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A PYTHON-BASED ANALYSIS OF ACADEMIC PERFORMANCE AND AGE ON ADMISSION OF STUDENTS IN SOME SELECTED UNIVERSITIES IN SOUTH-WESTERN PART OF NIGERIA

[1]Lawal Mohammed, *[2]Yusuff K. Monsuru and [3]Owolabi A. Abiodun

[1]Department of Mathematical and Computer Sciences Fountain University Osogbo Osun State Nigeria.
[2]Department of Statistics, Federal University of Agriculture, Abeokuta Nigeria.
[3]Department of Mathematical and Computing Sciences Thomas Adewumi University Oko-Irese Kwara State Nigeria.

*Corresponding authors' email: musodeeq3@gmail.com

ABSTRACT

Understanding the influence of admission age on students' academic performance remains a persistent concern in higher education, particularly in developing contexts where entry standards are inconsistently enforced. This study investigates the relationship between students' age at admission and their academic outcomes using a Python-based data analytics approach. A dataset comprising 1,401 undergraduate records from Fountain University, Osogbo, and the Federal University of Agriculture, Abeokuta located in the South-West region of Nigeria, spanning 2014–2024, was analyzed. Python libraries such as *pandas*, *matplotlib*, and *scipy.stats* were employed for data cleaning, visualization, and statistical testing. Descriptive analysis revealed that most students were admitted between ages 16 and 20, with a near-equal gender distribution. Inferential results indicated no statistically significant difference in academic performance across age groups (ANOVA, p = 0.1077), suggesting that admission age exerts minimal effect on cumulative grade point average (CGPA). However, gender-based comparison showed a significant difference (t-test, p < 0.001), with female students outperforming their male counterparts. These findings imply that cognitive maturity associated with age is less decisive for academic success than factors such as motivation and discipline, which may explain the observed gender disparity. The study underscores the potential of Python-driven analytics for evidence-based educational evaluation and advocates for gender-responsive academic support policies rather than rigid age-based admission criteria.

Keywords: Academic Performance, Admission Age, Python Analytics, Gender Difference, Educational Data Mining

INTRODUCTION

Academic performance in higher education is shaped by a complex interaction of cognitive, motivational, demographic, and contextual factors (Sosu & Phebe, 2018). Among these, the age at which a student gains admission into the university has received growing attention as a potential determinant of academic success. Younger students, often admitted below the conventional entry age, may face challenges of emotional immaturity, social adjustment, and independent learning (Ogunlade et al., 2019). Conversely, older entrants are assumed to possess greater psychological readiness and discipline but may experience competing responsibilities or declining cognitive flexibility (Adeniran & Okonkwo, 2016). Understanding how these dynamics affect academic outcomes is essential for designing equitable and effective educational policies.

Recent advances in data analytics have enabled a shift from traditional statistical evaluations toward computational and data-driven approaches. Python, a high-level open-source programming language equipped with libraries such as *pandas*, *NumPy*, and *seaborn*, has become a preferred tool for analyzing complex educational datasets (Zhu, 2021). By leveraging these resources, researchers can visualize patterns, perform robust inferential tests, and uncover latent relationships in student performance data that may elude conventional analyses (Hossain, 2020; Khan & Iqbal, 2023). Within the Nigerian context, where admission policies are often flexible and early university entry is increasingly common, such programming-based analytics provide a transparent and replicable means of assessing the academic implications of varying entry ages (Ajayi & Olayemi, 2017).

Existing empirical findings on the influence of admission age are mixed. Studies in Nigerian tertiary institutions suggest that older students tend to achieve slightly higher academic results, possibly due to greater maturity and self-management skills (Adebayo et al., 2018). Other works, however, have reported no significant correlation once confounding factors such as gender and motivation are controlled (Oluwole, 2017). International research presents similar inconsistencies, with some authors emphasizing psychological and socio-economic mediators rather than chronological age as the critical determinants of achievement (Smith & Allen, 2020; Gomez & Tan, 2021). This divergence highlights the need for context-specific, data-driven investigations that integrate computational rigor with educational insight.

