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INFLUENCE OF SELF-REGULATED LEARNING STRATEGIES ON ACADEMIC PERFORMANCE AMONG UNDERGRADUATE STUDENTS: AN EMPIRICAL STUDY

Dzafira Mohd Sharani

School of Languages, Civilisation and Philosophy, Universiti Utara Malaysia, Email: dzamosh83@yahoo.com, ORCID: 0009-0009-2318-0378

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ABSTRACT

Self-regulated learning has been widely recognized as a key determinant of students' academic success in higher education. This study used an empirical dataset with 14,003 observations to investigate the impact of self-regulated learning practices on undergraduate students' academic achievement. A quantitative research design was employed, and data were analyzed using descriptive statistics, Pearson correlation analysis, and multiple linear regression. Despite the regression model's generally poor explanatory power, the results showed that the chosen self-regulated learning indicators as a whole had a statistically significant impact on academic performance. While study hours, attendance, and motivation shown relatively small predictive impacts, online course participation, discussion involvement, assignment completion, and stress level emerged as significant predictors of academic achievement among the factors evaluated. The results suggest that academic achievement is shaped by multiple interacting factors and that active engagement in learning activities, consistent completion of academic tasks, and effective stress management contribute more substantially to student success than individual learning behaviors alone. The study highlights the importance of strengthening self-regulated learning through learner-centered instructional approaches, technology-enhanced learning, and academic support initiatives. These findings provide evidence-based insights for educators and higher education institutions seeking to improve student engagement, independent learning, and academic performance.

1. Introduction

Self-regulated learning (SRL) is a major framework in educational psychology as it provides an explanation as to how students actively control their learning through planning, monitoring, regulating, and evaluating cognitive, motivational, and behavioral processes. SRL shifts away from teacher-centered learning and provides opportunities for learners to take responsibility for their learning including goal setting, choosing effective learning strategies, planning their time, and self-regulating their learning. In the context of higher education, these skills are especially significant as students should be able to self-regulate their learning and adjust to varying teaching methods and technological innovations. In an era where universities are increasingly embracing technology and learner-centred pedagogies, self-regulated learning is key to students' success. In general, students who successfully use SRL strategies exhibit their higher level of academic engagement, persistence, and achievement compared to students who mainly rely on others' guidance (Xu et al., 2022).

Academic performance continues to be the most acceptable measure of educational success, as it demonstrates students' achievement of their learning outcomes and institutional expectations. While there are many cognitive, social, and environmental factors that impact academic achievement, self-regulated learning has become a topic of great interest because it is a set of skills which can be trained in the education system and practiced. Those students who are able to manage their study time efficiently, attend school consistently, turn in assignments on time and are involved in and effective at school activities tend to have better school results. Self-regulated learning has consistently been shown to have a positive impact on academic achievement, as it encourages student autonomy in learning and enhances students' accountability for their learning (Almoslamani, 2022). Broadly, the results show that high levels of self-regulatory skills positively influence students' perseverance, self-confidence, and academic performance in various learning environments (Elesio, 2023).

With the increase of digital technologies and blended learning and online education, the importance of self-regulated learning has also been highlighted. Flexible learning environments involve students in taking control of their learning, being motivated and engaged. According to a recent meta-analysis, there is a significant positive correlation between SRL and academic achievement in higher education institutions (Zhao et al., 2025). Similarly, students with effective learning self-regulation in blended learning exhibit increased engagement and better academic performance (Luo & Zhou, 2024). The same findings from the MOOCs literature demonstrate that SRL is associated with learning satisfaction and performance (Dinh & Phuong, 2024), and studies in Ethiopian universities have indicated that self-regulated learning strategies have a significant impact on students' perceived learning gains and educational development (Tadesse et al., 2022).

New studies in education have broadened the scope of self-regulated learning by showing that it is not only beneficial for short term academic success, it is also beneficial for continued educational development. Longitudinal studies have shown that developing students' self-regulatory skills can have a lifelong impact on their academic progress and development while they are at University, underscoring the enduring importance of these abilities (Higgins et al., 2023). In addition, learning analytics has enabled researchers to explore self-regulated behaviors through objective learning data, offering educators a firsthand account of students' learning styles and giving them a chance to intervene in a timely fashion to support students' learning (Alhazbi et al., 2024). In the same way, the introduction of self-regulated learning indicators into predictive models to account for the prediction of academic success has been more accurate, with evidence that academic success is the product of multiple related learning behaviors (Pérez-González et al., 2022).

