Learning Analytics for Predicting Academic Performance in Computer Science Courses

OPEN ACCESS

Volume: 13

Special Issue: 3

Month: March

Year: 2026

P-ISSN: 2321-788X

E-ISSN: 2582-0397

Citation:
Vijayanand Selvaraj. "Learning Analytics for Predicting Academic Performance in Computer Science Courses." *Shanlax Interantional Journal of Arts, Science and Humanities,* vol. 13, no. S3, 2016, pp. 16–20.

DOI:
https://doi.org/10.34293/sijash.v13iS3-Mar.10480

Vijayanand Selvaraj
Information Technology Professional
Houston, Texas, USA

Abstract

The acclaimed development of digital learning environment has produced massive volumes of pedagogical information, which has provided the chances to enhance the outcomes of the students using learning analytics. The paper explores the application of learning analytics in how academic performance is forecasted in undergraduate students pursuing Computer Science courses. The predictive insights were created by analyzing the variables of attendance, learning management system (LMS) participation, patterns of assignments submission, quiz grades, and programming lab activity, to detect at-risk learners. Data obtained by 200 undergraduate students was subjected to a quantitative research method with correlation and regression to get the relationship between smoking and ADHD. The results indicate that there is a great positive association between LMS engagement indicators and final academic performance. The models of early prediction proved to be very accurate in determining the students who were likely to perform poorly in order to initiate the academic intervention early. The paper highlights the necessity of incorporating the use of data-based decision-making tools into the Computer Science education system to improve student performance, decrease the dropout rates, and promote individualized learning experiences.

Keywords: Learning Analytics, Predicting Academic Performance, Computer Science Education, Educational Data Mining, Predictive Modeling, Learning Management Systems, Student Engagement, Data-Driven Education.

Introduction

The adoption of digital technologies in higher education has brought a lot of changes in the teaching, learning, and assessment procedures. In particular, Computer Science education leaves significant digital footprint since it involves programming platforms, online submissions, discussion forums and coding repository. These online records are informative on the learning behaviors of students. Learning analytics can be defined as the process of measuring, collecting, analyzing and reporting data relating to learners and the environments they find themselves in in order to comprehend and maximize learning outcomes.

The ability to predict the performance of students in institutions of higher learning has become a major source of concern. The academically at-risk students can be identified early enough to enable teachers to develop intervention measures on time. Predictive analytics have the potential to guide precise mentoring and instructional adaptations in Computer Science courses where abstract thinking and programming skills are problematic to learners. In this paper, I will discuss the way learning analytics tools can be used to make accurate predictions of academic performance as well as enhancing the rate of student success in Computer Science programs.

Review of Literature

Recent studies point out to the increasing topicality of predictive analytics in education. Research has shown that the frequency of interaction in LMS, the pattern of submitting assignments, and the coding lab attendance are all good predictors of academic achievement. Regression analysis, decision trees, and neural networks as the methods of Educational Data Mining are commonly used to forecast performance in STEM courses. Studies also indicate that first semester measures of engagement are highly associated with end of semester grades. Students that engage regularly with course materials, do their assignments punctually, and engage in discussions with their peers have a better likelihood of better academic performance. Nevertheless, the ethical issues related to the privacy of data, their transparency, and algorithm bias are important impediments to the implementation of the learning analytics systems. Regardless of the growing usage, however, there is a current shortage of studies specifically dedicated to the predictive learning analytics focused on Computer Science courses owing to the strong pragmatic and problem-solving orientation within these courses.

Significance and Need of the Study

Computer Science programs are known to have high dropout and failure rates because of the conceptual complexity and problems with programming. The conventional evaluation techniques recognize an issue with academic performance only during mid-term or high stakes tests. Learning analytics provides a solution in advance since it allows predicting the academic performance far beforehand.

This study is important in that it:

- Gives empirical data in Computer Science teaching predictive indicators.
- Favors decision-making based on data in academia.
- Helps institutions plan the framework of early intervention.
- Supports sustainable and personalised higher education systems.

Objectives of the Study

1. To examine the connection between learning analytics indicators and academic performance in courses in Computer Science.
2. To determine the important predictors of student success.
3. To create a predictive model of at-risk students that can be used in their early identification.
4. To analyze the validity of performance prediction using learning analytics.

Hypotheses

H 0: LMS engagement and academic performance do not have a significant relationship.

H 2: There is no significant variation in the academic performance as predicted by the assignment submission consistency.

H 0 3: The participation in programming laboratories does not affect end grades significantly.

Methodology

Research Design

The research design assumed was descriptive and predictive research design.

Sample

The research population was 200 undergraduate students of Computer Science who were chosen through stratified random sampling.

Data Sources

- LMS login frequency
- Records of submission of assignments.
- Quiz scores
- Programming laboratory completion rates.
- Attendance records
- Working examination marks on final semester.

Statistical Techniques

- Mean and Standard Deviation
- Pearson's Correlation

As a method of analyzing the data, multiple linear regression analysis will be used.

