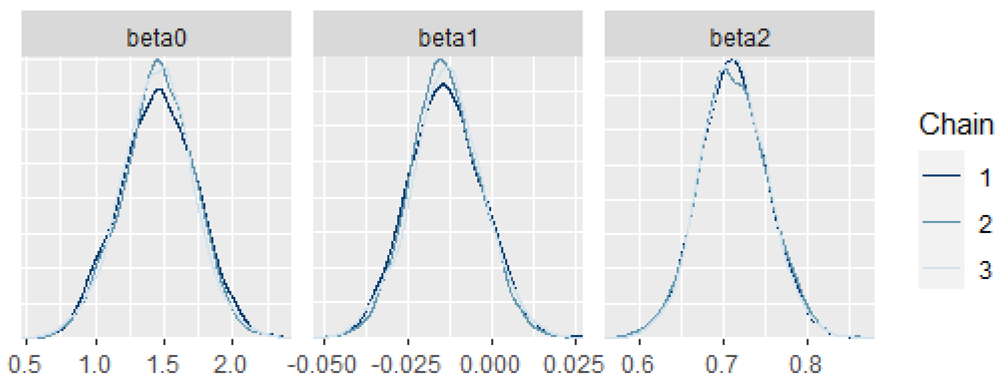

Figure 5. Density plot of the MCMC sample for three (3) different chains

5. Summary and Conclusion

The study used Bayesian and classical linear regression models to appraise students' academic performance. The study used first-year CGPA and Age as the independent variables and the final CGPA as the outcome variable. The posterior distribution was derived, and computations were made for the posterior mean, standard error, and Bayesian credible intervals, which were constructed to test for the significance of the regression coefficients. Also, computations were made for the parameters of the classical linear regression model and the p-values were used to test for significance. The parameter estimates and confidence intervals are presented.

Based on the standard error, as well as credible/confidence intervals, the Bayesian approaches performed better than classical linear regression. This suggests that the Bayesian approach is the preferred tool for the variables considered.

On the relevance of students' entering age and the first-year GPA, CGPA at graduation is not directly affected by the age of the students considered, even though some of them were 16 years old at the point of entering. The result is at variance with Sibanda, (2023) who shows that academic performance level is affected by age group, although his population of interest is high school children of Zimbabwe and not university students.

This study therefore recommends that age in isolation may not be responsible for poor academic performance, rather the government should take a holistic approach in considering other factors in pegging entering requirements for the universities.

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Reference

Abdullahi Z S (2023). The Consequence of ASUU Strike https://nairapen.com/posts/the-consequence-of-asuu-strike retrieved 25th March, 2025

Achugbu, C. M. (2024) Impact of Strike Actions on Academic Performance. Research Invention *Journal of Current Issues in Arts and Management* 3(1):13-20. ISSN 1597-8613 https://rijournals.com/current-issues-in-arts-and-management/

Adedeji, O. and Olekanma, O. (2024). Age Discrimination and Employee Commitment: The Role of Diversity Management in the Nigerian Banking Industry. BAM 2024 Conference, 2nd–6th September 2024. Achieving Transformation for Greater Good: Societal, Organisational and Personal Barriers and Enablers.

Albert, J. (2009). *Bayesian Computation with R*. 2nd ed. New York: Springer.

Bolaji, A. (2024, July 22). Students Under 18 are too Young for HE, Minister Decides. University World News. https://www.universityworldnews.com/post.php?story=20240722050050570#:~:text=Nigeria's%20Minister%20of%20Education%20Professor,JAMB)%20policy%20meeting%20in%20Abuja.

Balogun, O.S, Olaleje, S. A., and Ibidoja, O.J. (2020) University students Academic Performance, an Approach of Tau Statistics Pandemic Proceeding of the 38th International Business Information Management Association (IBIMA) ISBN: 9780-9998551-5-7,4-5 November 2020, Granada, Spain

Billari, F. C. and Pellizzari, M. (2008). The Younger, the Better? Relative Age Effects at University. IZA Discussion Paper No. 3795, Available at SSRN: https://ssrn.com/abstract=1293587 or http://dx.doi.org/10.2139/ssrn.1293587

Egwu, J. U. (2021). Impact of Strike Actions on University Students: A Study of Academic Staff Union of Universities. IOSR Journal Of Humanities And Social Science (IOSR-JHSS) 26(12)4:11-19 e-ISSN: 2279-0837, p-ISSN: 2279-0845. www.iosrjournals.org

Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., and Rubin, D. B. (2021). Bayesian data analysis (3rd ed.). Chapman and Hall/CRC.

Hanson, J.B. (2000). *Student performance and student growth as a measure of success*: A evaluator's perspective. Paper presented at the annual meeting of the American Educational Research Association New Orleans. Louisiana. 25 April.

Hijazi, S.T. and Naqvi, S.M.M.R. (2006). *Factor Affecting Students' Performance*: A Case of Private Colleges. *Bangladesh e-journal of Sociology*, 3(1). Journal of American College Health, 59(2), 91-97. https://doi.org/10.4236/ajibm.2016.63032

Koop, G. (2003). *Bayesian Econometrics*. England: John Wiley & Sons.

Mckenzie, K. and Schweitzer, R. (2001). Who Succeeds at University? Factors Predicting Academic Performance in First Australian University Students. *Higher Education Research and Development,* 20(1), 21-33. https://doi.org/10.1080/07924360120043621

Nahshon, N. (2023). Appraisal of Students' Academic Performance Using Bayesian Linear Regression Model (Unpublished). Moibbo Adama University, Yola.

Pellizzari, M. and Billari, F. (2011). The younger, the better? Age-related differences in academic performance at university. *Journal of Population Economics*. 25(2):697-739. https://doi.org/10.1007/s00148-011-0379-3

Sibanda T. (2023). Investigating the Influence of School-entry Age on Academic Performance at High School Level in Zimbabwe. *Sociology International Journal*, 7(2):60–73. doi: 10.15406/sij.2023.07.00325

Simmons, A.B., Musoba, G.D. and Choong, C.G. (2005). *Persistence among First-Generation College Students in Indiana:* The Impact of Precollege Preparation, College Experiences, and Financial Aid. Indian Project on Academic Success (IPAS) Research Report #05-01.

Tadese, M., Yeshaneh, A., and Mulu, G. B., (2022). Determinants of good academic performance among university students in Ethiopia: a cross-sectional study. BMC Medical Education 22:395 https://doi.org/10.1186/s12909-022-03461-0