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Learning Analytics for Predicting Student Academic Success

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Abstract

This study investigates the relationships among learning analytics, student engagement, and student academic success in higher education. The objective is to examine whether student engagement strengthens the influence of learning analytics on academic success. A quantitative research approach was employed using survey data collected from university students who actively utilized digital learning platforms. The data were analyzed using structural equation modeling to evaluate the direct and indirect relationships among the research variables. The findings indicate that learning analytics has a significant positive effect on student engagement and academic success, while student engagement partially mediates the relationship between learning analytics and academic success. The results suggest that learning analytics improves educational outcomes when supported by active student participation and personalized learning experiences. These findings contribute to the advancement of educational technology research and provide practical implications for universities in developing data-informed learning environments that enhance student engagement, academic achievement, and sustainable educational quality.

INTRODUCTION

Digital technologies have revolutionized higher education as they enable institutions to gather and process vast quantities of educational data and to analyse it. Of these innovations, learning analytics has become a strategic tool to better understand and enhance students' learning processes by systematically analysing academic, behavioural and engagement data. Learning analytics is being adopted by universities on a wide scale to track learning activities, detect learner at-risk situations, tailor the learning process to the learner, and assist in decision making for evidence-based learning. Learning analytics, which involves collecting, interpreting, and utilizing data to inform learning and teaching, has emerged as a crucial part of data-informed education management practices to improve the efficacy of learning and teaching (Gonugunta & Leo, 2024; Basha et al., 2025; Wang, 2025; Angeioplastis et al., 2025).

Student achievement continues to be a major measure of school quality and school performance (Feraco et al., 2023; Macnamara & Burgoyne, 2023; Dalgaard et al., 2022). Academic success is more than just a GPA; it is about student learning

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achievement, course completion, knowledge gained, retained, and overall educational development. Yet the higher education institutions are still grappling with a variety of issues with low student engagement, high dropout rates, variation in academic performance, and disparity in learning outcomes (Cabral-Gouveia et al., 2023; Assefa et al., 2025; De Silva et al., 2022; Moreeng et al., 2024). The challenges are more apparent in online and blended learning environments, in which teachers may have only limited chances to observe students learning interactions as they would in a regular classroom setting. Therefore, it is essential for the educational institutions to adopt creative solutions that will help identify learning difficulties at an early stage and provide academic support in time (Davar et al., 2025; Nabil et al., 2025; Santhiya et al., 2023; Boonma, 2025).

The challenges these present can be met with the significant opportunity learning analytics (LA) provides to reimagine educational data as actionable information. Learning analytics can be used to analyse students' learning behaviours, attendance, assessment performance, and learning management system activities, along with participation patterns, to inform educators about students' performance and planning interventions (Johar et al., 2023; Karaoglan et al., 2022; Yang & Ogata, 2023; Khor & K, 2023). Learning analytics in addition to end of semester assessments allows teachers to monitor student progress throughout the semester, and make decisions about what to do about an issue before it becomes critical (Ifenthaler et al., 2023; Alalawi et al., 2025; Divjak et al., 2023). This forward-thinking stance resonates with the trend towards tailoring education to individual needs and evidence-based practice.

While learning analytics is widely used, more than just collecting and analysing learning data is needed if academic success is to be improved. The active involvement of students in the learning process is still the most important factor in their learning success (Lynam et al., 2024; Sointu et al., 2023). The behavioral, emotional, and cognitive engagement of students in learning is a key factor in the success of students' digital learning experiences. Thus, the knowledge of how learning analytics can boost student engagement and, in turn, academic achievement has emerged as a critical focus of research. These connections are worthy of investigation for any university looking to create sustainable, learner-centred educational programs that lead to better learning outcomes and long-term academic success.

While the research of learning analytics has received significant attention, the literature has mostly been concerned with the creation of predictive algorithms, data mining methods and the analytics of learning management systems. However, the technical accuracy of predictive models or the effectiveness of learning analytics in identifying at-risk students has been primarily examined, and less attention has been paid to understanding of the behavioral mechanisms by which learning analytics contributes to student academic success. In addition, the empirical results are not consistent. Research results suggest that learning analytics has a positive impact on academic outcomes, because it allows for early interventions and personalized learning support, and some other studies indicate that the impact of learning analytics is limited to students' receptiveness to feedback, institutional support and instructional design. This inconsistencies indicate that learning analytics is not enough to improve academic achievement and other learning aspects should be taken into account. Furthermore, current studies have focused on the study of learning analytics and student engagement in isolation, which has led to little theoretical work on the relationship between the transformation of learning data to meaningful learning (Mikić et al., 2026; Nguyen er al., 2022; Caspari-Sadeghi, 2022; Li & Xue, 2023).