Effective self-regulated learning involves managing motivation and emotions, as well as cognitive and behavioural processes. High self-efficacy, resilience, and reflective learning are associated with students' ability to meet academic challenges and persist in learning. The development of these skills has been linked to greater student engagement and learning in postsecondary institutions (Öztürk, 2022). More recently, self-regulated learning is regarded as a dynamic process, in which the learners continuously adjust their learning strategies in response to feedback from others, to changes in the context, and to their own experiences in collaborative learning (Hadwin et al., 2025). Although there is increasing evidence to support the positive role of self-regulated learning in the success of students' academic achievement, the different contexts in which learning occurs indicate that certain learning behaviours may be more significant among undergraduate students. Therefore, more empirical studies on complete data sets are suggested to determine the most effective learning behaviours that predict learners' academic outcomes optimally (Mahama et al., 2024). It has also been noted that there are multiple indicators that should be taken into account to get a better understanding of how students are performing in their studies, such as study habits, attendance, motivation, completing assignments, participating in discussions, engaging in online learning, and managing stress (Kim, 2022). In this sense, the aim of the present study is to analyze the impact of SRL strategies on academic achievement of undergraduate learners, and to provide evidence that can guide institutional policies and instructional practices to enhance students' independent learning to improve learning outcomes (Nieva & Prudente, 2022).

Research Objectives

The study was guided by the following research objectives:

1.To examine the influence of self-regulated learning strategies on academic performance among undergraduate students.

2.To determine the relationship between selected self-regulated learning indicators, including study hours, attendance, motivation, online course participation, discussion participation, assignment completion, and stress level, and undergraduate students' academic performance.

3.To identify the most significant self-regulated learning indicators predicting academic performance among undergraduate students.

2. Methodology

2.1 Research Design

This study examined the impact of self-regulated learning practices on the academic performance of undergraduate students using a cross-sectional study design and quantitative approaches. A quantitative approach was used as it allowed the objective measurement of relationships among the study variables by using statistical techniques. A cross-sectional study design was used to analyze students' learning behaviors and academic achievements from the data gathered at one point in time. In addition, the research was conducted using an explanatory approach to know the prediction of the selected self-regulated learning indicators on the students' examination results. The existing educational dataset was used in this research, which was analyzed using secondary data analysis owing to the efficient investigation of the research objectives.

2.2 Data Source

A secondary data was used in the study and the source of the data was from a publicly available secondary data source titled Student Performance and Learning Style Dataset (Shamim, 2025). The data comprised 14,003 undergraduate students with 16 variables coded as students' learning behaviors, motivational factors, educational engagement, and academic performance, and demographic characteristics. Data was screened for completeness and consistency before data analysis. The screening process revealed no missing values. Duplicate observations were found, but were kept as there was no evidence that these observations were caused by data-entry error. This data was deemed suitable for analyzing the correlation between SRL and academic achievement of undergraduate students.

2.3 Study Variables

Academic performance, as represented by students' Examination Scores (ExamScore) served as the dependent variable in this study. Independent variables were indicators of self-regulated learning (study hours, attendance, motivation, assignments completed, participation in discussion, participation in online course, learning style, and stress level). Besides, age, gender, learning resources, Internet access, participation in extracurricular activities and use of educational technology were also taken into account as contextual variables in the analysis. The original coding in the data set was used for all variables.

2.4 Data Analysis Procedures

Data was analysed using Python in Google Collaboratory (Google Colab) environment. Initially, descriptive statistics were computed to give a broad overview of the study variables' mean, standard deviation, minimum, and maximum. The association between the indicators of self-regulated learning and students' achievement was then examined using Pearson's correlation analysis. To determine the predictive impact of the independent factors on the exam scores, multiple linear regression analysis was used. The coefficient of determination (R2), modified R2 regression coefficients, t-values, p-values, confidence intervals, and overall F-statistics were used to evaluate the regression model. The multicollinearity of the predictors was examined using the Variance Inflation Factor (VIF), and the homoscedasticity and normality assumptions were examined using diagnostic techniques. The 5% significance level ($p < .05$) was used to determine the statistical significance.

