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AI-Driven Predictive Analytics for Evidence-Based Education Policy: Evaluating Age and Sex Effects on Student Performance in Nigerian Higher Education

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Abstract

The rapid expansion of higher education systems globally has intensified the need for data-driven decision-making in educational policy. This study develops and evaluates an AI-driven data analytic model to inform evidence-based policy formulation in Nigerian higher education, specifically examining whether student age at university admission significantly affects academic performance. Using a quantitative research design with descriptive, inferential, and predictive analytics, we analyzed administrative records of 3,897 undergraduate students from Nigerian universities. Descriptive analysis revealed that students aged 19–25 years achieved the highest mean CGPA (3.01–3.08), while students aged 26+ years recorded the lowest (2.38). Female students consistently outperformed male students across most age categories (mean CGPA: 3.06 vs. 2.89). One-way ANOVA confirmed significant differences in CGPA across age categories ($F(3,3871) = 9.306, p < 0.00001$). However, Pearson correlation analysis revealed no meaningful linear relationship between age and CGPA ($r = 0.012, p = 0.3785$). Two-way ANOVA demonstrated a significant interaction effect between sex and age category ($F(1,8) = 7.716, p = 0.024$). Predictive modeling using linear regression ($R^2 = 0.0088, RMSE = 0.957$) and random forest ($R^2 = 0.0154, RMSE = 0.957$) indicated that age and sex alone explain less than 2% of CGPA variance. These findings suggest that while age category differences exist statistically, age alone is not a meaningful predictor of academic success. The findings support the integration of AI-driven analytics into higher education policy systems to enhance evidence-based decision-making and targeted student support interventions.

Keywords: Artificial intelligence, Educational Analytics, education policy, Academic Performance, Admission Age, Evidence-Based Policy

1. Introduction

Higher education institutions globally are increasingly embracing data-driven decision-making to improve educational quality, optimize institutional planning, and support student success. In Nigeria, the rapid expansion of universities and rising student enrollment have created a pressing need for evidence-based educational policies capable of addressing challenges such as declining academic performance, dropout rates, delayed graduation, and unequal access to higher education. Traditional policy formulation processes in many Nigerian institutions still rely heavily on manual

reporting systems, subjective judgments, and fragmented datasets, limiting the ability of policymakers to respond effectively to emerging educational realities.

The integration of artificial intelligence (AI) and data analytics into higher education has emerged as a transformative force for evidence-based policy formulation globally. Artificial Intelligence (AI) and data analytics have emerged as transformative tools capable of uncovering hidden patterns, forecasting outcomes, and supporting predictive decision-making in education. These technologies enable institutions to analyze large volumes of student data and generate insights that can improve academic planning, resource allocation, and student support systems. Consequently, AI-driven educational analytics is becoming increasingly important in

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the development of evidence-based education policy.

In Nigeria, with over 200 public and private universities serving millions of students, the pressure to develop policies that reflect actual educational challenges, demographic shifts, and performance patterns has never been greater. However, policy formulation in Nigerian higher education has traditionally relied on manual data processing, subjective judgments, delayed reports, and inconsistent data recording systems, creating a persistent gap between educational realities and policy interventions. One issue attracting considerable debate in Nigerian higher education is the age of admission into universities. Traditionally, students enter tertiary institutions between the ages of 17 and 20. However, recent trends show increasing numbers of exceptionally young students gaining admission before the age of 16. This shift raises fundamental questions about whether younger students can cope academically, socially, and emotionally in higher education environments.

In the landscape of Nigerian higher education policy-making, decisions are often made without robust empirical underpinnings, leading to outcomes driven by intuition rather than evidence (Obiora, 2022). This shortfall has resulted in policies that may inadequately address sector challenges or improve student outcomes. Notably, the recent policy setting a minimum admission age of 18 years for tertiary education elicited substantial opposition from parents, academia, and some stakeholders, shedding light on the need for a more robust data-driven approach (Mohammed, 2023). The absence of compelling data and statistics underpinning such policies has culminated in an apparent inability to substantiate and defend policy decisions.

