

PalArch's Journal of Archaeology
of Egypt / Egyptology

LEARNING ANALYTICS INTERVENTIONS AND CHALLENGES: A
TECHNICAL PERSPECTIVE

*Gomathi Thiyagarajan*¹, *Prasanna S*²

¹ Research Scholar (VISTAS, Chennai), CMR Institute of Technology, Bengaluru, India.

Email: gomathi.t@cmrit.ac.in

² Professor & Head, Department of Computer Applications, VISTAS, Chennai

Email: prasanna.scs@velsuniv.ac.in

Gomathi Thiyagarajan¹, **Prasanna S**; **Learning Analytics Interventions and Challenges: A Technical perspective-- PalArch's Journal Of Archaeology Of Egypt/Egyptology 17(9). ISSN 1567-214x**

Keywords: Learning analytics, LA Interventions, LA Data analysis techniques, LA Challenges

Abstract:

Educational Institutions and their stakeholders can derive multiple benefits from the changing landscape of Learning Analytics. Learning Analytics as a blended field in the area of research and education combines the power of learning, analytics, and user-centered design to enhance learning and teaching. In the current work, we presented the type of learner's data that can be collected from the various learning environment, techniques used to analyze these data, and the educational interventions from data collected. We further discussed the technical and educational challenges faced during the implementation of Learning Analytics. We believe the results of this review will give the head start to the researchers and academicians to instigate Learning Analytics projects.

1 INTRODUCTION

Learning Analytics provides educators and researchers the platform to develop and use existing pedagogical tools to contemplate the teaching-learning process. The data captured can be visualized, analyzed for personalized feedback, and recommendation. Learning Analytics (LA) is defined as a measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs in the first LAK conference held in the year

2011. Educators have been researching, teaching, learning, tracking the progress of students, and analyze student's data to transform the teaching-learning process.

Emerging technologies and new pedagogical approaches are making it possible to capture and analyze learner's data in the various learning environment and one of the best approaches to gather this data and analyze is through learning analytics [1]. The broad utilization of new advances such as the learning management system, intelligent tutoring system, and e-learning gives admittance to a lot of students' data. Audit trails, log files, and event traces are captured while students interact with these systems. By implementing learning analytics we can analyze the gathered information and deepen our understanding of how students.

The three major components of LA [2] are a) Data: The entity which is the basis for providing analytical insights. b) Analysis: Process of adding intelligence by using tools and techniques. c) Action: Applying the insights gained out of analysis and improving learner's performance. In this paper, we tried to explore the types of data which can be collected from Learning environments, various analytics techniques that can be applied to the data, and the challenges that need attention while implementing LA projects.

This paper is organized into four sections. The first section introduced the study; the second section is concerned with reporting the type of data, the most used analysis technique applied to learner data, and their interventions. The penultimate section addresses the challenges that need attention while implementing LA in higher education. Discussions and conclusions are presented in the last section.

2 DATA, ANALYTICS AND INTERVENTIONS

In this section, we present the type of data, statistical and machine learning techniques used to analyze the data by examining the existing research studies carried in the Learning analytics domain. Further, we discuss the interventions from the data analysis concerning the Learning environment in which it occurs. The type of data collected, analysis method, and educational interventions are represented in Table 1.

2.1 DATA

Nistor et al. [3] distinguish data as primary data, artifacts, repurposed data and transformed data. Primary data are collected from the learning environment through eye-tracking devices, IoT devices, simulators, and intelligent chatbots. Artifacts have resulted from the data collected in the process of communications initiated in social media or blogs in LMS. Repurposed data initially collected for different purposes and reanalyzed for understanding the learner's behavior or interaction. These data would be available in the form of a

survey, archived data, competitive exam scores, CGPA or percentage, final course grades, etc. Transformed data are entries from LMS logs or Student demographics data. Similarly Wu C J et al. [4] grouped data into three broad categories reflecting progress, behavior, and learning and further listed them as high level, mid-level, and fine grain data. In this work, the nomenclature of data suggested by Nistor et al. was adopted and presented in Fig. 1.

