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The Academic and Education Analytics of Student and Teacher Learning Process - An Empirical Study on Student Performance

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Abstract **- The main objective of educational institutions in India is to achieve the development of the student not only in knowledge but also in practical implementation of that knowledge. One of the way to achieve the mentioned objective is to monitor the students continuously and adapting the various methodologies or training needs for different students with different levels of understanding. In higher education academic institutions for improving student performance and retention, most of them have adopted the academic analytics and learning analytics. Due to this pandemic situation, the educational institutions under different universities should adapt the use of digital platforms. As the virtual teaching and learning has been initiated completely in full-fledged environment, it now became very easy to access the data of the learner. Hence, it made all the data collection an easy task and I am presenting the empirical study of the various articles, which have given their contribution towards the student learning and performance enhancement. I had discussed about the concept of big data analytics, learning analytics, academic analytics and education analytics in higher education, where the student learning, student performance evaluation and retention has been penetrated. While several studies have reported the implementation details and the successes of specific analytics initiatives, relatively fewer studies exist in literature that describe the possible constraints that can preclude an academic or learning analytics initiative from succeeding fully, meeting the criteria of success as defined by the stakeholders affected by such initiatives. In India, with the ubiquitous smart devices it made the life of the students to explore the various ways of online education and for the teachers, it made a new pace of teaching learning methodology.**

Index Terms **– Higher Education, Data mining, Big Data analytics, Learning Analytics, Academic Analytics, Education Analytics.**

I.INTRODUCTION

Education is an integral aspect of every society and in a bid to expand the frontiers of knowledge, educational research must become a priority. Educational research plays a vital role in the overall development of pedagogy, learning programs, and policy formulation. Educational research is a spectrum that bothers on multiple fields of knowledge, and this means that it draws from different disciplines.

Educational research is a type of systematic investigation that applies empirical methods to solving challenges in education. It adopts rigorous and well-defined scientific processes in order to gather and analyze data for problem-solving and knowledge advancement. The primary purpose of educational research is to expand the existing body of knowledge by providing solutions to different problems in pedagogy while improving teaching and learning practices. Data mining methods are successful in educational environments to discover new knowledge or learner skills or features. Unfortunately, they have not been used in depth with collaboration[1].

Learning analytics is about collecting traces that learners leave behind and using those traces to improve learning[4]. This is a nice definition of analytics for education, partly because it uses plain English, but also because it alludes to the cyclical nature of the analytics process.

Learning is a product of interaction. Depending on the epistemology underlying the learning design, learners might interact with instructors and tutors, with content and/or with other people. Many educators expend enormous amounts of effort to designing their learning to maximize the value of those interactions[4]. Learning analytics (LA) refers to the process of collecting, evaluating, analysing, and reporting organizational data for decision making [6].

People have been researching learning and teaching, tracking student progress, analysing school or university data, designing assessments and using evidence to improve teaching and learning for a long time. Learning Analytics builds on these well-established disciplines but seeks to exploit the new opportunities once we capture new forms of digital data from students' learning activity and use computational analysis techniques from data science and AI. Learning Analytics provides researchers with exciting new tools to study teaching and learning. Moreover, as data infrastructures improve — from data capture and analysis to visualization and recommendation — we can close the feedback loop to learners, offering more timely, precise, actionable feedback. In addition, educators, instructional designers and institutional leaders gain new insights once the learning process is persistent and visible.

The concept of learning analytics will be incomplete if I won't discuss about Big Data Analytics. The idea of Big Data derives from the long digital trails we leave behind us as we go about our daily online business. Almost every interaction a user has with a learning management system (or other educational space) leaves some kind of footprint—think logging on and off, browsing activities, completing quizzes—which, across a whole student body, aggregates to a lot of digital traces being left behind. The term is often attributed to any large data set, but for data to be truly 'big', the set should be at least one terabyte (TB). With the average day in 2020 producing around 2.5 quintillion bytes of information (that's up to 1.7MB of data created per second for every person on earth), producing enough data clearly isn't a problem.