Critical questions arise, such as whether student performance and mental health depend on a particular age of admission, or if students below 18 struggle more academically or mentally (Picton, Greenfield & Parry, 2022). These questions and several others can be answered with a comprehensive, data-driven approach to inform and guide education policy decisions. Therefore, there exists a compelling imperative to pursue a data-driven approach that can inform and guide

education policies, allowing policymakers to cultivate well-founded, defensible decisions underpinned by data rather than anecdotal evidence, sentiment, or isolated examples.

Despite these concerns, empirical evidence regarding the relationship between admission age and academic performance remains limited. This study therefore investigates whether age significantly influences academic achievement among university students in Nigeria. Using AI-driven data analytics and predictive modeling techniques, the study examines the interaction between age, sex, and CGPA to provide evidence-based insights for educational policy formulation. In this study an AI-driven data analytic model to provide evidence-based insights for education policy formulation was developed. The model was used for: Categorizing students into demographic groups, analyzing academic performance across age categories, comparing performance by sex, building predictive models, and generating actionable policy recommendations.

The research questions guiding this investigation were: What are the demographic characteristics of students in Nigerian higher education? How does academic performance vary across different age categories? Is there a significant difference in performance between male and female students? What interaction exists between sex and age categories in predicting performance? Can an AI-driven model accurately predict student performance patterns? What insights can be derived to support evidence-based policy?

2.0 Literature Review

Academic readiness extends beyond cognitive intelligence to include emotional maturity, social adaptability, and psychological preparedness. Previous studies suggest that younger university entrants may experience challenges associated with independence, time management, and social integration. Afolayan (2018) found that emotional readiness significantly affects the success of early university entrants in Nigeria.

Similarly, Okonkwo and Alabi (2020) reported no significant difference in CGPA between students below and above 16 years of age, although younger students faced greater adaptation difficulties. These findings suggest that social and

emotional factors may influence university success more strongly than age itself.

Several studies have explored the relationship between demographic characteristics and academic outcomes. Adeyemi (2020) and Eze and Okeke (2019) observed gender differences in academic performance, with female students often outperforming males in certain academic contexts. Richardson (1995) also noted that mature students frequently demonstrate better study habits and academic discipline.

Research by Yakubu and Abubakar (2022) using machine learning techniques showed that age was not a major predictor of CGPA among Nigerian undergraduates. Instead, variables such as motivation, study habits, and learning environment appeared more influential.

2.1 AI and Educational Analytics

AI-driven analytics have gained prominence in higher education for predictive modeling, student retention analysis, and policy formulation. Predictive models such as Random Forest, Support Vector Machines, and regression analysis enable institutions to identify at-risk students and intervene proactively (Siemens & Baker, 2012). Educational dashboards and visualization tools also facilitate interpretation of complex student datasets, supporting administrators and policymakers in making informed decisions. However, the adoption of AI-driven policy systems in Nigerian universities remains relatively limited.

2.2 Theoretical Framework

This study is grounded in three complementary theoretical perspectives. Systems theory posits that universities function as interrelated components where inputs (students, faculty, resources) interact to produce outputs (student performance, graduation rates). AI models serve as tools to capture these dynamics and inform decision-making.

Data-driven decision-making (DDDM) theory emphasizes empirical data, statistical analysis, and predictive modeling to guide decisions, reducing bias and increasing accountability. Human capital theory suggests that investment in students' knowledge and skills yields societal

benefits, with performance analytics ensuring optimal educational returns.

the modern Data-Driven Decision Theory for Big Data and Analytics (DECAS) by Elgendy, Elragal and Päivärinta (2021), which expands upon traditional data-driven decision-making frameworks by specifically addressing the complexities and opportunities presented by big data and advanced analytics. DECAS posits that in an era characterized by the vast availability of data, organizational decisions should be informed by sophisticated analytical techniques that harness the full potential of big data, rather than relying on intuition or basic observation alone.

DECAS goes beyond the foundational principles of earlier data-driven decision theories by emphasizing the integration of advanced analytics, such as machine learning and predictive modeling, into decision-making processes. This approach recognizes that the sheer volume, velocity, and variety of data in today's environment require not just traditional data analysis but also the application of cutting-edge techniques to extract actionable insights. By leveraging big data and analytics, DECAS provides a more nuanced and powerful framework for making decisions that are not only data-informed but also predictive, adaptive, and capable of addressing complex, multifaceted challenges.

