Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549638

EXPLORING THE USE OF EDUCATIONAL DATA MINING AND LEARNING ANALYTICS TO IMPROVE INSTRUCTIONAL PRACTICES AND STUDENT PERFORMANCE

Nidhi Agarwal
Professor, Faculty of Social Science and Humanities,
Lincoln University, Malaysia

Yogendra Babu
Assistant Professor, Department of Education,
Mahatma Gandhi Antarrashtriya Hindi Vishwavidyalaya, Wardha, M.H., India

Ram Awadh
Assistant Professor, Department of Education,
Mahatma Gandhi Antarrashtriya Hindi Vishwavidyalaya, Wardha, M.H., India

Vikas Mishra
Assistant Professor, Department of Education,
Akbarpur Degree College, Akbarpur, Kanpur Dehat, U.P., India

Corresponding Author:
Dr Nidhi Agarwal, dr.nidhi@lincoln.edu.my, 0000-0002-1590-9888

ABSTRACT
Learning analytics (LA) and educational data mining (EDM) are two new fields that use the power of data analysis to better educational practises and student performance. These approaches give teachers access to information about the behaviour, learning patterns, and performance of their students by analysing big datasets gathered from diverse educational resources. Personalising learning experiences, offering early interventions and assistance, informing curriculum and instructional design, utilising predictive analytics for preventative measures, improving assessment and feedback systems, and guiding institutional decision-making are all possible uses for this information. To achieve proper and efficient implementation, ethical issues like prejudice, consent, and data protection must be properly considered. Overall, educational data mining and learning analytics have enormous potential to alter education and give teachers the tools they need to optimise teaching learning Process.
Keywords: Learning Analytics, Educational Data Mining, Performance, Instructional Practices.

INTRODUCTION
In order to improve educational results, learning analytics refers to the gathering, examination, and interpretation of data produced throughout the learning process. To collect and analyse student data, including their interactions with learning management systems, online platforms,

digital materials, and exams, a variety of methodologies and tools are used. The knowledge acquired from learning analytics can improve student success and engagement, personalise learning experiences, and inform instructional decision-making.

Learning analytics (LA) and educational data mining (EDM) are two closely connected topics that use data analysis approaches to gain understanding and make decisions regarding teaching strategies and student performance. These strategies seek to enhance teaching and learning outcomes by making use of data. An investigation into the application of learning analytics and educational data mining to these objectives follows:

1. Finding Learning Patterns: The analysis of huge datasets in educational data mining is used to find patterns and trends in student performance, behaviour, and learning processes. Teachers can learn a lot about how students learn, their strengths, limitations, and areas where they might need more help by looking at data gathered through learning management systems, online platforms, tests, and other educational tools.

2. Learning analytics can be used to provide personalised learning experiences that are catered to specific students. In order to increase student engagement and achievement, educators can create personalised learning pathways, suggest pertinent resources, and give timely feedback by analysing data on students' learning preferences, progress, and performance.

3. Early Intervention and Support: Educational data mining and learning analytics can assist in identifying pupils who are in danger of falling behind or having academic difficulties. Educators can spot early warning signs and take necessary action by keeping an eye on indicators including attendance, participation, assessment results, and engagement levels. This proactive strategy can assist in preventing student disengagement and can offer focused treatments to meet each student's individual requirements.

4. Curriculum creation and instructional design can be influenced by data-driven insights from learning analytics and educational data mining. By reviewing student performance data, educators can pinpoint areas in which students frequently struggle and decide on appropriate curriculum changes, instructional approaches to better align with student needs.

5. Using predictive modelling techniques, learning analytics can be used to forecast student outcomes, such as test performance or the likelihood of dropping out. Teachers can foresee problems and take proactive steps to support struggling pupils by analysing previous data and identifying key predictors. To increase overall student success rates, predictive analytics can also aid to optimise resource allocation and lesson planning.

6. Evaluation and feedback: Educational data mining and learning analytics might make it easier to create efficient evaluation procedures. Educators can learn more about the

validity and reliability of assessment tools, spot areas for improvement, and modify assessments to be more in line with learning objectives by analysing assessment data. Additionally, learning analytics can provide students with timely and relevant feedback, encouraging self-reflection and directing their learning process.