From a theoretical standpoint, the relationship between age and academic performance can be interpreted through multiple lenses. Piaget's theory of cognitive development posits that formal operational thinking, essential for abstract reasoning, typically matures during late adolescence, suggesting possible advantages for older entrants (Santrock, 2018). Vygotsky's concept of the Zone of Proximal Development underscores the importance of scaffolding and peer interaction, implying that appropriate institutional support can mitigate age-related differences (Romero & Ventura, 2024). The Self-Determination Theory further emphasizes intrinsic motivation and autonomy as primary drivers of performance, irrespective of age (Parker et al., 2019). Collectively, these frameworks suggest that chronological age alone may not determine success; rather, it interacts with motivational and environmental variables that shape academic outcomes.

Despite extensive discourse, few studies in Sub-Saharan Africa have employed programming-based analytics to evaluate age-related performance differences. Most available research relies on small samples and traditional statistical packages, limiting reproducibility and scalability (Nwankwo & Adeyemi, 2022). The present study addresses this gap by applying Python-based data analysis to a large institutional dataset from Fountain University, Osogbo, and the Federal University of Agriculture Abeokuta, situated in the South-Western region of Nigeria. Specifically, it investigates whether students admitted below 18 years perform differently from those admitted at or above 18 years and whether gender moderates this relationship. Through descriptive visualization and inferential testing, the study aims to provide empirical, data-driven insights that can inform university admission policies and targeted academic support strategies in Nigeria and comparable contexts.

MATERIALS AND METHODS

Research Design

This study adopted a quantitative, retrospective research design aimed at examining the relationship between students' age at university admission and their academic performance. The approach was computationally grounded, utilizing Python programming for data processing, visualization, and statistical analysis. This design was selected to ensure objectivity, replicability, and empirical rigor in identifying age- and gender-related performance patterns within a large student dataset.

Data Source

The study utilized secondary data obtained from the academic records of Fountain University, Osogbo, and the Federal University of Agriculture Abeokuta, located in South-Western Nigeria. Two institutional datasets covering the period 2010–2024 were integrated for analysis:

i. Graduation Records Dataset: containing biographical and completion details of students (name, gender, date of birth, program, and class of degree).
ii. CGPA Records Dataset: comprising final cumulative grade point averages (CGPAs) for students admitted between 2014 and 2024.

Both datasets were retrieved from the Universities Records and merged using matriculation numbers as unique identifiers. The resulting dataset represented a total of 1,401 undergraduate records, ensuring sufficient statistical power for inferential testing. All data were anonymized to preserve confidentiality and ethical compliance.

Variables

The study focused on two main independent variables; age at admission and gender, and one dependent variable; academic performance, measured by final CGPA.

i. ***Age at Admission:*** computed as the difference between each student's year of admission and year of birth, and subsequently classified into categories: *Below 16, 16–17, 18, 19–20,* and *Above 20 years.*
ii. ***Gender:*** coded as *Male* or *Female.*
iii. ***Academic Performance:*** represented by each student's final CGPA on a five-point grading scale, consistent with Nigerian university standards.

Data Cleaning and Preparation

A rigorous preprocessing workflow was conducted using Python to ensure data reliability and integrity:

i. Duplicate and irrelevant entries (e.g., administrative notes, redundant identifiers) were removed.
ii. Text normalization standardized course titles and degree classifications for uniformity.
iii. Missing values were handled by imputation, where absent CGPAs were estimated based on corresponding class of degree using the standard Nigerian grading scale (e.g., *First Class = 4.75*, *Second Class Upper = 4.00*).
iv. Derived variables such as *AGE_AT_ADMISSION* and *AGE_GROUP* were programmatically generated.
v. Gender inference was applied for incomplete records using a curated mapping of common Nigerian first names.

The resulting clean dataset contained 13 standardized variables, including demographic, academic, and computed fields necessary for analysis.

Analytical Procedure

All analyses were conducted in Python (version 3.9+) using its robust data science ecosystem.

i. Exploratory Data Analysis (EDA): Conducted with *pandas*, *matplotlib*, and *seaborn* to examine distributions, identify outliers, and visualize demographic and performance trends.
ii. Descriptive Statistics: Summary measures (mean, standard deviation) were computed for CGPA across gender and age groups.

Inferential Statistics

i. An independent samples t-test assessed gender-based performance differences.
ii. A one-way Analysis of Variance (ANOVA) evaluated differences in CGPA across age groups.
iii. All tests were conducted at a 5% level of significance ($\alpha = 0.05$) using the *scipy.stats* and *pingouin* libraries.