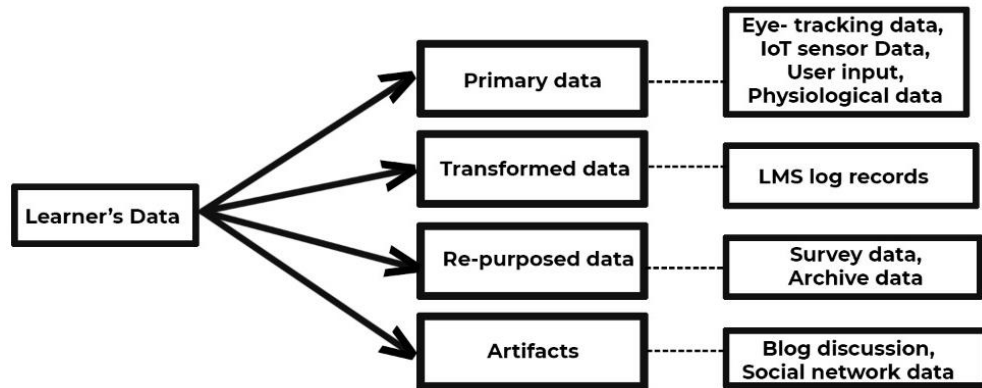


Fig. 1 Types of Learners data

2.2 ANALYTICS AND INTERVENTIONS

Clara, N et al. [5] by a thorough analysis of existing research concluded that learning analytics techniques applicable to the education domain comprise classification, clustering, association, and predictive analytics. The study by Lonn, S et al. [6] focuses on understanding the impact of data on student's motivation in a Summer Bridge Program by collecting online surveys and by conducting paired sample t-tests, and building a regression model. The research carried out by Bos, N et al. [7] indicated the insights of how students learning regulations and learning resource usage contributed to course performance in a blended learning environment by performing a two-step cluster analysis on data collected from LMS and classroom attendance. The analytical method adopted by Jovanovi, J et al.[8] identified patterns in learner's behavior and detected the learning strategies and association between them in a flip class setting by performing exploratory analysis and clustering on trace data collected from the Learning Management System. Zhao, Y et al. [9] investigated the passing score achieved is highly influenced by learner's behaviors in the MOOC environment by performing observation and clustering analysis on log traces of data.

Table 1: Data type, analysis method, and educational interventions

Authors & Year	Data Type	Method of Analysis	Educational Interventions	Learning Environment
Lonn, S et al. (2015)	Repurposed Data	T-Test and regression	Academic motivation	Summer Bridge Program
Bos, N et al (2016)	Transformed and Repurposed data	Two-step Cluster Analysis	Regulation and use of the resource	Blended Learning
Jovanovic, J et al. (2017)	Transformed Data	Exploratory learning sequence analysis, Clustering	Effective Learning Strategies	Flip Environment
Zhao, Y et al. (2017)	Transformed Data	Observation and Clustering analysis	Behavior	MOOC
Oliveiar, L et al. (2017)	Artifacts	SNA, sentiment analysis, topic classification	Degree of controversy.	Social Media
Silva, J. C. S et al. (2018)	Transformed Data	Descriptive Statistics and feature selection technique	Learning Strategies	Flip Environment
Charleer, S et al. (2018)	Repurposed data	Visualization tool	Peer Comparison	LA Dashboard
Choi, S. P. M et al. (2018)	Transformed Data	Regression	Identify user at risk	Traditional
Lu, O. H. T et al. (2018)	Repurposed and transformed data	Regression	Predict academic performance	Blended Learning
Alonso-Fernández, C (2019)	Primary Data	Regression and decision trees	Measure knowledge	Game-based Learning environment
Gasevic, D et al. (2019)	Artifacts	Social Network Analysis, Content Analysis,	Participant's enactment	MOOC

Oliveiar, L et al. [10] presented a methodology that combines topic categorization, social network analysis, and sentiment analysis to provide insights by characterizing the learner's interaction from a Facebook post. Silva, J et al. [11] attempted to determine the effects of measuring learner's self-regulation in a flipped environment by collecting data from LMS, reporting system, academic management system, and applying features selection techniques in addition to descriptive analysis. Charleer, S et al. [12] reported the dashboard presented supports dialogue, motivates, triggers conversation, and adds personalization by effective visualization on historical and grade data collected. The study reported by Choi, S et al. [13] showcased the identification of at-risk students in a course by collecting clicker data, demographic data, and summative assessments and applying hierarchical regression models to predict students at risk in traditional classroom models. Lu, O. H. T et al. [14] reported the experimental results to predict the academic performance of students in a blended learning environment and identified the factors that affect the performance combining data from online and traditional learning mode by incorporating Linear regression residual analysis. Alonso Fernandez, C et al. [15] collected trace data from serious games and developed and tested a prediction model to measure previous and predicts postgame knowledge by using decision trees, Naïve Bayes classifiers, and regressions.