Data Analysis and Interpretation

Table 1: Correlation between Learning Analytics Indicators and Academic Performance

Variables	r-value	Significance Level
LMS Engagement	0.68	$p < 0.01$
Assignment Submission Consistency	0.72	$p < 0.01$
Programming Lab Participation	0.75	$p < 0.01$
Attendance	0.60	$p < 0.01$

Interpretation

The correlation analysis shows that there is a strong positive correlation between the programming lab ($r = 0.75$) and academic performance and then the assignment consistency ($r = 0.72$). There is also a high positive correlation between LMS engagement ($r = 0.68$) and attendance ($r = 0.60$). All p-values are less than 0.01 which means that the null hypotheses are rejected. It means that academic performance is highly forecasted by learning analytics indicators.

Table 2: Multiple Regression Analysis

Predictor Variable	Beta Value	t-value	Significance
LMS Engagement	0.29	4.85	0.000
Assignment Submission	0.32	5.21	0.000
Programming Lab Participation	0.35	6.03	0.000
Attendance	0.18	3.10	0.002

$R^2 = 0.63$

Interpretation

A total of 63 percent of the academic performance can be accounted by the regression model. The strongest predictor becomes the participation in programming laboratories. The findings affirm that digital learning practices are influential in determining the outcomes of performance.

Major Findings

- The learning analytics indicators have a powerful predictive ability.
- The most influential factor is programmed laboratory participation.
- Early engagement measurements are at an acceptable degree of accuracy to point at vulnerable students.
- Instructional effectiveness is increased by data-driven monitoring.

Educational Implications

The conclusions indicate that real-time analytics dashboards should be incorporated in instructional institutions. Students can be observed to have low patterns of engagement and faculty alerted at an early stage. Struggling learners can be supported by the use of personalized feedback mechanisms. In addition, the curriculum developers are advised to focus more on the practical laboratory involvement and systematic monitoring of assignments. Besides that, universities and colleges need to create central learning analytics units, which can track academic information in a systematic manner and deliver viable insights to the faculty. The professional development programs should be organized to educate the instructors on the interpretation of analytics reports, comprehension of the predictive indicators, and data-supported instructional strategies development. Analytics tools can also in the absence of proper training be under-utilized or mis-interpreted. Adaptive learning systems should also be adopted by institutions where the supplementary resources, coding exercises or remedial tutorials are automatically suggested to the students based on their performance pattern. By integrating analytics and the Learning Management Systems (LMS) it would be possible to allow automated tracking of progress and milestone alerts to ensure that students are on track with the semester.

Academic departments, IT teams, and data analysts have to collaborate with each other to provide a smooth deployment of analytics frameworks. There should be clear policies concerning the data privacy, ethical utilization of the student data, and transparency to create trust among the learners. The students ought to be aware of how their learning information is utilized to facilitate their educational progress instead of to assess punishments. Further, predictive analytics can be applied in institutions to refine the curriculum by revealing problematic subjects, high failure courses or poor assessment patterns within Computer Science courses. The evidence-based process of reviewing the curriculum is capable of resulting in the ongoing improvement of teaching strategies and course design. Last but not least, integrating learning analytics into institutional quality assurance frameworks may help to achieve long-term academic planning, increased retention rates, a higher satisfaction level among students, and sustainable digital transformation in higher education.

Issues and Moral Aspects

Although learning analytics offers effective predictive information, the ethical considerations of data privacy, permission, and algorithmic unjustness are to be considered. Clear policies of data governance and safes are mandatory. Schools should make sure that predictive analytics are there to assist the students and not to stigmatize them.

Future Directions

Future research may explore:

- Neural network based AI-based predictive models.
- Comparisons of cross-institutional analytics.
- Combination of emotional intelligence and behavioural information.
- Tracking learning patterns of students in the long run.

Conclusion

Learning analytics is a disruptive technology in Computer science learning. The research illustrates that the indicators of digital engagement are very important predictors of academic performance. Through predictive modeling, the institutions will be able to deploy proactive intervention strategies to increase the student achievement and retention rates. As modern higher education transforms into data-driven ecosystems, a combination of ethical, open, and student-oriented analytics systems will be needed to achieve sustainable academic greatness.

References

1. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. Learning Analytics Review, 1(1), 61–75.
2. Ferguson, R. (2012). Learning analytics: Drivers, developments and challenges. International Journal of Technology Enhanced Learning, 4(5–6), 304–317.
3. Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics for study success. Educational Technology Research and Development, 68, 1961–1975.
4. Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 31–40.
5. Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data mining. Educational Technology & Society, 17(4), 49–64.
6. Siemens, G. (2013). Learning analytics: The emergence of a discipline. American Behavioral Scientist, 57(10), 1380–1400.
7. Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. American Behavioral Scientist, 57(10), 1510–1529.
8. Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation. Computers in Human Behavior, 47, 157–167.