3. Results

3.1 Sample Characteristics and Descriptive Statistics

The research data was obtained from 14,003 undergraduate students and consisted of 16 study variables. No missing values were found among the analytical variables and all of the observations were retained for statistical analysis after data screening. But in the source data 1,534 duplicate records were found. These duplicate observations were retained to preserve the integrity of the original data set since there was no proof that they were the result of data input errors. The participants' ages were from 18 to 29 years, which was a typical undergraduate age range. Table 1 provides an overview of the sample profile and data-quality assessment.

Table 1. Sample and Data-Quality Profile

Indicator	Value
Total records in source dataset	14,003
Complete analytical records	14,003
Number of variables in source dataset	16
Missing values in analytical variables	0
Duplicate rows identified	1,534
Minimum participant age (years)	18
Maximum participant age (years)	29

The mean and standard deviation scores for the independent and dependent variables are shown in Table 2. The mean score of the exam was 70.35 (SD = 17.69) and the score ranged from 40 to 100, indicating that there was a large variation in the students' performance in the examination. On average, students reported 19.99 study hours (SD = 5.89), an attendance rate of 80.19% (SD = 11.47), and an assignment completion score of 74.50 (SD = 14.63). The number of online courses completed by students had an average of 9.89 (with a standard deviation of 6.11), and there was moderate variability across the sample in discussion participation, motivation, and stress level. Descriptive statistics in general shown that the students' learning behaviors and learning outcomes are quite diverse.

Table 2. Descriptive Statistics of the Study Variables

Variable	N	Mean	SD	Minimum	Median	Maximum
Study Hours	14,003	19.99	5.89	5	20	44
Attendance	14,003	80.19	11.47	60	80	100
Motivation	14,003	0.91	0.70	0	1	2
Online Courses	14,003	9.89	6.11	0	10	20
Discussion Participation	14,003	0.61	0.49	0	1	1

Assignment Completion	14,003	74.50	14.63	50	74	100
Stress Level	14,003	1.30	0.79	0	2	2
Examination Score	14,003	70.35	17.69	40	70	100

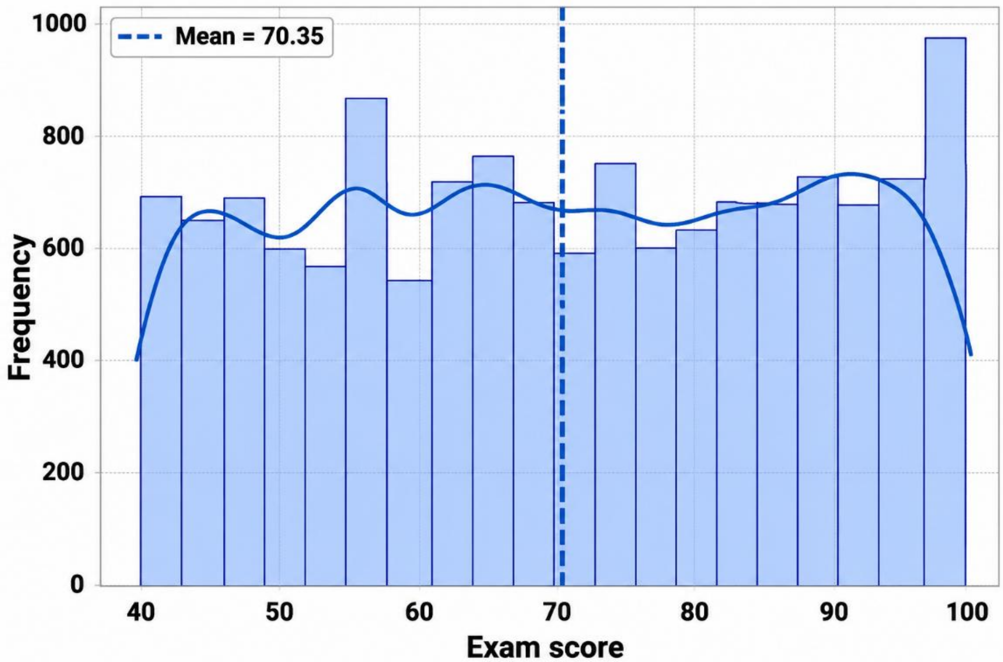

Figure 1. Distribution of Examination Scores

Figure 1 illustrates the distribution of examination scores across the study sample, demonstrating the central tendency and variability of students' academic performance.