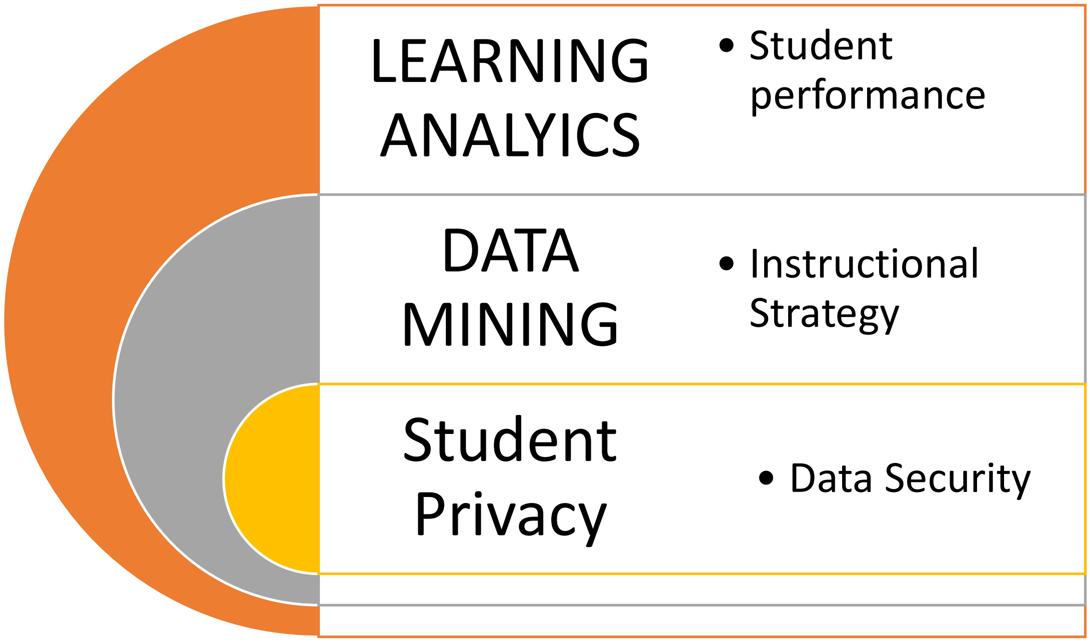
7. Decision-making at the institutional level can be influenced by educational data mining and learning analytics. Educational institutions can get a comprehensive understanding of student performance, instructional efficacy, and resource allocation by collecting and analysing data from various courses, departments, or schools. To improve educational outcomes, these insights can direct the creation of policies, strategic planning, and resource allocation.

Research Objectives

1. Introduce the concepts of EDM and LA and their relevance in collecting and analyzing educational data.
2. Examine different approaches and tools utilized in EDM and LA to gain insights into student learning behaviors and identify learning difficulties.
3. Investigate the ethical considerations and challenges associated with the use of educational data, ensuring student privacy and data security.
4. Explore the benefits of implementing EDM and LA techniques, such as personalized learning, early identification of at-risk students, adaptive instruction, and curriculum development.

Theoretical Framework

By employing this framework, the research aims to provide a systematic and comprehensive exploration of the use of EDM and LA in improving instructional practices and student performance. It will facilitate a structured approach to data collection, analysis, implementation, evaluation, and ethical considerations, contributing to the understanding and application of these techniques in educational contexts.



METHODOLOGY

Data Collection

Respondents of this study were the collegiate students enrolled in higher educational institutions. They were selected using a random sampling technique. Group of students from each higher educational institution. The 5-point Likert scale was used to determine the level of respondents' digital and information literacy skills as a result of 2-year utilization of educational technology such as computer assisted education through Learning Management System, online and electronic educational resources. Two separate Google forms were made for each of the higher educational institutions. Data were generated and analyzed using descriptive statistics.

Data Analysis

Analyse the collected data using the proper data analysis methods. To find patterns, trends, and correlations in the educational data, quantitative analysis, such as statistical analysis, data mining methods, and machine learning approaches, may be used. Insights from qualitative data sources like interviews or open-ended survey responses can also be gleaned using qualitative analysis techniques like thematic analysis and content analysis.

Learning analytics enables personalized learning experiences by utilizing student data to tailor instruction and resources to individual needs. By analyzing data on students' strengths, weaknesses, learning preferences, and progress, educators can provide targeted interventions, adaptive learning pathways, and customized feedback to optimize learning outcomes.

RESULTS AND DISCUSSION

The results and discussion of the study based on the survey conducted for the learning analytics on the two variables instructional practices and student performance with collegiate students as respondents are hereby presented.