To fill these gaps, this study aims to propose an integrated framework to investigate the relationships between learning analytics, student engagement, and student

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academic success. The novelty of this research is the focus on student engagement as a mechanism through which learning analytics supports academic achievement, rather than focusing on the technological and predictive aspects of the field, as conducted in previous studies (Huppes & Schaubroeck, 2022; Venkatesh, 2022; Afifuddin & Seo, 2024). This research combines learning analytics and educational engagement theory to achieve a more holistic view of the application of data-driven learning to sustainable student learning outcomes. In this regard, the aim of this study is to first investigate the influence of learning analytics on student engagement, the latter's effect on academic success, and the mediating role of student engagement between learning analytics and academic success. The results will be the theoretical contribution of the scientific work to the existing scientific literature on learning analytics and educational technology, and offer a practical guidance for the design of data-informed learning strategies at higher education institutions to enhance the student's engagement in a learning process, student achievement and long-term educational outcomes.

METHODS

Research Design

This study employed a quantitative research approach with a cross-sectional survey design to examine the relationships among Learning Analytics (LA), Student Engagement (SE), and Student Academic Success (SAS) in higher education. The quantitative approach was selected because it enables the systematic measurement of latent constructs and the empirical examination of hypothesized relationships between variables. A cross-sectional design was adopted to obtain data from undergraduate students at a single period of observation, allowing the researchers to investigate the associations between students' experiences with learning analytics, their engagement in academic activities, and their perceived academic success.

The study was guided by a conceptual framework positioning student engagement as a mediating variable in the relationship between learning analytics and academic success. Specifically, the research examined the direct influence of learning analytics on student engagement, the relationship between student engagement and academic success, the direct effect of learning analytics on academic success, and the indirect effect of learning analytics on academic success through student engagement. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to evaluate the proposed relationships and assess the explanatory capability of the research model.

Research Setting, Population, and Sampling Technique

The research was conducted among undergraduate students enrolled in higher education institutions that utilize digital learning platforms, learning management systems (LMS), or other technology-supported learning applications. The target population consisted of students who had actively participated in digital learning activities for at least one academic semester. This eligibility criterion was established to ensure that respondents possessed sufficient experience to evaluate the implementation and perceived usefulness of learning analytics in their academic activities. A purposive sampling technique was employed to select respondents based on their relevance to the research objectives. The sampling criteria included undergraduate enrollment, experience using digital learning platforms for a minimum of one academic semester, and familiarity with technology-supported learning activities. A total of 320 valid questionnaires were obtained and included in the final analysis. This sample size was considered adequate for examining the relationships among the three latent constructs through PLS-SEM and evaluating both direct and indirect effects within the proposed structural model.

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Research Instruments and Measurement of Variables

Primary data were collected using a structured questionnaire adapted from measurement instruments reported in previous studies on educational technology, learning analytics, student engagement, and academic achievement. The questionnaire consisted of two main sections. The first section collected demographic information, including gender, age, year of study, academic discipline, and duration of experience using digital learning platforms. The second section measured the three principal research constructs, namely Learning Analytics, Student Engagement, and Student Academic Success.

Learning Analytics was operationalized through indicators reflecting students' perceptions of the usefulness of digital learning data, monitoring of academic progress, availability of learning feedback, and support for personalized learning activities. Student Engagement was measured through behavioral, cognitive, and emotional dimensions, reflecting students' participation in academic activities, involvement in learning processes, and commitment to educational goals. Student Academic Success was assessed through students' perceptions of their academic performance, learning achievement, and educational outcomes. All measurement items were evaluated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Prior to the main survey, the questionnaire underwent expert review involving specialists in educational technology and higher education management. A pilot test was also conducted to assess the clarity, readability, and comprehensibility of the questionnaire items before their application in the main data collection process.