3.2 Correlation Analysis

Pearson's product-moment correlation analysis was used to investigate the relationships between the selected self-regulated learning indicators and students' academic achievement. Table 3 shows the correlation coefficients. As a whole, the correlation between the predictor variables and examination scores were low, all with low values of the correlation coefficient. The most significant correlation with examination score was seen with stress level ($r = -0.032$) followed by discussion participation ($r = -0.029$). In contrast, assignment completion ($r = 0.025$) and online course participation ($r = 0.021$) had weak positive relationships with examination scores. Study hours ($r = 0.004$), attendance ($r = -0.015$), and motivation ($r = -0.002$) showed weak to nonexistent relationship with academic performance.

Table 3. Pearson Correlation Matrix

Variables	1	2	3	4	5	6	7	8
1. Study Hours	1.000							
2. Attendance	0.028	1.000						
3. Motivation	−0.007	−0.006	1.000					
4. Online Courses	−0.005	0.000	0.005	1.000				
5. Discussion Participation	0.027	−0.005	−0.020	0.003	1.000			
6. Assignment Completion	0.011	0.006	0.010	0.008	−0.003	1.000		
7. Stress Level	0.005	−0.018	−0.001	0.007	−0.015	0.021	1.000	
8. Examination Score	0.004	−0.015	−0.002	0.021	−0.029	0.025	−0.032	1.000

Figure 2. Heatmap of Pearson Correlation Coefficients

The heatmap in figure 2 is a visual summary of the relationships among all variables in the study, both in terms of strength and direction. Higher scores in the examination were found for the three categories of motivation, although these differences were statistically insignificant. The highest mean examination score was for students with motivation code 1 (M = 70.48), followed by motivation code 0 (M = 70.28) and motivation code 2 (M = 70.12). The dataset did not contain a codebook that would explain these categories, and thus the original, numeric codes were kept without the addition of labels.

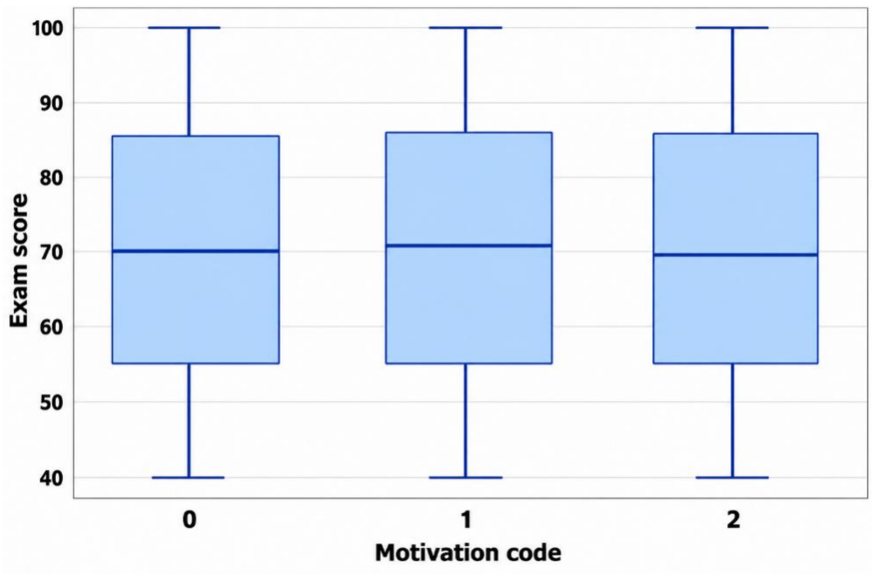

Figure 3. Examination Scores Across Motivation Categories

Figure 3 the boxplot illustrates the distribution of examination scores for each motivation category and highlights the similarity in score distributions across the three coded groups.

3.3 Multiple Linear Regression Analysis

A multiple linear regression analysis was conducted to analyze the simultaneous effect of selected SRL indicators on students' examination scores. Study hours, attendance, motivation, participation in online courses, participation in discussions, completion of assignments and stress level were all included as predictor variables. The regression model was significant ($F(7, 13{,}995) = 6.612$, $p < .001$); however, the amount of variance accounted for by the model was not high ($R^2 = 0.003$, Adjusted $R^2 = 0.003$).