Within the educational context, DECAS offers a particularly relevant lens for understanding how educational data can be used to inform policy and practice. The theory underscores the importance of using large-scale data sets and advanced analytical tools to gain deep insights into student performance, institutional effectiveness, and educational equity. By applying DECAS, this research aims to develop an AI-powered platform that will analyze educational data in ways that are both comprehensive and forward-looking, enabling policymakers to craft strategies that are not only responsive to current trends but also anticipatory of future needs.

Existing research presents mixed findings on age-performance relationships. Afolayan (2018) found that younger Nigerian students often struggle with time management, independence, and social integration compared to older peers. Conversely,

Okonkwo and Alabi (2020) reported no significant CGPA differences between students below and above 16 years, though younger students experienced adaptation difficulties. Yakubu and Abubakar (2022) applied machine learning models to Nigerian higher education data and found that age was not a significant predictor of high CGPA.

International studies similarly show inconsistent results. Richardson (1995) observed that mature students demonstrated better study approaches and equal or superior academic performance. Billari and Pellizzari (2012) found that younger students outperformed older peers, possibly due to higher energy levels and recent exposure to formal schooling. Naderi et al. (2009) demonstrated that creativity and emotional intelligence were more influential than age in predicting achievement. These conflicting findings underscore the need for context-specific empirical investigation using robust analytical methods.

The literature reveals several gaps: limited application of AI-driven models for policy-making in Nigerian higher education; inadequate studies focusing on age-performance interactions and sex differences; lack of integrated visualization tools to present complex performance patterns; and scarcity of studies connecting predictive analytics to actionable policy recommendations. This study addresses these gaps by developing an AI-driven analytic model incorporating demographic variables, predicting academic outcomes, and generating visual insights for evidence-based policymaking.

3.0 Methodology

3.1 Research Design

The study adopted a quantitative research design integrating descriptive, inferential, and predictive analytic approaches. Administrative student datasets from Nigerian universities were analyzed to examine the relationship between admission age and academic performance.

The study population comprised undergraduate students enrolled between 2015 and 2024. The final dataset comprised 3,897 undergraduate students with complete records for age, sex, and Cumulative Grade Point Average (CGPA). The

demographic and academic information were analyzed.

The key variables used in the study are presented in Table 1.

Table 1: Variables used in the study

Variable	Type	Description
Age	Independent	Age at admission
Age Category	Independent	≤18, 19–21, 22–25, 26+
Sex	Independent	Male/Female
CGPA	Dependent	Academic performance indicator

Exclusion criteria included missing or incomplete records and part-time or distance learning students where data were not standardized. Age categories were operationalized as: ≤18 years, 19–21 years, 22–25 years, and 26+ years. CGPA was measured on a 0.0–5.0 scale.

3.2 Data Analysis Techniques

The study employed: Descriptive statistics, One-way and two-way ANOVA. Pearson correlation analysis, Linear regression, Random Forest modeling, and Data visualization techniques. Model performance was evaluated using: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). Descriptive statistics (mean, median, standard deviation, frequency distributions) summarized demographic and performance patterns. Inferential statistics included one-way ANOVA to test CGPA differences across age categories, two-way ANOVA to examine Sex × Age Category interaction effects, Tukey HSD post-hoc tests for pairwise comparisons, and Pearson correlation to assess linear relationships between age and CGPA.

Predictive modeling employed linear regression and random forest algorithms to predict CGPA based on age, age category, and sex. Model evaluation used R^2 , Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). All analyses were conducted using R (version 4.3+) with packages dplyr, ggplot2, janitor, rstatix, and

psych. An interactive Shiny dashboard was developed for stakeholder visualization.

3.3 Ethical Considerations

Student identifiers were removed before analysis, data were stored securely, ethical approval was obtained from the university Research Ethics Committee, and results were presented objectively without discriminatory interpretation.