Gasevic D et al. [16] proposed an approach that explains the collaborative process and group learners and predicts their performance by collecting data from discussion forums and applying social network analysis and epistemic network analysis. Ahmad Uzir N. et al. [17] emphasized a methodology to analyze time management in a blended learning environment by combining cluster analysis and process mining on digital traces. In their study, Virvou et al. [18] believed a multi-module model will support learners and enhance their learning experience. In this study survey data, log information, personal information, and learning styles of the students were recorded, and by using K-Mean clustering the learners were grouped to find the cognitive style. Niemela, M et al. [19] proposed a novel method for analyzing learners in a game-based learning environment by collecting game log data and perform clustering-based profiling to identify a reading disability. In their research work Moreno Marcos, P. M et al. [20] analyzed factors that influence the performance of a student and believed concept-oriented assignments had best-predicting powers than click stream data and applied predictive algorithms.

3 CHALLENGES

We sourced and analyzed existing studies and stated the challenges in Fig.2. Tsai, Y. S, and Gasevic, D [21] identified six strategic planning and policy challenges to be monitored during LA implementation and stated the shortage in leadership capabilities, pedagogy based approaches, stakeholder engagement, training opportunities, and issues related to ethics and privacy. Jivet I et al. [22] expressed that the biggest hurdle of implementing LA can be tackled by training and facilitating the metacognitive competencies of critical stakeholders like students and teachers. They also believed this will help in improving the competencies to understand the information and use of interventions. Wilson, et al. [23] point out that the assumptions about humans and society are coded into algorithms and may produce biases in Learning Analytics systems hence a new level of data literacy and interpretation competencies need to be developed and essential for best results. Galen A et al. [24] states only part of the learner's data is collected in a learning context in much online learning and judging the quantitative data on learning Management System is like a single puzzle piece and students might be misled from the visualization tools that reduce the complexity of learning process by just showing the number of login into LMS or other resources.



Fig. 2 Challenges in implementing LA

Tsai, Y. S et al. [26] in their work expressed the cognitive and skill gaps would be a worrying factor when scaling LA-based innovation since the perceptions, knowledge, and skills of LA vary significantly among different stakeholders. Shibani A et al. [27] highlighted that in addition to the normal teaching load the set-up of the intervention and related work consumes extra time and effort. Involving all stakeholders in the implementation of LA in the classroom is one of the biggest challenges but involving the tutor would be a key part of success. Working with the limitations of the tool and train the students to use it effectively are the other challenges. Mah D K, et al. [28] presented the serious challenges and concerns to embrace Learning analytics and pointed out all educational data are not always relevant, ethical and privacy strategies are to be considered and professional learning among key stakeholders is required. They also emphasized the quality analysis of learner's data is required to enable a better understanding of the learning process and interpretation.

Lietner P et al. [29] mentioned the ethics differs strongly around the world and needs different levels of moderation for use of data they also classified the challenges as three parts a) The location and interpretation of data b) Informed consent c) Classification and storage of data. Wong J. et al. observed regression and clustering techniques were widely used in several studies from rich data sources available from log files, discussion forums, and interactions with systems. They also point out the behavior of a student depends on interest, self-learning capability, cognitive skill, and experience in using the tool so data sources from multiple sources such as prior knowledge and self-report should complement the analysis of student data[30].

4 DISCUSSIONS AND CONCLUSION

This study demonstrates the learning analytics from a technical perspective and sets out to identify the type of data collected from the learning environments, how the learner's data collected are analyzed, and what interventions are made by researchers. The authors analyzed 25 peer-reviewed articles selected between 2015-2020. From the existing literature, it has been identified that

learner's data collected from any learning environment can be categorized as per progress made by students, their learning, behavior, and data can be further defined as primary, transformed, artifacts, or repurposed data. This study identified researchers and educationalist performs learning analytics to predict academic performance, identify students at risk, measure knowledge, and factors affecting grades.