Ethical Considerations

Institutional permission was obtained before accessing academic records. All data were anonymized, ensuring that no personally identifiable information was included in the analysis. The study complied with ethical research standards governing the use of secondary institutional data for academic purposes.

Justification for Python-Based Analysis

Python was chosen as the analytical framework due to its open-source accessibility, efficiency, and suitability for large-scale data analysis in educational research (Zhu, 2021; Khan & Iqbal, 2023). Its libraries; *pandas* for data manipulation, *seaborn* for visualization, and *scipy.stats* for hypothesis testing facilitated a replicable and transparent workflow. This computational approach extends beyond traditional statistical packages by offering flexibility, automation, and scalability in handling complex educational datasets.

RESULTS AND DISCUSSION

Dataset Overview

The cleaned dataset comprised academic records of 1,401 undergraduate students from Fountain University, Osogbo, and the Federal University of Agriculture Abeokuta, covering a ten-year period (2014–2024). The variables analyzed include students' gender, program of study, date of birth, year of graduation, and final cumulative grade point average (CGPA). Derived variables such as Age at Admission and Age Group were computed programmatically. The datasets were obtained from academic records maintained by the institutions.

The distribution of students by age at admission as displayed in Figure 1 indicates that most entrants were between 17 and 19 years old, with a steep decline beyond age 20. This pattern reflects the prevailing trend of early university enrollment in Nigeria's South-West region.

As illustrated in Figure 2, the majority of students graduated with Second Class Lower (45.9%) or Second Class Upper (35.4%) honors, while smaller proportions achieved First Class (6.1%) or Third-Class standings (10.3%). This pattern aligns with expected academic outcomes in private Nigerian universities.

Gender distribution was nearly balanced, with female students representing 50.5% of the cohort and males 49.5% as illustrated in Figure 3. This near parity supports the suitability of the dataset for comparative gender analysis.

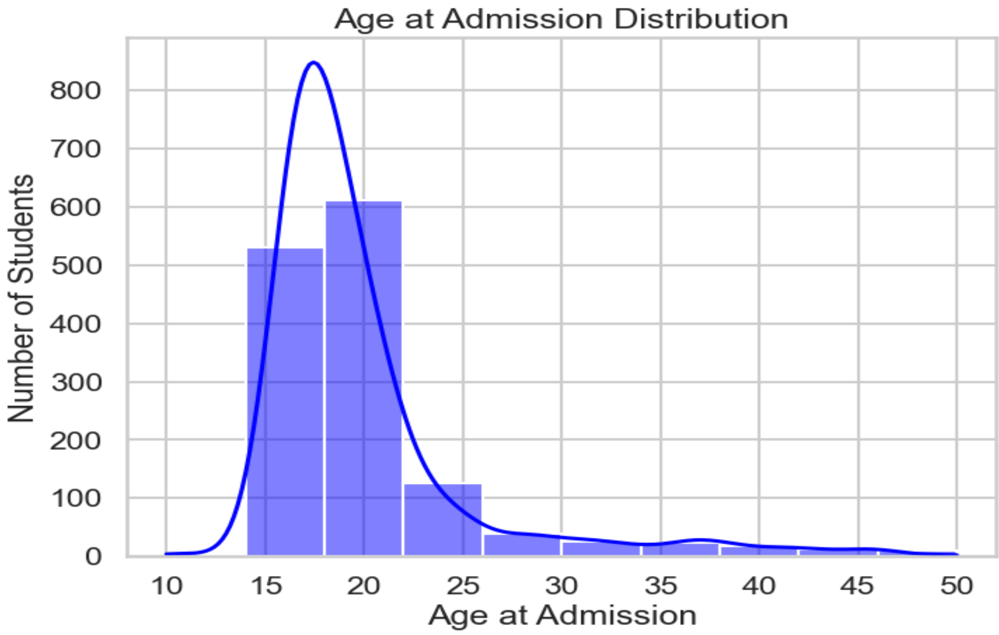

Figure 1: Histogram Showing the Distribution of Students' age at Admission. Most Students Entered Between Ages 17 and 19, with a Sharp Decline Beyond age 20, Indicating that University Entry Typically Occurs During Late Adolescence in South-Western Nigeria