4.0 Results

4.1 Descriptive Statistics

The dataset comprised 3,897 students aged 16–32 years. Males constituted 61.81% (n=2,397) and

females 38.16% (n=1,480). Age category distribution showed 22.8% aged ≤18 years (n=883), 37.2% aged 19–21 years (n=1,443), 38.5% aged 22–25 years (n=1,494), and 1.5% aged 26+ years (n=57). This is presented in Table 2 and Table 3.

Students aged 22–25 years demonstrated the highest mean CGPA (3.08), while those aged 26+ years showed the lowest (2.38). Variability was largest in the 22–25 age group (SD=1.11) and smallest in the 26+ group (SD=0.786).

Table 2: CGPA Descriptive Statistics by Age Category

Age Category	Count	Percentage	Mean CGPA	Median CGPA	SD CGPA
≤18 years	883	22.80%	3.00	3.04	0.976
19–21 years	1,443	37.20%	3.01	3.03	1.010
22–25 years	1,494	38.50%	3.08	3.09	1.110
26+ years	57	1.50%	2.38	2.60	0.786

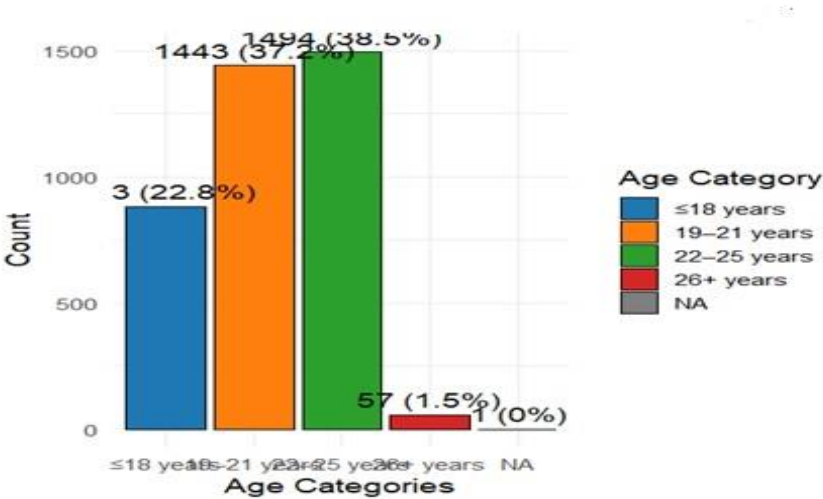


Figure 1: Count and Percentage of Students by Age Category

Table 3: CGPA Descriptive Statistics by Sex

Sex	Mean CGPA	Median CGPA	SD CGPA	Min CGPA	Max CGPA
Male	2.89	2.94	0.929	0.00	5.00
Female	3.06	3.15	0.899	0.00	4.99

Female students outperformed male students by approximately 0.17 CGPA points. CGPA distribution was slightly right-skewed, with most students clustering between 2.0 and 3.6.

4.2 Inferential Statistics

One-way ANOVA revealed a statistically significant difference in mean CGPA across age categories ($F(3,3871) = 9.306$, $p < 0.00001$). This indicates that age category has a significant effect on academic performance, though the effect size was modest. Tukey HSD post-hoc tests identified that students aged 26+ years differed significantly from all other age categories ($p < 0.05$), while differences among the ≤ 18 , 19–21, and 22–25 categories were not statistically significant.

Pearson correlation between age (as a continuous variable) and CGPA yielded $r = 0.012$ ($p = 0.3785$), with a 95% confidence interval ranging from -0.392 to 0.157. This indicates no meaningful linear relationship between age and academic performance. The t-value of 0.264 further confirmed the absence of statistically significant correlation.

Two-way ANOVA examining Sex $\times$ Age Category interaction effects showed a non-significant main effect for sex ($F(1,8) = 0.111$, $p = 0.747$) and age group ($F(1,8) = 0.605$, $p = 0.459$), but a significant interaction effect ($F(1,8) = 7.716$, $p = 0.024$). This indicates that the effect of sex on CGPA depends on age category, or vice versa. However, no individual pairwise comparison reached statistical significance in the Tukey HSD test, suggesting the interaction is driven by subtle combined effects rather than large differences between specific groups.

