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PATHBREAKING ROLE OF BIG DATA AND LEARNING ANALYTICS IN EDUCATION: A SURVEY

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ABSTRACT
The purpose of this paper is to survey the emergence of learning analytics-related educational technologies. This survey throws light on how learning analytics, in confluence with big data, has the power to render education and learning in a more personalized way to every student, and in the process, do away with the instructional model geared towards the average student and create a more socially equitable and fair educational milieu for all learners. The survey briefly dwells on the many merits as well as some cautionary considerations to be taken account in the process of implementation of learning analytics-related educational technologies**.**

KEYWORDS: Learning Analytics, Educational Technologies, Personalised Learning, Socially equal and fair Education.

I. INTRODUCTION
With the emergence of technology, the field of education has undergone seismic changes. Technology has made it possible to bring all aspects of education into focus. One of the results is that there is an increasing demand on higher educational institutions to make available updated information on their effectiveness [1]. Even the successes achieved by students have become attributable to institutions [2]. So, educational institutions are nowadays obliged to find new ways to apply analytical and data mining methods to diverse aspects of their domain. Thus, mining of data pertaining to education and analytics has become a mushrooming field that aims to apply data harvesting and analytics techniques and devices to areas concerning educational institutions [3][33]. Researchers within the field employing data analytics zero in on myriad educational aspects. These topics range from how to enhance institutional effectiveness, better student learning processes, evaluate student learning within course management systems (CMS), suggest personalised recommender systems, find out ratios of retention, attrition, success etc. In short, the whole field of educational data mining and analytics has evolved to discover unique patterns and ways of using data analytics methods to come up with solutions for educational-related concerns.

The educational analytics field is rapidly producing novel possibilities for collecting, interpreting and presenting student data. Teachers may soon be able to employ these new data sources as beckons for redesigning course material and as proof for creating new tests and directions of communication between teachers and pupils. Of particular interest are allied disciplines that have emerged under the broad term of educational analytics. For instance, learning analytics (LA) is an evolving area in which state-of-the-art analytic devices are brought into play to enhance education, studies and learning. Learning analytics is aligned with similar areas of studies such as academic analytics, web analytics, business intelligence, decision-making and action-oriented analytics. Learning analytics is defined as "an educational application of web analytics aimed at learner profiling, a process of gathering and analysing details of individual student interactions in online learning activities" [4].

Goldstein and Katz [5] came up with the moniker academic analytics to portray the use of tools and principles of business intelligence to education. Their aim was to study aspects, such as managerial and technological, that influence how institutions collect, interpret and use data. In defining what constitutes academic analytics, Campbell and Oblinger[6] took a constricted view; they chose to analyse issues directly linked to "one of higher education's most important challenges: student success." But Dawson[7] advanced the real concern of learning analytics: “the potential to register the actual-time deployment of learning analytics by pupils, teachers and

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academic mentors to enhance student success." Thus, the thrust seems geared towards choosing, collecting and handling of data that would assist both the pupils and teachers at different levels. Moreover, learning analytics appears designed to create systems that can offer support and individualized service to students. Although the field of educational data mining and analytics comprises wide range of aspects,

This paper aims to briefly survey the emerging learning analytics-driven educational technologies that seek to triumph over the challenge of individual students' learning needs by embracing elements of personalized learning to scale.

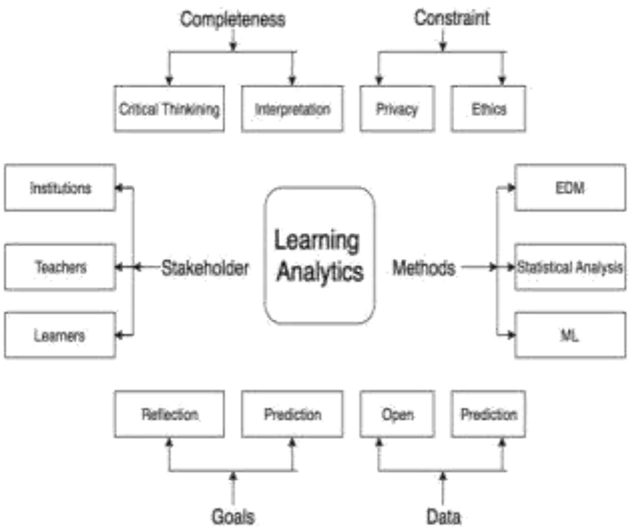

Fig 1.1 Learning Analytics in education

II. RELATED WORK

2.1 Personalised Education

This commentary shows how the emerging technology of learning analytics has the power to render education and learning in a more personalized way, and by doing this, how it can create socially fair and equitable results for pupils, who might otherwise be deemed as average. It is predicted that in the coming years, the technology of learning analytics will do away with the concept of average student and cater on a personal level to the individual needs of students, thus creating a socially equal footing for all learners.

It has been argued that, as a potent tool, education has the potential to effect social change. For that to happen, though, it needs to reach everyone. Or, "if it contributes to the full growth of all of society's individuals" (Dewy) [8]. Here, the quality of teachers has been shown to be both crucial and changeable, which leads to the creation of differences in the results the students achieve. (Darling-Hammond) [9]. This is made worse by the chasm between teaching methods and practices and standards of contents because most often they do not always synchronize [10]. This undermines the former's potential to enhance the accomplishments of students. Thus, dealing with students in an individualistic or personalized way poses a challenge. Personalized teaching is by no means a modern concept [11] delineated the concept about fifty years back, terming his mode as the Personalized System of Instruction or PSI. The hallmarks of his PSI were: the course material be gradually increased, its pace determined by the student, it should teach mastery through repetition and should enjoy the backing of others [12]. The real problem of PSI, though, is that it needs huge human capital investment.