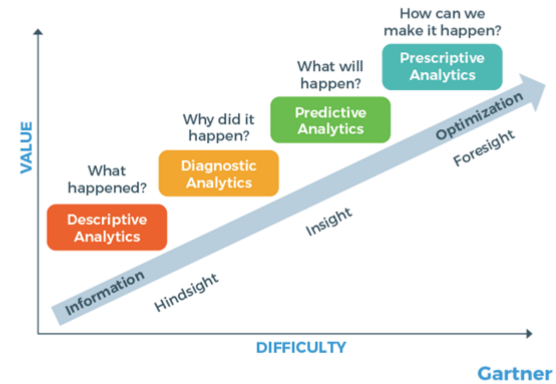

Fig. Phases in Learning Analtytics

The information held within Big Data means that today, analytics speaks not only on past performance, but can give insights into future behaviour, too.

According to most industry experts, learning analytics can now be divided into four phases:

- Descriptive analytics—using data analysis to tell a story of past performance.
- Diagnostic analytics—using data to answer questions about why things happened as they did.
- Predictive analytics—using Big Data to follow trends and suggest what is likely to happen next.
- Prescriptive analytics—using Big Data and complex simulations to answer questions about what the next steps taken should be.

With the right resources and enough time to explore such large data sets, predictive analytics can yield impressive results. Predictive analytics takes the power of Big Data and uses it to focus on the future. This is a change for many people in the training and education industry, who will mostly encounter retrospective analytics—looking at what's already happened.

II.RELATED WORK

Jeong, H., and G. Biswas. (2008)[7]. This paper discusses our approach to building models and analyzing student behaviors in different versions of our learning by teaching environment where students learn by teaching a computer agent named Betty using a visual concept map representation. We have run studies in fifth grade classrooms to compare the different versions of the system. Students' interactions on the system, captured in log files represent their performance in generating the causal concept map structures and their activities in using the different tools provided by the system. We discuss methods for analyzing student behaviors and linking them to student performance. At the core of this approach is a hidden Markov model methodology that builds students' behavior models from data collected in the log files. We discuss our modeling algorithm and the interpretation of the models. 1

Köck, M., and A. Paramythis.(2011)[8] Monitoring and interpreting sequential learner activities has the potential to improve adaptivity and personalization within educational environments. We present an approach based on the modeling of learners' problem-solving activity sequences, and on the use of the models in targeted, and ultimately automated clustering, resulting in the discovery of new, semantically meaningful information about the learners. The approach is applicable at different levels: to detect pre-defined, well-established problem-solving styles, to identify problem solving styles by analyzing learner behaviour along known learning dimensions, and to semi-automatically discover learning dimensions and concrete problem solving patterns. This article describes the approach itself, demonstrates the feasibility of applying it on real-world data, and discusses aspects of the approach that can be adjusted for different learning contexts. Finally, we address the incorporation of the proposed approach in the adaptation cycle, from data acquisition to adaptive system interventions in the interaction process.

Koedinger, K. R., R. Baker, K. Cunningham, A. Skogsholm, B. Leber, and J. Stamper.

(2010)[9] the Pittsburgh Science of Learning Center's DataShop is an open data repository and set of associated visualization and analysis tools. DataShop has data from thousands of students deriving from interactions with on-line course materials and intelligent tutoring systems. The data is fine-grained, with student actions recorded roughly every 20 seconds, and it is longitudinal, spanning semester or yearlong courses. As of April 8, 2011, over 270 datasets are stored including over 58 million student actions and over 165,000 student hours of data. Most student actions are "coded" meaning they are not only graded as correct or incorrect but are categorized in terms of the hypothesized competencies or knowledge components needed to perform that action. DataShop provides repository users a central hub to satisfy long term data management needs. DataShop also has a number of features to facilitate data analysis including a data schema that allows researchers to import data into DataShop or export data from the repository in order to perform additional analysis.

YiChuan Wang, LeeAnn Kung, Chaochi Ting (2015)[10] To date, the health care industry has paid little attention to the potential benefits to be gained from big data. While most pioneering big data studies have adopted technological perspectives, a better understanding of the strategic implications of big data is urgently needed. To address this lack, this study examines the development, architecture and component functionalities of big data, and identifies its capabilities, including traceability, the analysis of unstructured data and patterns of care, and its predictive capacity to support healthcare managers seeking to formulate more effective big-data-based strategies. Our findings will help healthcare organizations respond strategically to the challenges they face in today's highly competitive healthcare market.