Data Collection Procedure

Data collection was conducted through the distribution of structured questionnaires to eligible undergraduate students with experience using digital learning environments. The questionnaire was designed to obtain consistent responses regarding students' perceptions of learning analytics, their engagement in academic activities, and their academic success. Respondents were selected according to the predetermined sampling criteria to ensure that the collected information was relevant to the research objectives. Following the completion of data collection, the returned questionnaires were examined to determine their completeness and suitability for statistical analysis. A total of 320 valid responses were retained for further analysis. The data were subsequently organized and prepared for analysis using SmartPLS 4. The resulting dataset was used to evaluate the measurement properties of the research constructs and test the hypothesized relationships within the structural model.

Data Analysis Technique

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. This analytical technique was selected because the study aimed to examine the predictive relationships among multiple latent constructs and assess the mediating role of student engagement. The analytical procedure consisted of two principal stages, namely measurement model assessment and structural model assessment.

Measurement Model Assessment

The measurement model was evaluated to establish the reliability and validity of the research instruments. Indicator reliability was examined through outer loading values, with a threshold of 0.70 used to assess the adequacy of individual indicators. Internal consistency reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR), with values exceeding 0.70 indicating satisfactory reliability. Convergent validity was assessed using the Average Variance Extracted (AVE), where

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values greater than 0.50 indicated that the constructs explained an adequate proportion of variance in their respective indicators. Discriminant validity was examined using the Heterotrait–Monotrait Ratio (HTMT), with values below 0.90 considered acceptable. These procedures were conducted to ensure that the measurement items adequately represented their respective constructs and that Learning Analytics, Student Engagement, and Student Academic Success were empirically distinguishable.

Structural Model Assessment

Following the evaluation of the measurement model, the structural model was assessed to examine the relationships among the research constructs. Collinearity was examined using the Variance Inflation Factor (VIF), with values below 5.00 indicating that multicollinearity was not a critical concern. The explanatory power of the model was evaluated through the coefficient of determination (R^2), which measured the proportion of variance in the endogenous constructs explained by their predictors. Predictive relevance was assessed using Stone–Geisser's Q^2 statistic, with values greater than zero indicating predictive relevance. Effect size (f^2) was also examined to determine the relative contribution of each predictor to the explained variance of the endogenous constructs. Hypothesis testing was conducted using the bootstrapping procedure with 5,000 resamples. The significance of the hypothesized relationships was evaluated using standardized path coefficients (β), t-statistics, and p-values at a significance level of 0.05.

The analysis focused on three direct relationships: Learning Analytics → Student Engagement, Student Engagement → Student Academic Success, and Learning Analytics → Student Academic Success.

Mediation Analysis

The mediating role of Student Engagement was examined by evaluating the indirect relationship between Learning Analytics and Student Academic Success through the bootstrapping procedure. The indirect effect was assessed using the path coefficient, t-statistic, and p-value. The mediation analysis was intended to determine whether student engagement functions as an explanatory mechanism through which learning analytics contributes to academic success. The direct and indirect effects were considered together to establish the nature of the mediation relationship and evaluate the proposed conceptual framework.

Validity, Reliability, and Common Method Bias

To strengthen the methodological rigor of the study, instrument quality was evaluated through expert assessment, pilot testing, and statistical examination of the measurement model. Construct reliability was assessed using Cronbach's Alpha and Composite Reliability, while convergent and discriminant validity were examined using AVE and HTMT, respectively. In addition, Harman's single-factor test was specified to assess the potential influence of common method bias arising from the use of self-reported questionnaire data. These procedures were intended to establish the consistency, validity, and analytical suitability of the research instrument.

RESULTS AND DISCUSSION

This study examined the relationships among Learning Analytics (LA), Student Engagement (SE), and Student Academic Success (SAS) using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The empirical analysis was conducted in three stages. First, descriptive statistics were used to summarize the demographic characteristics of the respondents and describe the distribution of the research variables. Second, the measurement model was evaluated to assess the reliability and validity of the research constructs. Finally, the structural model was

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examined to test the proposed hypotheses concerning the direct and indirect relationships among learning analytics, student engagement, and student academic success. The overall findings indicate that students perceive learning analytics as an important educational tool that enhances engagement and contributes positively to academic success.

Respondent Characteristics

A total of 320 valid questionnaires were collected from undergraduate students enrolled in universities that actively utilize learning management systems and digital learning platforms. The respondents represented different academic disciplines and years of study, providing comprehensive insights into students' experiences with learning analytics.

