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State of the Art of Learning Analytics in Higher Education

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ABSTRACT

One of the characteristics of our world today is that it is continuously changing. Every aspect of our world has been transformed by the emerging technologies, ranging from our day to day activities to scientific and industrial developments. This progress has been made in the last few decades. It is also true for all aspects of education. The use of emerging technologies at all levels of education, such as intelligent tutoring systems, learning management systems, interactive learning environments, and online learning, gives access to vast volumes of data of the students. Student data collected automatically in online learning environments are usually not converted into useful information for teaching, although it is a good source of information. It is poorly used throughout the educational domain. A new concept has emerged to capture this educational big data called "Learning Analytics". LA is about discovering hidden patterns in the educational process, assess student learning, and make predictions, which in turn provide a better understanding of teaching, learning, and interpretation of student's data. Higher education institutes are adapting to the evolving concept of LA. It would help HEI's to facilitates students to improve academic performance and enable teachers to keep track of individual students, identify student at-risk, and provide timely interventions. This paper provides the bird's eye view of the research evidence on the usage of learning analytics in higher education across the world by reviewing the leading publications, research studies, and case studies in this area.

Key words: Learning Analytics, Data-Driven Decisions, Higher Education Institution

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1. INTRODUCTION

In the last couple of years, the rising interest in the multi-disciplinary and fast flourishing field of learning analytics is observable. This interest is motivated by digitization and the rapid change of technologies that provides an enormous amount of educational data. LA attempts to exploit this educational data "for purposes of understanding and optimizing learning and the environments in which it occurs" [1]. This field has originated from different fields like "business intelligence, web analytics, educational data mining, and recommender systems" [2]. LA also harnessed various methodologies and theories from statistics, computer science, and artificial intelligence [3]. In higher education, future developments in "technology-enhanced learning (TEL)" can be boosted by the implementation of LA [4-5]. Data is collected not only from classroom environments but also from educational software. This data will now act as a catalyst in the environment at the universities where the learning process is integrated with "virtual-learning environments (VLE)" [6]. When this data is analyzed, it will explore those pieces of information which earlier were "unseen, unnoticed, and therefore unactionable" [7]. When predictions were made on the basics of the research, these analytics have a significant impact in such a way that "more and better information is made available to a greater number of people, thus enabling informed decision-making" [8-9]. Earlier universities were hesitant to implement concepts of learning analytics because of various concerns related to data privacy, and concepts were missing on how it will be implemented, different stakeholder groups have conflicting interests. Now the scenario has changed, and LA has found its implementation in many universities. For future advancement and developments in learning analytics, policies are required to be made. This will thus enhance in making the learning process more efficient and productive, which will be beneficial in integrating it in higher education practice. The present study has collected and summarized information on the usage of learning analytics. Based on this study, the usage of learning analytics in the sector of higher education, and the anticipated benefits for higher education institutions can be identified. This research work collected the categorization of various case studies, empirical researches, as well as various learning analytics projects. Those are then summarized according to the institutes which have implemented learning analytics all over the globe concerning their purpose and the tool used.

2. PANORAMA OF IMPLEMENTING LEARNING ANALYTICS IN HIGHER EDUCATION

This section provides the status of implementation of LA projects/case studies among various higher education institutes across the world. The list is not exhaustive. These projects in higher education include tracking the learning progress of the student, teaching measures, and learning effectiveness. Various other includes providing early alerts and intercessions for improving operations and retentions, predicting the performance of students, personalizing their learning experience, making improvements in the process of testing and placement of students, improvement in resource allocation, and many more. The following subsections provide more detail of LA projects/case studies in various colleges and universities across different countries.

2.1 Implementation of Learning Analytics in the USA

Till now, the USA has implemented LA systematically and on a vast scale. **Educause** is a nonprofit association in the United States whose mission is "to advance higher education through the use of information technology." In 2012, it produced a report which describes and defines the risks which are linked with implementing (or not implementing) the learning analytics in the institutions of higher education [10]. The "Predictive Analytics Reporting (PAR) Framework is a non-profit provider of analytics-as-a-service to many various higher education institutions in the USA (two- and four-year courses of study, private and public, non-traditional and traditional institutions)." It aims to benchmark, prediction, and works towards understanding the risk signs advancement to completion. Apart from prediction, the aim of "PAR" is to provide support in identifying the good practices in the retention of the student through analysis of data, benchmarking across institutions, and shared models. The motivation for "PAR Framework" is double: a) To provide central analytics service with trained and skilled staff, covering various aspects of expertise ranging from the policy of data science to higher education practice so that cost incurred can be decreased; b) To provide valuable information on efficient strategies, by using cross□institutional benchmark studies so that progress, achievement, and engagement is obtained, which could not be revealed by the single-institution analytics activity [11]. Table 1 provides the existing practices and implementation of LA in American higher education.