4.3 Predictive Modeling Results

The predictive modeling results are presented in Table 4. Linear regression using age, age category, and sex as predictors yielded $R^2 = 0.0088$, MAE = 0.78, and RMSE = 0.957. Sex was a significant predictor ($p < 0.05$), but age was not. The model explained less than 1% of CGPA variance.

Random forest modeling, capable of capturing non-linear interactions, produced marginally improved performance: $R^2 = 0.0154$, MAE = 0.78, RMSE = 0.957. Feature importance analysis indicated that sex contributed more to prediction accuracy than age, with age showing minimal predictive value. Both models demonstrated similar prediction errors, confirming that age and sex alone provide almost no predictive information about CGPA.

4.4 Key Findings Summary

1. Age group differences exist but are small: Students aged 19–25 years show slightly higher mean CGPA than younger (≤ 18) or older (26+) students, but the effect is modest.
2. No linear age-performance relationship: Correlation analysis reveals that age as a continuous variable has no meaningful linear relationship with CGPA ($r = 0.012$).
3. Sex differences favor females: Female students consistently outperform male students across most age categories by approximately 0.17 CGPA points.
4. Significant interaction effect: The combination of sex and age category significantly affects CGPA, though pairwise differences did not reach significance.
5. Poor predictive power of demographic variables: AI models using only age and sex explain less than 2% of CGPA variance, indicating that academic success depends primarily on other factors.

4.5 Interpretation of Findings

The finding that students aged 19–25 years achieve the highest mean CGPA aligns with the optimal balance hypothesis: this age range provides sufficient cognitive maturity and recent secondary education exposure without the competing life responsibilities faced by older students. The higher variability among students aged 22–25 years ($SD = 1.11$) suggests that while some excel, others struggle, potentially due to heterogeneous academic preparation or external commitments.

Table 4: Model Performance Comparison

Model	R^2	RMSE	MAE	Key Finding
Linear Regression	0.0088	0.957	0.78	Sex significant ($p < 0.05$); age non-significant
Random Forest	0.0154	0.957	0.78	Non-linear model provides no meaningful improvement

The absence of a linear correlation between age and CGPA ($r = 0.012$, $p = 0.3785$) challenges assumptions that younger students are systematically disadvantaged or that older students inherently perform better. This finding supports Yakubu and Abubakar's (2022) machine learning study in Nigerian institutions, which found age was not a significant predictor of high CGPA. It also aligns with Richardson's (1995) conclusion that mature students perform equally well or better than younger students, while simultaneously supporting Billari and Pellizzari's (2012) observation that younger students can outperform older peers in certain contexts.

The significant interaction effect between sex and age category ($p=0.024$) indicates that age policies should not be applied uniformly across genders. Female students in the 19–25 age group performed consistently well, while male performance showed greater age-related variability. This finding is consistent with Lovat and Darmawan's (2019) Australian study, which found that older female students performed better, implying life experience can enhance academic outcomes differentially by gender.

The poor predictive performance of both linear ($R^2 = 0.0088$) and non-linear ($R^2 = 0.0154$) models using only age and sex underscores the multidimensional nature of academic success. As Nasir and Masrur (2010) demonstrated, emotional intelligence is a stronger predictor of academic achievement than age. Similarly, Naderi et al. (2009) found that creativity and emotional intelligence were more influential than age, reinforcing that demographic variables alone are insufficient for understanding or predicting student performance.

Younger students (≤ 18 years) exhibited greater variability in performance, supporting arguments that emotional and social maturity may influence academic adjustment. Similarly, older students (26+) demonstrated inconsistent outcomes, likely due to competing life responsibilities. The superior performance of female students aligns with previous studies suggesting greater academic diligence and engagement among female undergraduates.

Although ANOVA revealed significant differences across age groups, the extremely weak correlation and predictive modeling results indicate that age alone is insufficient for

predicting academic success. Other factors such as motivation, socio-economic background, study habits, emotional intelligence, and learning environment likely play more substantial roles.

4.6 Policy Implications

Despite the weak predictive power of age-based models, the statistically significant age category differences warrant policy attention.