Table 1. Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	154	48.1
	Female	166	51.9
Age	Below 20 years	74	23.1
	20–22 years	168	52.5
	Above 22 years	78	24.4
Year of Study	First Year	62	19.4
	Second Year	88	27.5
	Third Year	96	30.0
	Fourth Year or Above	74	23.1
Digital Learning Experience	1–2 Years	101	31.6
	3–4 Years	145	45.3
	More than 4 Years	74	23.1

Source: Authors' Survey Data, 2026

As presented in Table 1, female students constituted 51.9% of the respondents, while male students accounted for 48.1%. The majority of respondents (52.5%) were between 20 and 22 years old, representing students in the middle stage of their undergraduate education. Most respondents had between three and four years of experience using digital learning platforms, indicating that they possessed sufficient familiarity with learning analytics tools to provide informed responses.

Descriptive Statistics

Descriptive statistics were calculated to examine students' perceptions of the three research constructs.

Table 2. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation	Interpretation
Learning Analytics	4.18	0.57	High
Student Engagement	4.09	0.61	High
Student Academic Success	4.15	0.58	High

Source: Authors' Survey Data, 2026

The results presented in Table 2 indicate that Learning Analytics obtained the highest mean score (4.18), suggesting that students generally perceived learning analytics systems as useful for monitoring academic progress, providing timely feedback, and supporting their learning activities. The relatively low standard deviation (0.57) indicates a high level of agreement among respondents regarding the effectiveness of learning analytics.

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The Student Engagement construct achieved a mean score of 4.09, reflecting positive levels of behavioral, cognitive, and emotional engagement in learning activities. This finding suggests that students actively participated in academic tasks, interacted with learning resources, and remained committed to achieving their educational goals. Similarly, Student Academic Success recorded a mean score of 4.15, indicating that respondents generally perceived themselves as achieving satisfactory academic performance and learning outcomes. The relatively small standard deviation demonstrates consistency in students' perceptions of their academic achievement.

Measurement Model Assessment

Indicator Reliability

Indicator reliability was evaluated by examining the outer loading values of each measurement item. An outer loading of 0.70 or higher indicates that an indicator adequately represents its corresponding latent construct. As shown in Table 3, all indicators exceeded the recommended threshold, with loading values ranging from 0.756 to 0.918.

Table 3. Indicator Reliability

Construct	Indicator	Outer Loading
Learning Analytics	LA1	0.845
	LA2	0.882
	LA3	0.918
	LA4	0.867
	LA5	0.821
Student Engagement	SE1	0.891
	SE2	0.874
	SE3	0.856
	SE4	0.814
	SE5	0.756
Student Academic Success	SAS1	0.903
	SAS2	0.885
	SAS3	0.861
	SAS4	0.834
	SAS5	0.779

Source: Authors' Survey Data, 2026

The results demonstrate that all measurement items possess satisfactory loading values, indicating strong correlations between the observed indicators and their respective latent constructs. Consequently, no indicators were removed from the measurement model because each item met the recommended reliability criterion.

Internal Consistency Reliability and Convergent Validity

Table 4. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
Learning Analytics	0.914	0.936	0.748
Student Engagement	0.899	0.925	0.712
Student Academic Success	0.907	0.932	0.732

Source: Authors' Survey Data, 2026

Table 4 demonstrates that all constructs exhibit excellent internal consistency. Cronbach's Alpha values range from 0.899 to 0.914, while Composite Reliability values range from 0.925 to 0.936, exceeding the recommended minimum threshold. Furthermore, the AVE values vary between 0.712 and 0.748, confirming that each

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construct explains more than half of the variance of its indicators. These findings verify that the measurement model possesses satisfactory convergent validity.

Discriminant Validity

Table 5. HTMT Ratio

Constructs	HTMT
Learning Analytics ↔ Student Engagement	0.694
Learning Analytics ↔ Student Academic Success	0.661
Student Engagement ↔ Student Academic Success	0.738

Source: Authors' Survey Data, 2026

The HTMT values presented in Table 5 range from 0.661 to 0.738, all of which are well below the recommended threshold of 0.90. These findings confirm that Learning Analytics, Student Engagement, and Student Academic Success represent distinct conceptual constructs. Therefore, discriminant validity has been successfully established. The assessment of the measurement model demonstrates that all constructs satisfy the recommended standards for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. These results provide strong evidence that the research instrument is both reliable and valid, thereby establishing a solid foundation for evaluating the structural relationships and testing the proposed hypotheses in the subsequent analysis.