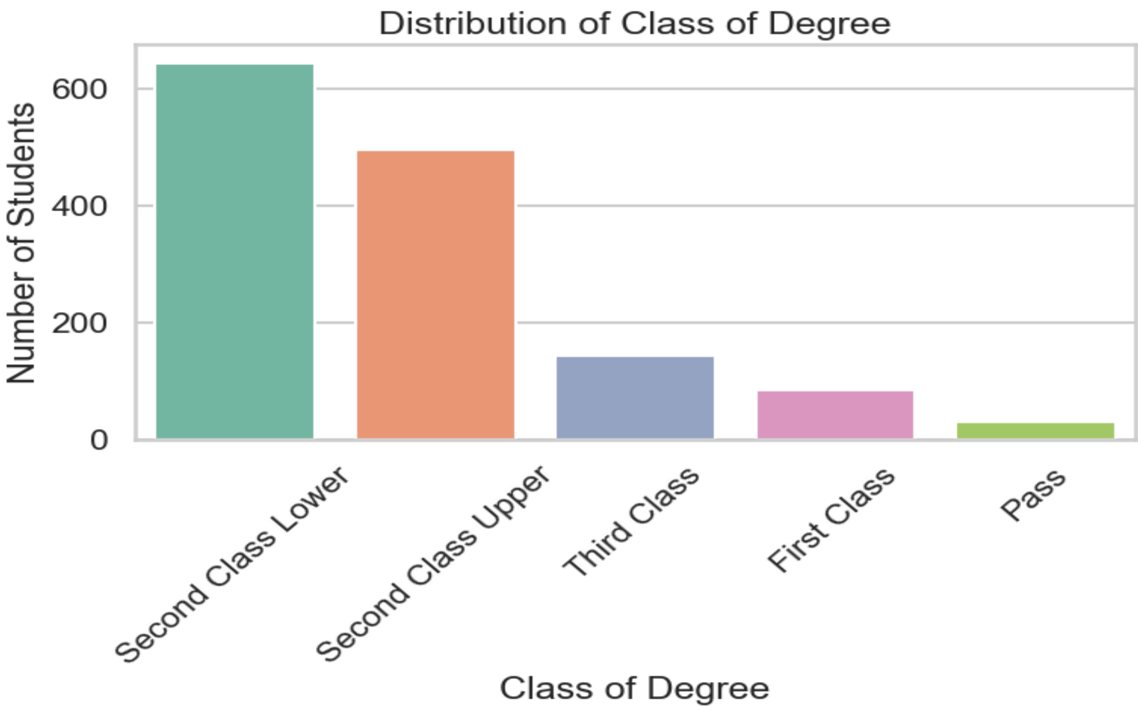

Figure 2: Distribution of Class of Degree Among Sampled Students. Most Students Graduated with Second Class Lower or Upper Honors, while Relatively few Attained First Class or Pass Grades, Indicating a Predominantly mid-to-high Performance Profile

Descriptive Patterns

Preliminary visualizations revealed consistent trends in student performance across the age spectrum. A histogram of *Age at Admission* indicated that most students entered at 17 or 18 years, while violin plots of CGPA by age group showed modest variation between categories. When disaggregated by gender, boxplots revealed that female students attained slightly higher median CGPAs than males, a pattern consistent with earlier observations in Nigerian private universities (Oluwole,2017).