Table 1: Learning Analytics of Collegiate Students for Instructional Practices Based

Items	**Mean**	**Verbal Interpretation**
Time To Proficiency	4.01	High level
Knowledge	3.97	High level
Transfer Of Training	4.08	High level
Impact On Organizational Performance Metrics	4.2	High level
Employee Engagement	4.26	Very High level
Net Promoter Score	4.36	Very High level
Stakeholder Satisfaction	4.18	High level
Skill Retention	4.47	Very High level
Grand Mean	4.19	High level

The table presents the learning analytics of collegiate students based for instructional practices. The highest recorded mean of college students is 4.47 or Very High Level for Respect for Skill retention. It means that college students value skill retention so much. Having a very high level on skill retention also signifies that college students are more knowledgeable on the skills and they can recall their skills to transfer learning for long term memory. However, the lowest mean of the respondents is in the area of Content Knowledge with 3.97.

Table 2: Learning Analytics of Collegiate Students Based for Performance

Items	**Mean**	**Verbal Interpretation**

Time To Proficiency	4	High Level
Knowledge	3.97	High Level
Transfer Of Training	4.07	High Level
Impact On Organizational Performance Metrics	4.07	High Level
Employee Engagement	4.22	Very High Level
Net Promoter Score	4.36	Very High Level
Stakeholder Satisfaction	4.25	Very High Level
Skill Retention	4.45	Very High Level
Grand Mean	4.15	High Level

The table shows the learning analytics of collegiate students based for performance. The highest mean is 4.45 or Very High Level for the item skill retention.

The highest recorded mean of college students is 4.47 or Very High Level for Respect for Skill retention. It means that college students value skill retention so much. Having a very high level on skill retention also signifies that college students are more knowledgeable on the skills and they can recall their skills to transfer learning for long term memory. However, the lowest mean of the respondents is in the area of Content Knowledge with 3.97. The grand mean of all items is 4.15 or High Level.

Table 3: Recorded Variable

N	Valid	1
	Missing	0

Table 4: Statistics Value of Recorded Variable

	Frequency	Percentage	Valid Percentage	Cumulative Percentage

Validity of Mean	1	100.00	100.00	100.00

Table 5: Statistical Value of Variable

Variable	Count	Mean	S.D.	Coefficient of Variation
	6	4.4950	0.46198	10.3%
Knowledge	1	3.9700	0.00214	0.01%
Skill Retention	1	4.9800	0.01064	0.02%
Total	8	4.4900	0.47476	10.6%

Table 6: Modality of Dependent Variable

	Number of Levels	Number of Parameters
Fixed Effects	1	1
Residual		1
Total	1	2

The results of this study offer a number of significant insights into how instructional practises affect student performance. These instructional tactics may improve student accomplishment, according to the positive associations between active learning strategies, project-based learning, personalised learning, and formative assessment. The study also emphasises how crucial it is to use a variety of teaching strategies in order to meet different learners' requirements and preferences. In order to ascertain the frequency and variety of instructional practises among the sample, the survey responses were examined. This investigation highlighted both conventional and cutting-edge techniques used by educators in a wide spectrum of educational methods. To determine the connection between instructional practices and student's performance, a correlation analysis was carried out. The findings showed that active learning techniques and project-based learning, for example, have a substantial positive link with better student performance While controlling for other pertinent characteristics, multiple regression models were built to investigate the predictive potential of instructional practises on student performance. The data showed how particular teaching strategies, such individualised instruction and formative evaluation, had a big impact on how well students performed and skill retention played an important role for college students in performance based and instructional practices.

CONCLUSION

Learning analytics can identify students who may be at risk of falling behind or struggling academically. By analyzing data on student engagement, attendance, assessment scores, and other indicators, educators can detect early warning signs and provide timely interventions and support to prevent further difficulties. Learning analytics can inform instructional design and delivery by providing insights into the effectiveness of teaching strategies, learning resources, and assessment methods. Educators can analyze data on student interactions, engagement levels, and performance to refine their instructional practices and make data-informed decisions. Learning analytics enhances the assessment and feedback process by analyzing student performance data. Educators can gain insights into the validity and reliability of assessments, identify areas of improvement, and provide timely and targeted feedback to students to enhance their learning progress. Learning analytics can inform institutional-level decision making by analyzing data across multiple courses, departments, or schools. Educational institutions can gain insights into student success rates, resource allocation, and instructional effectiveness, enabling informed policy development, strategic planning, and allocation of resources. Learning analytics has the potential to revolutionize education by leveraging data to understand and support student learning. However, ethical considerations, such as data privacy, consent, and transparency, must be prioritized to ensure the responsible and ethical use of student data in the learning analytics process.