Structural Model Assessment

Collinearity Assessment

Table 6. Collinearity Assessment

Structural Relationship	VIF
Learning Analytics → Student Engagement	1.821
Learning Analytics → Student Academic Success	2.063
Student Engagement → Student Academic Success	2.063

Source: Authors' Survey Data, 2026

The VIF values presented in Table 6 range from 1.821 to 2.063, indicating that no multicollinearity issues exist among the predictor variables. Therefore, the structural model satisfies the assumptions required for hypothesis testing.

Coefficient of Determination and Predictive Relevance

Table 7. Model Evaluation

Endogenous Construct	R^2	Q^2
Student Engagement	0.571	0.389
Student Academic Success	0.694	0.503

Source: Authors' Survey Data, 2026

The findings indicate that Learning Analytics explains 57.1% of the variance in Student Engagement. Furthermore, Learning Analytics and Student Engagement jointly explain 69.4% of the variance in Student Academic Success. These values indicate substantial explanatory power. In addition, the Q^2 values of 0.389 and 0.503 are greater than zero, confirming that the proposed model possesses satisfactory predictive relevance and is capable of accurately predicting the endogenous constructs.

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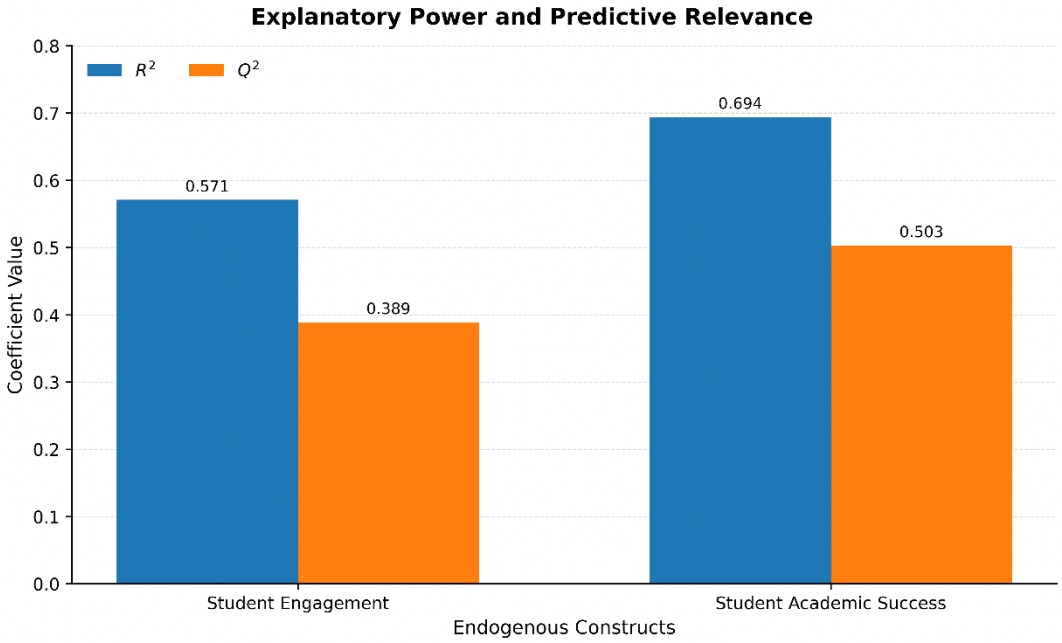


Figure 2. Explanatory Power and Predictive Relevance

Source: Authors' Survey Data, 2026

Figure 2 the explanatory power (R^2) and predictive relevance (Q^2) of the structural model. Student Academic Success demonstrates an R^2 value of 0.694 and Q^2 value of 0.503, while Student Engagement exhibits an R^2 value of 0.571 and Q^2 value of 0.389.

Effect Size

The practical contribution of each predictor variable was evaluated using Cohen's effect size (f^2).

Table 8. Effect Size

Relationship	f^2	Interpretation
Learning Analytics → Student Engagement	0.652	Large
Learning Analytics → Student Academic Success	0.201	Medium
Student Engagement → Student Academic Success	0.376	Large

Source: Authors' Survey Data, 2026

The effect size analysis demonstrates that Learning Analytics has a large effect on Student Engagement (f^2 = 0.652). Similarly, Student Engagement exerts a large influence on Student Academic Success (f^2 = 0.376), while the direct effect of Learning Analytics on Student Academic Success is moderate (f^2 = 0.201). These findings suggest that student engagement plays an important role in strengthening the educational benefits of learning analytics.