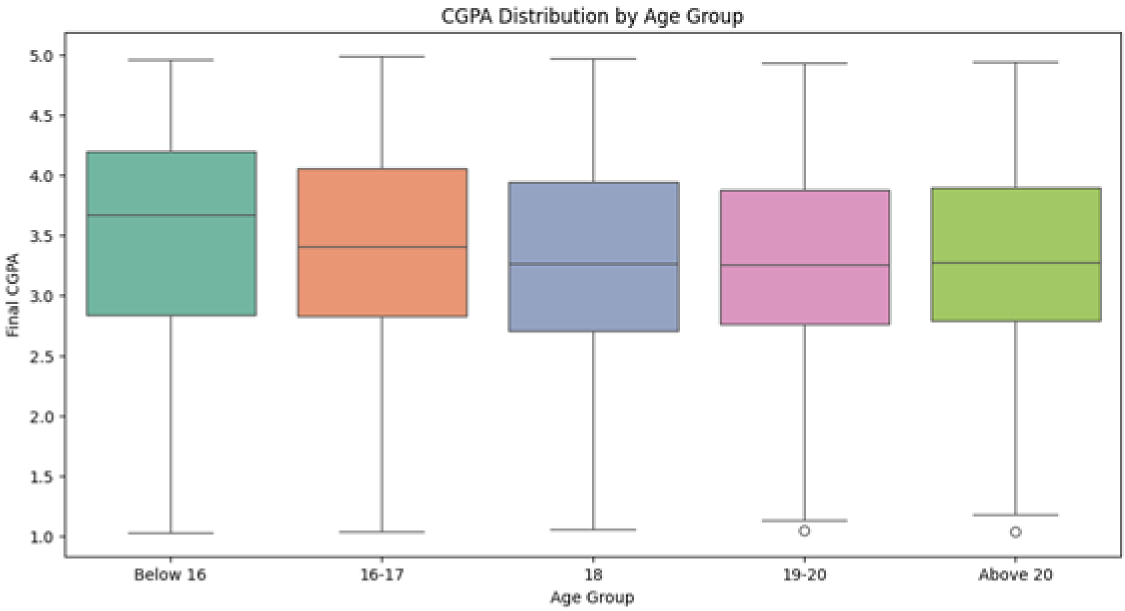

Figure 3: Boxplot Showing Distribution of Students' CGPA by Age Group

Median CGPA appears slightly higher for students aged 18 and above, though group differences are not statistically significant (ANOVA, $p = 0.1077$).

Figure 3 shows that students admitted at ages 18 and above displayed slightly higher median CGPAs compared to younger entrants, though variability within groups remained comparable. The absence of major outliers suggests relative performance stability across age categories.

Similarly, Figure 4 below illustrates a visibly higher median CGPA among female students, with a narrower interquartile range than that of male students. This pattern supports earlier observations that females tend to maintain steadier academic outcomes, potentially due to stronger self-discipline and time management (Oluwole, 2017; Adebayo et al., 2018).

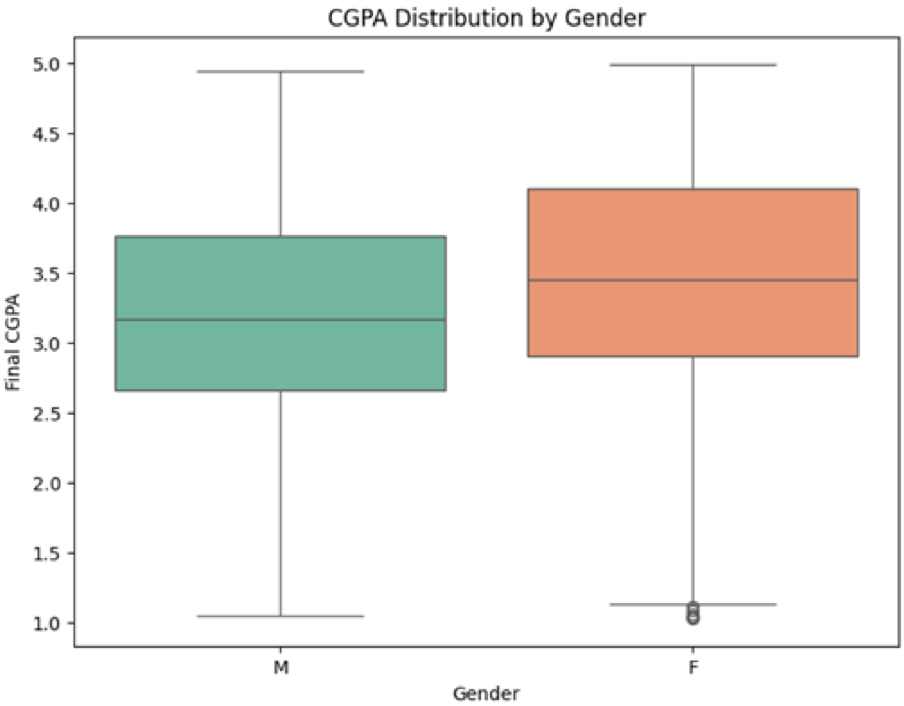

Figure 4: Boxplot Showing Distribution of Students' CGPA by Gender

Female students demonstrate a higher median CGPA and tighter performance spread compared to male students (t-test, $p < 0.001$).