REFERENCES

1. Deswal, Ankit and Kumar, Dr Sanjay (2022). Technological Aspects in Cloud Computing. Cosmos Journal of Engineering & Technology, 12(2), 05-07.
2. Kasan, Fatima D. and Buenavides, Elmer C. (2022). Development Of Web-Mobile Based Teachers' Performance Evaluation System (W-M BTPES). Globus An International Journal of Management & IT, 14(1), 32-39.
3. Kapri, Tapan and Kumar, Puneet (2010). Web Content Management System. Information and Communication Technology: Challenges and Business Opportunities. Excel Publishers, 56-62, ISBN: 978-93-81361-00-9.
4. Dwivedi, Dr. Archana (2022). Development of Educational Model for E-Learning. Globus Journal of Progressive Education, 12(2), 95-98.
5. Jaramillo, Rosenda N, Liezl Mae G. Macaraeg, Bucao, Thania Pauline, Bueno, Bryan James, Bulatao, Lemuel Rhae, Cabrera, Samantha, Cacho, Luther Carl Caldona (2022). Projected Action Plan and Timeline in Pilot Testing of Simulation-Based Learning in The College of Nursing at Phinma-University of Pangasinan. Cosmos An International Journal of Art and Higher Education, 11(2), 04-15.
6. Agarwal, Nidhi and Pundir, Neelam (2019). A Comparative Study of Personality Traits and Thinking Styles of ICT Users and Non Users. International Journal of Dynamic Educational Research Society, 1(1), 74-83.
7. Salinda, Ma. Theresa, Tuzaon, Alicia and Lachica, Perla (2021). Integrity of Third Year Nursing Students to Online Related Learning Experiences: A Concept Analysis. Globus An International Journal of Medical Science, Engineering and Technology, 10(2), 87-98.
8. Deswal, Ankit and Kumar, Dr Sanjay (2022). A Study on Enterprise Architecture in Cloud Computing. Cosmos An International Journal of Management, 12(1), 04-07.
9. Agarwal, Nidhi and Verma, Monika (2019). A Study on Taxonomy of Innovations. Globus An International Journal of Management & IT, 11(1), 57-64, ISSN: 0975-721X, doi:10.5281/zenodo.3872090.
10. Punla, Nara Fe D., Regalado, Danniel Rick B. and Navarro, Rica M. (2022). Perceived Social Support as Moderator Between Self-Stigma and Help-Seeking Attitudes. Globus

An International Journal of Medical Science, Engineering and Technology, 11(1), 87-98.

11. Singh, Mukul Kumar, Tripathi, Sakshi and Singh, Preeti (2022). Cybersecurity And Data Privacy. Cosmos An International Journal of Management, 11(2), 01-04.
12. Agarwal, Puneet Kumar and Verma, Rajesh Kumar (2020). Mathematical Solution for Analysing of Ordinary Differential Equations Using Data Assimilation Approach. Journal of Critical Reviews, 7(15), 4844-4848.
13. Cabaguing, Jordan M. and Lacaba, Teresita Villa G. (2022). Predictors of Faculty Readiness to Flexible Learning Management System. Globus An International Journal of Management & IT, 14(1), 40-49.
14. Mendoza, Rose Marie N. and Dayao, Edna F. (2021). LCUP Student Use of Gmetrix System: An Evaluation of Usefulness, Ease of Use, and Satisfaction. Cosmos Journal of Engineering & Technology, 11(2), 63-67.
15. Agarwal, Nidhi and Shiju P.S. (2018). "A Study on Content Generation for Internet Usage". International Journal of Advanced Research and Development, 3(2), 1380-1382, http://doi: 10.5281/zenodo.3764806.
16. Reyla, June S. (2022). Translanguaging in The Classroom: Impact on The Academic Performance of The Learners. Cosmos An International Journal Art & Higher Education, 11(1), 72-87.
17. Cahapin, Erwin L., Malabag, Beverly A., Samson, Brylle D. and Santiago, Cereneo S. (2022). Stakeholders' Awareness and Acceptance of The Institution's Vision, Mission and Goals and Information Technology Program Objectives in A State University in The Philippines. Globus Journal of Progressive Education, 12(1), 51-60.
18. Galvez, Rosalyn S. (2021). Graduate Studies Students' Scholastic Abilities and Their Effects on Comprehensive Examination. Cosmos An International Journal of Management, 11(1), 112-119.