Hypothesis Testing

Table 9. Direct Effects

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1	Learning Analytics → Student Engagement	0.756	18.241	<0.001	Supported
H2	Student Engagement → Student Academic Success	0.548	10.186	<0.001	Supported

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H3	Learning Analytics → Student Academic Success	0.286	4.931	<0.001	Supported

Source: Authors' Survey Data, 2026

The results reveal that all direct relationships are statistically significant. Learning Analytics has a strong positive influence on Student Engagement (β = 0.756, p < 0.001), indicating that students who actively utilize learning analytics tools tend to exhibit higher levels of engagement in learning activities. Student Engagement also has a significant positive effect on Student Academic Success (β = 0.548, p < 0.001), suggesting that actively engaged students are more likely to achieve favorable academic outcomes. Moreover, Learning Analytics directly influences Student Academic Success (β = 0.286, p < 0.001), although the magnitude of this relationship is smaller than the indirect effect through student engagement.

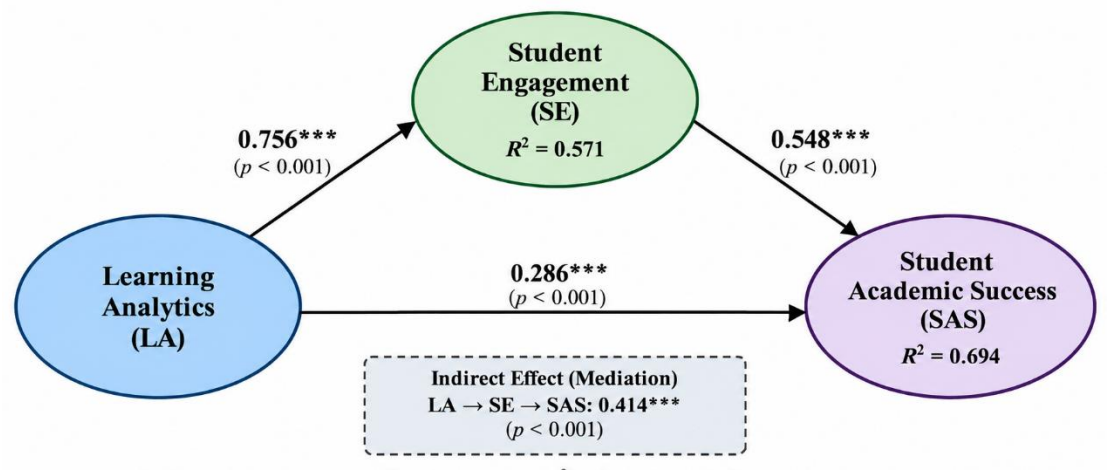


Figure 3. Structural Relationships among Research Variables

Source: Authors' Survey Data, 2026

Figure 3 presents the structural relationships among Learning Analytics, Student Engagement, and Student Academic Success. The model illustrates the direct effects of Learning Analytics on both Student Engagement and Student Academic Success, as well as the mediating role of Student Engagement in the relationship between Learning Analytics and Student Academic Success.

Mediation Analysis

Table 10. Indirect Effect

Hypothesis	Indirect Path	β	t-value	p-value	Decision
H4	Learning Analytics → Student Engagement → Student Academic Success	0.414	9.472	<0.001	Supported

Source: Authors' Survey Data, 2026

The mediation analysis demonstrates that Student Engagement significantly mediates the relationship between Learning Analytics and Student Academic Success (β = 0.414, p < 0.001). The indirect effect is stronger than the direct effect, indicating that learning analytics contributes to academic success primarily by increasing students' behavioral, emotional, and cognitive engagement with learning activities. These findings suggest that learning analytics systems become more effective when students actively interact with the feedback, recommendations, and personalized learning support generated by these systems.

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The Mediating Role of Student Engagement in the Relationship between Learning Analytics and Academic Success

The findings of this study demonstrate that learning analytics significantly enhances student academic success both directly and indirectly through student engagement. These results suggest that the effectiveness of learning analytics extends beyond its technical capability to collect and analyze educational data. Instead, learning analytics creates educational value by encouraging students to become more actively involved in their learning processes. The positive relationship between learning analytics and student engagement indicates that timely feedback, personalized learning recommendations, and continuous monitoring of academic progress motivate students to participate more actively in academic activities. Consequently, students who regularly interact with learning analytics systems are more likely to demonstrate stronger behavioral, cognitive, and emotional engagement, which ultimately contributes to improved academic performance. These findings reinforce the growing recognition that educational technologies achieve their greatest impact when they actively support learner-centered educational practices rather than simply providing institutional database (Kim, 2025; Yeboah, 2026; Shehata et al., 2024).