Here, learning analytics technologies are stealing a march by adopting aspects of personalized learning to scale. This by no means a totally new idea. For the last two decades, intuitive and cognitive instructors have been created [13]. They have done the process of personalization through computers and were recognized for fostering meta-cognitive plans and strategies [14]. Thus, educational technologies like learning analytics promise to usher in a new era in which the concept of teaching to the average student is done away with, pupils and teachers are offered new insights about the learning process and students who are lagging behind are discovered and individually

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catered to. In effect, they promise to become an instrument of social change, reducing social disparities by meeting the learning requirements of separate, individual students.

2.2 Learning Analytics and Big Data

An intrinsic connection has been shown between learning analytics and big data. although work in this arena is still to be developed. Areas focusing on the enhancement of learning analytics modalities are certainly growing [15]. It was predicted that learning analytics – showing pathways to better students' participation and offering premier quality, personalized education to pupils – are poised to be widely embraced [16]. This prediction was featured in the 2014 Horizon Report, brought out together by the New Media Consortium and the EDUCAUSE.

Taking advantage of the demographic information of students, the confluence of learning analytics and big data is poised to revolutionize the educational field. The problems of student success and retention could be analyzed, making instruction more personalized. Students could get effective tools to think about their own learning methods. Hitherto concealed practices like behaviours and attitudes about online discussions could be brought out into the open and measured [17], although the specter of students being exposed to learning analytics is still in its infancy [18].

The main objective of learning analytics is to enhance learning for students through the gathering and analysis of data [19]. And any segments can use learning analytics including students, teachers or counsellors [20]. The ability to cull data from the interactions of users is the one hallmark of learning analytics that sets it apart from other methods of feedback. This feedback is distinctive: it is personal, subjective and offers insights that assist in finding patterns and trends among students and their study courses. This feedback also points to possible solutions that help the decision-makers [21] to plan actions and inspire students to become better [22].

There is another distinguishing aspect of learning analytics. It uses obtained data in any form and aligns it with a specific student for the aim of personalizing that pupil's learning journey. Earlier, this type of work was being done by cognitive teachers in digital learning milieu [23]. The confluence of big data and learning analytics also helps in gauging how students write. In fact, an automated writing Evaluation (AWE) programme was created by Snow et al.[24]. The programme was designed to find out whether pupils could gear their writing style towards their writing assignment. AWE can help gauge the quality of any student's writing, when used in conjunction with other information like demographic data, test results etc.

Another advantage is that teachers can access the results of students' learning efforts by using dashboards and can benefit from the information and plan further strategies accordingly [25]. For example, tutors can get crucial information about students who are lagging behind academically and are likely candidates for failure [26]. Furthermore, teachers can effectively tackle such issues by adopting learning analytics-related programmes like Early Warning Systems to help the concerned students in due time [27].

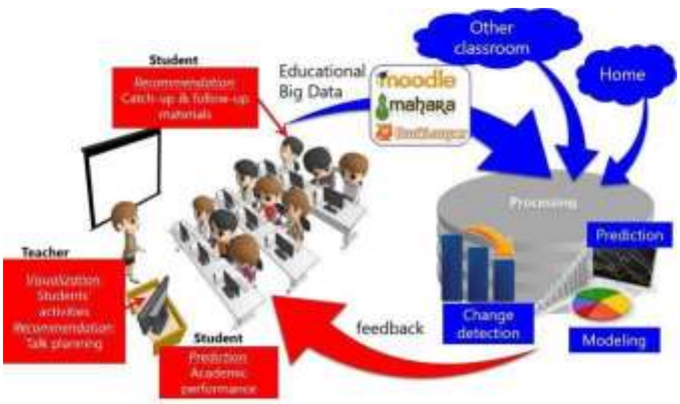

Fig 2.2.1 Big Data in Education

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2.3 Cautionary Considerations

Finally, having sung the praises of learning analytics-based promises, it is imperative to acknowledge that educational technologies are not a panacea for all the ills afflicting the educational sector. It is true that such technologies, through their use and applications, carry the potential to bring about dramatic changes in how students are taught. But there are other cautionary considerations that need to be heeded. It must be understood that advancements in the area of data mining, analytics, storage etc. carry inherent risks and can give rise to moral conundrums that require tackling, even as these technologies are being executed and applied.

For example, there is the issue of breach of privacy. As Hoel and Chen [28] have pointed out that any perceived breach of privacy by students whose data is being mined and used can raise a storm of doubt about the use of learning analytics technologies even as they are being launched. In smaller scenarios, especially, these problems get worsened simply because there are no guarantees that privacy would be protected to start with [29]. In addition to privacy concerns, there might be more practical and immediate aspects that would need tackling. For example, even as learning analytics-related solutions are being created, it would be worth to be aware of inadvertent outcomes [30]. For instance, portions of some content mined and analysed could be perceived as racially charged, and both teachers and pupils need to be wary of such findings [31].

III. CONCLUSION

Finally, as we have seen, all the educational programmes until now have been created keeping in mind the average student. But we can now move away from that. With the help of learning analytics-related technologies, we can aspire to more personalised and individualised teaching methods propounded by Keller [32]. The path is shown by learning analytics. Combining the use of big data, the backing of stake-holders and effective design, learning analytics technologies would help us to address the educational needs of students on one-to-one, more personalised basis. But before that happens, all the problems and issues, technical, ethical and others, would have to be sorted out. In the coming years, however, these technology breakthroughs will help us to discard the old-fashioned models of education catering to the notion of the average pupil and help us put in place a system that can ensure a more socially even and fair one. A system that considers and backs the personal educational requirements of every pupil on one-to-one basis.

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