Table 1: Summarizes Mean CGPA by Age Group, Confirming that Students Admitted at Age 18 or Above Tended to Perform Marginally Better, Though Variability Increased Among Younger Entrants

Age Group	Mean CGPA	SD
Below 16	3.02	0.68
16–17	3.26	0.74
18	3.34	0.69
19–20	3.30	0.65
Above 20	3.31	0.60

The descriptive evidence suggests that performance differences across age brackets were minor, whereas gender differences appeared more pronounced.

Inferential Analysis
To determine whether the observed variations were statistically significant, inferential tests were conducted using *scipy.stats*.

Gender-Based Comparison:
An independent samples t-test indicated a significant difference in academic performance between male and female students ($p < 0.001$). Female students' mean CGPA exceeded that of males, corroborating prior studies highlighting female academic discipline and self-regulation advantages (Sosu & Phebe, 2018; Oluwole, 2017).

Age-Based Comparison
The one-way ANOVA examining CGPA across five age groups yielded $F(4, 1396) = 1.84$, $p = 0.1077$, indicating no statistically significant difference in mean CGPA among students of different admission ages. This finding implies that chronological age at university entry does not exert a measurable effect on overall academic performance once students adapt to tertiary learning environments.

Interpretation of Findings
The absence of significant age-related performance differences aligns with international evidence that cognitive and motivational factors, rather than age itself, are primary predictors of academic success (Smith & Allen, 2020; Gomez & Tan, 2021). Within the Nigerian context, where early admission is common due to accelerated programs or flexible entry policies, the results suggest that younger entrants can achieve comparable outcomes when provided with adequate institutional support and academic mentoring (Ajayi & Olayemi, 2017).

In contrast, the significant gender effect underscores persistent performance disparities favoring female students. Similar trends have been attributed to higher academic diligence, consistent study habits, and stronger self-discipline among females (Adebayo et al., 2018; Ogunlade et al., 2019). These behavioural dimensions resonate with Self-Determination Theory, which posits that intrinsic motivation and autonomy drive sustained academic achievement (Parker et al., 2019).

The findings also lend empirical support to the notion, advanced by Piaget's cognitive development framework, that once students reach the formal operational stage typically during mid-to-late adolescence, age-related cognitive differences narrow considerably (Santrock, 2018). Vygotsky's Zone of Proximal Development further explains that supportive educational contexts can compensate for residual maturity gaps by providing the necessary scaffolding for effective learning (Romero & Ventura, 2024).

Implications
The evidence suggests that rigid age-based admission policies may be unnecessary for predicting academic success in tertiary institutions. Instead, universities should focus on data-driven support interventions that enhance student engagement across age groups. The demonstrated effectiveness of Python-based analytics in uncovering such insights illustrates the potential of computational tools in educational management and research (Zhu, 2021; Khan & Iqbal, 2023). Adopting similar frameworks can facilitate continuous performance monitoring, early-warning systems, and evidence-based policymaking within higher education.

CONCLUSION

The analysis revealed that while gender significantly influences academic outcomes, admission age does not constitute a decisive factor once students integrate into the university system. These results challenge the assumption that younger entrants are inherently disadvantaged, emphasizing instead the importance of academic motivation, discipline, and institutional support structures. Using a Python-based data analytics framework on 1,401 undergraduate records from Fountain University, Osogbo, the study demonstrated that gender differences in academic performance were statistically significant in favor of female students, whereas age at admission had no significant effect on final CGPA.

These findings align with earlier studies highlighting motivation, learning orientation, and academic discipline as stronger predictors of success than chronological age (Adebayo et al., 2018; Parker et al., 2019). The consistent female advantage also supports related Nigerian and international research advocating targeted interventions to enhance male students' engagement and academic drive (Oluwole, 2017; Ogunlade et al., 2019). Beyond these insights, the research underscores the versatility of Python as a transparent and replicable tool for educational analytics, reinforcing the value of data-driven approaches in institutional planning. Policy-wise, the results suggest that admission criteria should prioritize academic readiness over age, while the university should design gender-sensitive support systems to improve student performance. Future studies may extend this work by integrating larger, multi-institutional datasets and applying predictive machine learning models to explore student success trajectories more comprehensively.

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