The significant influence of student engagement on academic success is consistent with contemporary educational theories that identify engagement as one of the strongest predictors of learning achievement. Students who are actively engaged tend to devote greater effort to learning activities, participate more frequently in academic discussions, complete assignments on time, and develop stronger self-regulated learning behaviors (Park & Kim, 2022; Sun et al., 2023). The present findings further indicate that learning analytics strengthens these positive behaviors by providing students with continuous information regarding their learning progress and performance. Unlike traditional assessment approaches that often provide feedback only after course completion, learning analytics enables early identification of learning difficulties and supports timely academic intervention (Ravichandran, 2024; Pan et al., 2024). This finding supports previous research suggesting that data-driven learning environments improve educational outcomes by facilitating personalized instruction and adaptive learning strategies.

An important contribution of this study is the confirmation of the mediating role of student engagement in the relationship between learning analytics and academic success. Although learning analytics has a direct positive effect on academic performance, the indirect effect through student engagement is considerably stronger. This finding suggests that educational institutions should not expect technological platforms alone to improve student achievement. Instead, universities should encourage students to actively utilize learning analytics dashboards, interpret performance feedback, and participate in learning activities that promote collaboration, reflection, and continuous improvement. Therefore, the effectiveness of learning analytics depends largely on how students engage with the information generated by digital learning systems rather than on the availability of technology itself (Kew & Tasir, 2022; Liu & Yu, 2023).

From a theoretical perspective, this study contributes to the literature by integrating learning analytics and student engagement into a unified framework for explaining student academic success. Previous studies have frequently examined predictive models of academic performance or the technical development of learning analytics systems independently. In contrast, this study demonstrates that student engagement serves as a critical behavioral mechanism through which learning analytics influences educational outcomes. By combining educational technology with student engagement theory, this research provides a more comprehensive explanation of how digital learning environments contribute to sustainable academic achievement.

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The findings also provide important practical implications for higher education institutions. University administrators and educators should integrate learning analytics into teaching strategies rather than using it solely as an institutional monitoring tool. Providing personalized feedback, early academic intervention, student mentoring, and data-informed instructional support can increase students' engagement and improve learning outcomes. Furthermore, universities should strengthen digital literacy among both students and instructors to ensure that learning analytics is effectively utilized as part of everyday teaching and learning practices.

The novelty of this study lies in its integration of learning analytics, student engagement, and student academic success within a single empirical model. While previous studies have predominantly emphasized predictive accuracy or technological implementation, this research highlights the behavioral processes through which learning analytics contributes to educational success. Nevertheless, several limitations should be acknowledged. The study employed a cross-sectional research design, preventing observation of changes in student engagement over time. In addition, the model focused on one mediating variable and did not include other influential factors such as self-regulated learning, academic motivation, digital literacy, or institutional support. Future research is therefore encouraged to adopt longitudinal research designs, incorporate additional mediating and moderating variables, and conduct comparative studies across different educational systems and cultural contexts to provide a broader understanding of learning analytics and student academic success.

CONCLUSION

This study examined the relationships among learning analytics, student engagement, and student academic success in higher education. The findings reveal that learning analytics has a significant positive influence on student academic success both directly and indirectly through student engagement. The results indicate that learning analytics becomes more effective when students actively engage with personalized feedback, learning progress monitoring, and data-driven academic support. Student engagement emerged as a critical mechanism that strengthens the relationship between learning analytics and academic success, emphasizing that technological innovation alone is insufficient to improve educational outcomes without active student participation.

This study contributes to the literature by integrating learning analytics and student engagement into a comprehensive framework for explaining student academic success. The findings extend existing research by demonstrating the behavioral pathway through which learning analytics enhances learning outcomes. From a practical perspective, the study provides valuable guidance for higher education institutions to integrate learning analytics into instructional practices, strengthen academic advising, and promote personalized learning strategies that encourage greater student engagement. Despite these contributions, the study is limited by its cross-sectional research design and its focus on a single mediating variable. Future research should employ longitudinal designs, investigate additional factors such as self-regulated learning, academic motivation, digital literacy, and institutional support, and conduct comparative studies across different educational settings to improve the generalizability of the findings.

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