First, universities should implement targeted support programs for students aged 26+ years, who demonstrated the lowest mean CGPA (2.38) and highest risk of underperformance. Flexible scheduling, online learning options, and counseling services addressing work-life-academic balance may improve outcomes for this group.

Second, while students aged ≤ 18 years achieved mean CGPA (3.00) comparable to traditional-age peers, the developmental challenges identified in prior research (Afolayan, 2018) suggest value in mentorship programs, study skills workshops, and enhanced orientation focusing on time management and social integration.

Third, the consistent female outperformance (mean CGPA 3.06 vs. 2.89) suggests male students, particularly in specific age categories, may benefit from targeted academic engagement interventions. However, caution is warranted given the small effect size.

Fourth, the significant interaction effect between sex and age category indicates that one-size-fits-all age policies are inappropriate. Interventions should be tailored to specific demographic combinations rather than applying uniform age restrictions or requirements.

Fifth, the poor predictive power of demographic-only models demonstrates that admission policies based primarily on age criteria are not empirically justified. Institutions should consider broader indicators of readiness, including prior academic achievement, emotional intelligence assessments, and motivational factors.

5.0 Conclusion and Recommendations

5.1 Conclusion

This study developed and evaluated an AI-driven data analytic model to inform evidence-

based education policy in Nigerian higher education, specifically examining the effects of student age and sex on academic performance. Based on analysis of 3,897 undergraduate records, four primary conclusions emerge.

First, admission age has a statistically measurable effect on CGPA, with students aged 19–25 years achieving the highest average performance. However, the absence of linear correlation ($r = 0.012$) indicates that age alone is not a meaningful predictor of individual student success.

Second, female students consistently outperform male students across most age categories, with a mean difference of approximately 0.17 CGPA points. This pattern was consistent across both descriptive and predictive analyses.

Third, a significant interaction effect exists between sex and age category ($p = 0.024$), demonstrating that age policies cannot be applied uniformly across genders and that nuanced, targeted interventions are required.

Fourth, AI-driven predictive models using only age and sex explain less than 2% of CGPA variance ($R^2 = 0.0088$ – 0.0154), confirming that academic success depends primarily on factors beyond basic demographics, including prior academic achievement, emotional intelligence, motivation, study habits, and institutional support structures.

Admission age alone is not a strong predictor of CGPA and AI-driven analytics can support evidence-based educational policy and institutional planning. The study therefore concludes that while admission age may influence university performance to some extent, academic success is multidimensional and cannot be determined solely by age.

5.2 Recommendations

For universities and administrators: Implement support programs for students aged 26+ years (lowest performers), including flexible scheduling and counseling services. Develop mentorship initiatives for students aged ≤ 18 years focusing on time management and social integration. Integrate predictive analytics into student information systems for early identification of at-risk students, while recognizing the limitations of demographic-only models.

Policymakers should avoid age-based admission restrictions that lack empirical justification and instead adopt evidence-based student support frameworks, as age alone is not a meaningful predictor of academic success. Allocate resources for collecting comprehensive student data including prior academic achievement, socioeconomic status, and psychological factors to enable more accurate predictive modeling. Fund research on non-cognitive factors affecting academic performance across different demographic groups. Flexible learning support should be provided for older students balancing academic and personal responsibilities.

For future research the analyses can be expanded to multiple universities with diverse student populations to improve generalizability. Incorporate additional variables including entrance examination scores, secondary school performance, socioeconomic status, emotional intelligence measures, and study habit assessments. Conduct longitudinal studies tracking individual students across their academic careers to identify causal mechanisms. Investigate institutional factors (class size, teaching quality, resource availability) that may moderate age-performance relationships. Develop and validate AI models specifically designed for educational policy applications in resource-constrained contexts.

5.3 Limitations

This study is limited by its cross-sectional design, which precludes causal inference. The sample, while substantial ($N=3,897$), was drawn from limited institutions, potentially restricting generalizability. The small number of students aged 26+ years ($n=57$) reduces statistical power for analyses involving this group. Data constraints prevented inclusion of socioeconomic, psychological, and prior achievement variables known to influence academic performance. Predictive model accuracy is data-dependent and may not generalize to different student populations without recalibration.

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