Table 4 shows that the stress level had the highest standardized regression coefficient ($\beta = -0.034$, $p < .001$), which means that the relationship between stress level and examination scores is slightly negative. There was also a strong negative correlation with participation in discussion ($\beta = -0.030$, $p < .001$). By comparison, positive relationships of assignment completion ($\beta =$

0.026, p = .002) and online course participation (β = 0.021, p = .012) were found with academic performance. There is no significant relationship between the study hour, attendance and motivation with the examination scores at 5 % significance level. Multicollinearity diagnostics showed no sign of multicollinearity issues as all Variance Inflation Factor (VIF) values were around 1.00.

Table 4. Multiple Linear Regression Results

Predictor	B	SE	β	t	p	95% CI	VIF
Study Hours	0.017	0.025	0.006	0.677	.498	−0.033, 0.067	1.002
Attendance	−0.024	0.013	−0.016	−1.870	.062	−0.050, 0.001	1.001
Motivation	−0.076	0.215	−0.003	−0.356	.722	−0.497, 0.344	1.001
Online Courses	0.061	0.024	0.021	2.510	.012*	0.013, 0.109	1.000
Discussion Participation	−1.071	0.306	−0.030	−3.504	<.001**	−1.670, −0.472	1.001
Assignment Completion	0.031	0.010	0.026	3.053	.002**	0.011, 0.051	1.001
Stress Level	−0.757	0.190	−0.034	−3.983	<.001**	−1.130, −0.385	1.001

Model Summary: $F(7, 13{,}995) = 6.612$, $p < .001$; $R^2 = 0.003$; Adjusted $R^2 = 0.003$; N = 14,003.

Significance: $p < .05$, $p < .001$.

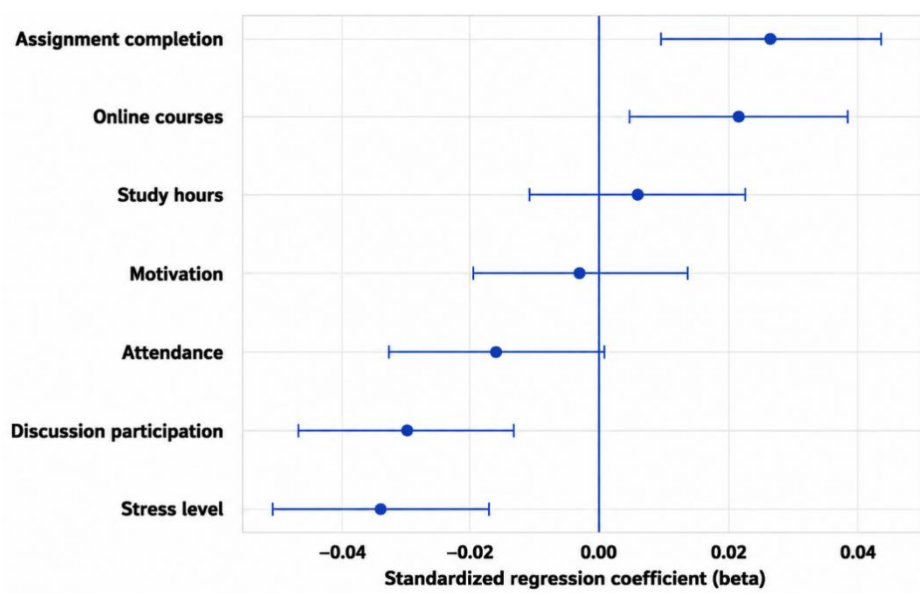

Figure 4. Standardized Regression Coefficients with 95% Confidence Intervals

Figure 4 the coefficient plot displays the standardized regression estimates and confidence intervals for all predictor variables, illustrating their relative contribution to examination scores.

4. Discussion

Based on the results of this study, it can be concluded that the self-regulated learning strategies for undergraduates' academic achievement are significant, but the degree of influence is different for each learning behavior. The results of descriptive statistics showed that the study hours, attendance, assignments and examination performance of students in general were in the medium to high category, which meant that the sample had relatively homogeneous academic engagement. However, the correlation analysis's findings revealed that there were only weak correlations between the students' exam performance and the chosen self-regulated learning indicators, indicating that exam success was dependent on a number of interrelated factors rather than a single self-regulated learning component. The regression analysis also indicated that the overall model was statistically significant but not very powerful; that is, other factors not examined in the current study have significant effects on students' academic achievement. The results confirm the multi-faceted character of academic attainment and the complexity of the learning process in higher education.