Learning Analytics includes the design and development of algorithms in mathematics and computer science. Classification, Clustering, and Regression are the techniques used widely by researchers in LA. The researchers broadly used decision trees, support vector machines, and random forest methods for classification and regression tasks. Clustering techniques were used to group learners based on similarity and dissimilarity. Implementing Learning Analytics in higher education can be risky if we don't understand the barriers and challenges likely to be faced. From this study, we highlight various challenges that need attention while implementing LA at educational institutions are Leadership capabilities, Stakeholder engagement, Pedagogical approaches, Metacognitive competencies, Complexity of learning context, Ethics & Privacy, Quality data, and Lack of rich data source.

We conclude the paper by discussing some aspects of implementing LA projects. To successfully implement Learning Analytics projects in higher education the educational institution or its stakeholders should understand the valid purpose of applying analytics to learner's data. The type of data to be collected from the different learning environments and the technique to analyze these data will need resources, skills, or personnel to involve, support, and train. The personnel capable of building tools and developing scripts to gather data from learning environments would play a key role in the data collection process and resources with expertise in data science and business intelligence can add value to LA projects by heading in the right direction to meet the purpose. We believe the study presented here will give a head start to budding researchers and academicians in planning LA projects.

REFERENCES

- “Learning Analytics,” Accessed on: Aug .19, 2020. [Online] Available: <https://www.solaresearch.org/>
- Wong, J., Baars, M, De Koning, B., Van der Zee, T., Davis, D., H.S Khalil, G.J Houben, and G.W.C Paas, “Educational theories and learning analytics: From data to knowledge,” in Utilizing learning analytics to support study success, 2019.
- Nicolae Nistor and Ángel Hernández-García , “What types of data are used in learning analytics? An overview of six cases,” Computers in Human Behavior, Volume 89, pp 335–338, 2018.

- Wu C J, “An Overview of Learning Outcomes,” *Journal of Library and Information Science*, Volume 34(2), pp 115–123, 2014.
- Clara Nkhoma, Duy Dang-Pham, Ai-Phuong Hoang, Mathews Nkhoma, Tram Le-Hoai, Susan Thomas, “Learning analytics techniques and visualization with textual data for determining causes of academic failure,” *Behaviour & Information Technology*, Volume 39, pp 808-823, 2020.
- Lonn, S., Aguilar, S. J., and Teasley, S. D., “Investigating student motivation in the context of a learning analytics intervention during a summer bridge program,” *Computers in Human Behavior*, Volume 47, pp 90–97, 2015.
- Bos, N., and Brand-Gruwel, S, “Student differences in regulation strategies and their use of learning resources,” *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, pp 344–353, 2016.
- Jovanović, J., Gašević, D., Dawson, S., Pardo, A., and Mirriahi, N, “Learning analytics to unveil learning strategies in a flipped classroom,” *Internet and Higher Education*, Volume 33, pp 74–85, 2017.
- Zhao, Y., Davis, D., Chen, G., Lofi, C., Hauff, C., and Houben, G. J., “Certificate achievement unlocked: How does MOOC learners’ behavior change?,” *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, pp 83–88, 2017.
- Oliveiar, L and Figueira A, “Visualization of sentiment spread on social networked content: Learning analytics for integrated learning environments,” *IEEE Global Engineering Education Conference, EDUCON*, pp 1290–1298, 2017.
- Silva, J. C. S., Zambom, E., Rodrigues, R. L., Ramos, J. L. C., and Da Fonseca De Souza, F, “Effects of learning analytics on students’ self-regulated learning in the flipped classroom,” *International Journal of Information and Communication Technology Education*, Volume 14(3), pp 91–107, 2018.
- S. Charleer, A. V. Moere, J. Klerkx, K. Verbert, and T. De Laet, "Learning Analytics Dashboards to Support Adviser-Student Dialogue," in *IEEE Transactions on Learning Technologies*, vol. 11, no. 3, pp. 389-399, 2018.
- Choi, S. P. M., Lam, S. S., Li, K. C., Wong, B. T. M., Journal, S., April, N., Wong, B. T. M, “*International Forum of Educational Technology & Society Learning Analytics at Low Cost: At-risk Student Prediction with Clicker Data and Systematic Proactive Interventions*,” *International Forum of Educational Technology & Society*, Volume. 21(2), 2018.