Baker, R. S. J. D. (2016)[11] Educational Data Mining (EDM) is an emerging multidisciplinary research area, in which methods and techniques for exploring data originating from various educational information systems have been developed. EDM is both a learning science, as well as a rich application area for data mining, due to the growing availability of educational data. EDM contributes to the study of how students learn, and the set- tings in which they learn. It enables data-driven decision making for improving the current educational practice and learning material." (Calders and Pechenizkiy, 2012).

Ben K. Daniel, (2015)[12] the author proposed that During periods of uncertainty and disruption, we transform data into business intelligence through prescriptive analytics, machine learning, and AI. The result is intelligent recommendations that help our clients transform. It will give better result as compared to previous work details.

III.ANALYTICS IN EDUCATION AND ELEARNING

The term e-Learning Analytics (e-LA) refers to the set of techniques aimed to extract useful information from existing online education datasets.

The final goals of E-Learning Analytics fall within one the following categories:

Educational: Targeting to improve online education impact and student's performance, such us:

- Reducing students' dropouts
- Improving students' understanding and learning
- Deciding which content is relevant for a given user
- Improving training materials
- Enhancing tutoring capabilities

There is great interest in assessing student learning in unscripted, open-ended environments, but students' work can evolve in ways that are too subtle or too complex to be detected by the human eye[4].E-Learning analytics comprise the use of data science techniques over data coming from multiple sources. In a typical online education environment, the most common data sources are:

- Learning Management System (LMS) activity records describing the users' interaction with the online platform and training content.
- Learning Management System (LMS) performance records describing the users' results over the proposed evaluation tests.
- User profile information, specially those characteristics that could impact the way students learn.

In environments where online content is used as a supporting tool and student interaction also happens outside the Learning Management System, teachers may collect data that could be used as an additional input to the analysis. In this case, educators' engagement is key to make the overall process relevant.

Collected data is processed and analyzed, using advanced data science techniques, and a set of relevant analytics are obtained as a result. These analytics provide insights into the learning process, that should be used to perform whatever actions are required to meet the educational or business goals. Another visualization tool gaining popularity in learning analytics facilitates social network anaylsis (SNA).

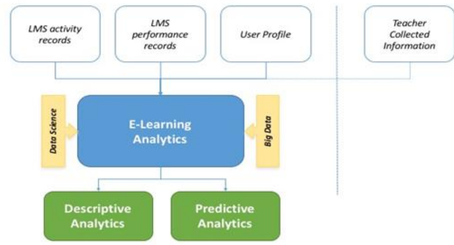

Fig. E-Learning Analytics Model

When the volume of data to analyze is considered "big", traditional data processing applications cannot deal with it in a reasonable time. Then, we have not only a problem of obtaining valuable insights from data, but also the challenge of processing this data at volume. This requires the use of Big Data computing techniques.

Sometimes, the terms analytics and big data are misused. It is true that obtaining analytics, most of time, requires processing important volumes of data, but it is not always the case.

When facing an e-Learning analytics project, we should have in mind the model defined by Dr. Mohamed Amid at Aachem University. This model describes the most relevant questions you should ask yourself in order to set the ground for a successful project:

- What? What kind of data does the system gather, manage, and is available for the analysis?
- Who? Who is targeted by the analysis?
- Why? What are our objectives (educational and business)?
- How? How does the system perform the analysis of the collected data?

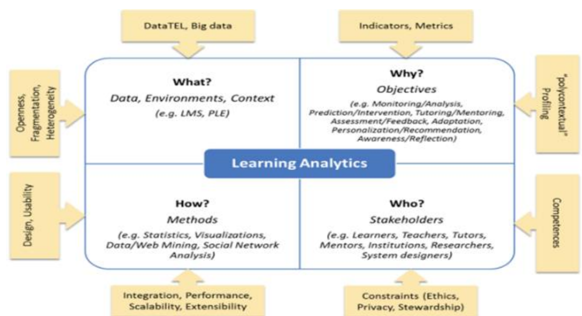

Fig. Learning Analytics Data Model

The final objective of e-Learning Analytics is facilitating action that brings us closer to our goals.

Academic analytics helps address the public's desire for institutional accountability with regard to student success, given the widespread concern over the cost of higher education and the difficult economic and budgetary conditions prevailing worldwide[2].