Predictive power of the regression model was limited, but some self-regulated learning indicators proved to be important predictors of academic achievement. Among the factors investigated, the participation in online courses, the participation in discussion, the completion of assignments and the stress level had a significant impact on the examination score of the students. The results indicated that students' active participation in learning and students' learning management are the factors that still play an important role in learning outcomes. This aligns with the evidence that the level of confidence that students develop in using online learning tools is closely linked to their self-regulated learning strategies and learning competencies (Zhang et al., 2023). The use of technology in teaching and learning in higher education is growing and students actively involved in technology-supported learning environments could be more able to manage their learning, access learning resources effectively and maintain their interest in learning.

Working on assignments, and taking part in class discussions, also became significant factors in academic performance, indicating that it is important to be engaged in learning activities throughout the learning period and not just during exam preparation. Students who complete coursework and engage in course interactions have a greater opportunity to get formative feedback, make sense of course content, and close learning gaps. These findings align with the existing evidence that demonstrates how formative assessment practices, such as the use of well-designed rubrics, positively impact academic performance and self-efficacy, as well as fostering self-regulated learning (Panadero et al., 2023). Likewise, explicit strategy-based instruction helps students to monitor their learning, adjust their ineffective strategies, and develop to become more independent learners that lead to better academic results (Teng, 2022).

Further, the result of the regression model reveals that the stress level is also an important factor in self-regulated learning, which supports the result above. Students can have good cognitive strategies, but under too much stress, concentration, motivation, and persistence can wane and academic performance is limited. This result is in line with the results of research showing that in university students, the relationship between mindfulness and procrastination and academic functioning is mediated by attention control and self-regulated learning (Taghavi-Nejad et al., 2024). Therefore, programs aimed at stress management and emotional control can enhance students' abilities to better utilize SRL strategies in their learning.

Additionally, the current results confirm that a learning process should be viewed as a socially and technologically supported one (Kumyoung et al., 2024). While study hours and attendance alone were not significant factors in the regression model, it is likely that effective learning is dependent on students taking advantage of the learning opportunities created, and not just the number of hours spent studying. Past studies have indicated that perceived social support has a positive effect on self-regulated learning, goal orientation, self-management, and academic achievement, highlighting that supportive learning contexts may foster better learning behaviors in students (Martínez-López et al., 2024). Similarly, causal modeling research indicated that various cognitive, motivational and environmental components act together in students' self-regulated learning, which also corroborates the multidimensional relationships found in the current study.

5. Conclusion

In this study, the effect of SRL strategies on academic achievement of the undergraduate students was analyzed by using an empirical data and statistical analyses such as descriptive statistics, Pearson correlation and multiple linear regression. The results showed that the selected indicators of self-regulated learning as a whole had a statistically significant effect on academic performance but the R-square was still low. This indicates that achievement is a complicated phenomenon that is influenced by a number of cognitive, behavioural, psychological and environmental determinants, of which those reported in the current study are only a few. However, online course involvement, discussion involvement, assignment completion and stress level were found to be significant predictors, placing importance on active learning involvement and effective self-management in higher education. The results show that the academic achievement is not only a result of the time that the students spend studying or attending school, but also of the effectiveness of their learning behavior regulation. Students who continually turn in assignments, actively involve themselves in the learning process, access online learning and are able to manage academic stress are more likely to have better learning outcomes. The results support the importance of self-regulated learning as a multifaceted process that encompasses behavioral, emotional, motivational, and cognitive aspects of learning. Study offers implications for higher education institutions interested in enhancing student achievement. Universities should encourage Teaching-learning methods, Technology, Formative Assessment, and Academic Support programmes that facilitate learner-centred teaching and learning and foster students' active participation and self-regulated learning skills. Future studies should introduce other factors, such as self-efficacy, learning motivation, institutional support, socioeconomic factors and new technologies like artificial intelligence, and should also be longitudinal or mixed methods. These investigations will help to increase the understanding of the factors that affect undergraduate students' academic performance and help create evidence-based approaches to improve learning outcomes and student success in higher education.

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