- Lu, O. H. T., Huang, A. Y. Q., Huang, J. C. H., Lin, A. J. Q and Yang, S. J. H , “Applying Learning Analytics for the Early Prediction of Students Academic Performance in Blended Learning,” *Journal of Educational Technology & Society*, Volume 21(2), pp 220–232,2018.
- Alonso-Fernández, C., Martínez-Ortiz, I., Caballero, R., Freire, M., and Fernández-Manjón, B, “Predicting students’ knowledge after playing a serious game based on learning analytics data: A case study,” *Journal of Computer Assisted Learning*, pp 1–9, 2019.
- Gašević, D., Joksimović, S., Eagan, B. R., and Shaffer, D. W,” SENS: Network analytics to combine social and cognitive perspectives of collaborative learning,” *Computers in Human Behavior*, Volume 92, pp 562–577, 2019.
- Ahmad Uzir N. et al.,”Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques”, Springer, pp 555-569, 2019.
- Troussas C., Krouska A., Virvou M, “Using a Multi Module Model for Learning Analytics to Predict Learners’ Cognitive States and Provide Tailored Learning Pathways and Assessment,” In *Intelligent Systems Reference Library*, Volume 158, Springer 2020.
- Niemelä, M., Kärkkäinen, T., Äyrämö, S., Ronimus, M., Richardson, U and Lyytinen, H., “Game learning analytics for understanding reading skills in transparent writing system,” *British Journal of Educational Technology*, pp 1–15, 2020.
- Moreno-Marcos, P. M., Pong, T. C., Munoz-Merino, P. J., and Kloos, C. D, “Analysis of the Factors Influencing Learners’ Performance Prediction with Learning Analytics,” *IEEE Access*, Volume 8, pp 5264–5282, 2020.
- Tsai, Y. S and Gasevic, D,” Learning analytics in higher education - Challenges and policies: A review of eight learning analytics policies,” *ACM International Conference Proceeding Series*, pp 233–242, 2017.
- Jivet, I., Scheffel, M., Drachsler, H., and Specht, M,” Awareness Is Not Enough : Pitfalls of Learning Practice”, *Data-Driven Approaches in Digital Education*, Volume 1, pp 82–96, 2017.
- Wilson, A., Watson, C., Thompson, T. L., Drew, V and Doyle, S., “Learning analytics: challenges and limitations”, *Teaching in Higher Education*, Volume 22(8), pp 991–1007, 2017.
- Gelan, A., Fastré, G., Verjans, M., Martin, N., Janssenswillen, G., Creemers, M., Thomas, M,” Affordances and limitations of learning analytics for computer-assisted language learning: a case study of the VITAL project”, *Computer Assisted Language Learning*, Volume 31(3), 294–319, 2018.
- Tsai, Y. S., Poquet, O., Gašević, D., Dawson, S and Pardo, A.” Complexity leadership in learning analytics: Drivers, challenges and

- opportunities”, *British Journal of Educational Technology*, Volume 50(6), pp 2839–2854, 2019.
- Shibani, A., Knight, S., & Buckingham Shum, S, “Educator perspectives on learning analytics in classroom practice,” *Internet and Higher Education*, February 2020.
- Mah DK., Yau J.YK and Ifenthaler D,” Epilogue: Future Directions on Learning Analytics to Enhance Study Success,” In *Utilizing Learning Analytics to Support Study Success*. Springer 2019.
- Banihashem, S.K., Aliabadi, K., Ardakani, S.P., Delaver, A. and Ahmadabadi, M.N, “Learning analytics: A critical literature review”, *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, 2018.
- Leitner P., Khalil M and Ebner M, “Learning Analytics in Higher Education—A Literature Review,” In *Studies in Systems, Decision, and Control*, volume 94. Springer 2017.
- Wong J. et al, “Educational Theories and Learning Analytics: From Data to Knowledge,” In *Utilizing Learning Analytics to Support Study Success*. Springer, 2019.