Academic analytic's is the application of business intelligence (BI) tools and strategies to guide decision-making practices in educational institutions. The goal of an academic analytics program is to help those charged with strategic planning in a learning environment to measure, collect, decipher, report and share data in an effective manner so that operational, program and student strengths and weaknesses can be identified.

By using business analytics (BA) tools, which include predictive modeling, educators and administrators can make data-driven decisions. Learning management systems, which provide students with course content and interactive tools, can be a valuable resource for gathering student data.

In order to retrieve meaningful information from institution sources i.e. LMS, the information has to be correctly interpreted against a basis of educational efficiency, and this action requires analysis from people with learning and teaching skills. Therefore, a collaborative approach is required from both the people guarding the data and those who will interpret it, otherwise the data will remain to be a total waste [3].

IV.CONCLUSION

In the present study, we have discussed the various Analytical study methods which can support education system via generating Digital information. This pilot study provides fundamental inferences to develop basic heuristics for the educational institutions for developing the skills in students and to measure the performance of the students. The researchers scope of study regarding use of analytics in the various ways of learning has given a clear picture about the use of new technologies to improve the teaching learning process. Hopefully these areas of application will be discussed in our next paper.

V.SUGGESTIONS AND RECOMMENDATIONS

Lot of changes require in education analytics. Machine learning approaches are never used for statistical analysis for data mining techniques. The use of data mining and analytical tools will help to improve the student analysis process to a teacher.

REFERENCES

[1] Anaya, A. R., and J. G. Boticario. 2009. ―A Data Mining Approach to Reveal Representative Collaboration Indicators in Open Collaboration Frameworks. In Educational Data Mining 2009: Proceedings of the 2nd International Conference on Educational Data Mining, edited by T. Barnes, M. Desmarais, C. Romero, and S. Ventura, 210–219.

[2] Arnold, K. E. 2010. ―Signals: Applying Academic Analytics. EDUCAUSE Quarterly 33 (1).

[3] Baepler, Paul; Murdoch, Cynthia James (July 2010). "Academic Analytics and Data Mining in Higher Education". *International Journal for the Scholarship of Teaching and Learning*. 4 (2). Article17. doi:10.20429/ijsotl.2010.040217. S2C ID 8688376

[4] Blikstein, P. 2011. ―Using Learning Analytics to Assess Students' Behavior in Open-Ended Programming Tasks. ‖ Proceedings of the First International Conference on Learning Analytics and Knowledge. New York, NY: Association for Computing Machinery, 110–116.

[5] Campbell, J.P. and Oblinger, D.G. (2007), "Academic analytics", EDUCAUSE, available at: https://net.educause.edu/ir/library/pdf/PUB6101.pdf (accessed 28 December 2016).

[6] Elias, T. (2011). Learning analytics. *Learning*, 1-22.

[7] Jeong, H., and G. Biswas. 2008. ―Mining Student Behavior Models in Learning-by-Teaching Environments. ‖ In Proceedings of the 1st International Conference on Educational Data Mining, Montréal, Québec, Canada,127–136.

[8] Köck, M., and A. Paramythis. 2011. ―Activity Sequence Modeling and Dynamic Clustering for

Personalized E-Learning. Journal of User Modeling and User-Adapted Interaction 21 (1-2): 51–97.

[9] Koedinger, K. R., R. Baker, K. Cunningham, A. Skogsholm, B. Leber, and J. Stamper. 2010. ―A Data Repository for the EDM Community: The PSLC DataShop.‖ In Handbook of Educational Data Mining, edited by C. Romero, S. Ventura, M. Pechenizkiy, and R.S.J.d. Baker. Boca Raton, FL: CRC Press, 43–55.

[10] YiChuan Wang, LeeAnn Kung, Chaochi Ting, “Beyond a Technical Perspective: Understanding Big Data Capabilities in Health Care”, publications on ResearchGate, 2015.

[11] Baker, R. S. J. D. “Learning, schooling, and data analytics”. Handbook on innovations in learning for states, districts, and schools, Philadelphia, PA: Center on Innovations in Learning , 2013, pp. 179–190.

[12] Ben K. Daniel, “Big Data and analytics in higher education: Opportunities and challenges”, British journal of educational technology. September 2015.