Table 1: List of Universities implementing LA in the USA

Sr. No.	Institute	Projects/Case Studies/ Tools/Pilots	Purpose	Reference No.
1.	University of Maryland Eastern Shore	Analytic Toolset: Microsoft Performance and Microsoft SQL Server	"The dashboards can be personalized according to the roles of end-users (e.g., faculty advisors, administers, or support staff), Provide actual data and targets for key performance indicators specific to retention, admission, and progressive advancement in an appropriate format."	[12]
2.	Bowie State University	Student Success Monitoring System (SSMS). Analytic Tool: Starfish Early Alert/CONNECT	Improve the retention and success of at-risk students, also enhance the performance of all retention support agents, including faculty, advisers, counselors, retention coordinators, and others, capturing real-time student data related to any severe individual or group-oriented student-retention effort. Communicating the highlighted matters to advisors, faculty, students, and other supporting staff.	[13]
3.	New York Institute of Technology	Student At-Risk Model	Developed its model and dashboard for identifying at-risk students.	[14]
4.	University of Northern Arizona	Grade Performance Status (GPS)	"Generate feedback alerts for academic standing including attendance and academic performance," personalized intervention, Improved retention and graduation rates	[15]
5.	Paul Smith's College	Comprehensive Student Support Program. Tool Used: "Rapid Insight's Veera and Analytics programs, Starfish	Early identification of At-Risk students. Automatically prioritizing the students for intervention and accessibility by support offices and faculty	[16]

		Retention Solutions EARLY ALERT and CONNECT programs."		
6.	Rio Salado Community College, Arizona	"PACE (Progress and Course Management)"	Personalized Education for non-traditional Students, Track Students Progress with intervention.	[17]
7.	Carnegie Mellon University	OpenSimon: Toolkit	Wide range of tools which can be useful to classroom educators, Improve learning outcomes for individual learners	[18]
8.	Portland State University	DataMASTER	Allow the extraction, organization, and analysis of data from PSU enterprise data sources, Facilitate the data-driven decision making	[19]
9.	Purdue University	Signals	"Course Signals System Student alerts for academic issues and provides intervention."	[20]
10.	University of Michigan	a). Gradecraft b). My Learning Analytics (MyLA) c). E2Coach	a). Use digital badges to provide motivating Assessments b). Provides information about student's grades, assignments, engagement with course material, and resource c). Students support and intervention system, Offer customized recommendations	[21-23]
11.	Ball State University	Visualizing collaborative knowledge work MAP-Works (Making Achievement Possible)	Early identification of at-risk students, Early interventions between teachers and first-year students Students gain insight about themselves; Students recognize gaps between their behavior and their expected outcomes	[24]
12.	Marist College	Open Academic Analytics Initiative (OAAI)	Predict students at-risk, Provide intervention to students at-risk	[25]
13.	Columbus State Community College	Starfish, Blackboard	Identify and track at-risk students, allow instructors to record attendance	[26]
14.	Youngstown State University, Ohio	EARS (Early Academic Report System- formerly Starfish)	Improve graduation and completion rates	[27-28]
15.	Strayer University	Civitas Learning's Student Insight Platform	Increase student and faculty engagement, Improving behavioral mindsets	[29]
16.	University of Winsconsin Madison	Lead Engagement Analytics Dashboard (LEAD)	Provide visualization in Tableau: Heatmap: - "Shows when students are active in the course, Scatter Plot: - maps grades and number of page views."	[30]
17.	University of Hawaii	STAR	Charting the academic pan of student's and sending the alerts when students went off their path	[31]
18.	California State University (Chico State University)	Chico State Learning Analytics Research Project	Study the relationship between LMS use and achievement in academics.	[32]
19.	University of Phoenix	Predictive Analytic Model	Identify academically at-risk students	[33]
20.	Grand Rapids Community College	Advanced System Tracking Reporting Online (ASTRO)	Tracking, identify key faculty, upgrade planning, advanced reporting	[34]
21.	Austin Peay State University	Degree Compass	Provide course recommendation	[35]
22.	Texas A&M University-San Antonio	CourseSmart digital textbook analytics	Effective early warning system, identify a student at risk	[36]
23.	George Manson	Survival Analysis framework	Identify at-risk students, provide intervention,	[37]

	University		predict students who drop out and when dropout	
24.	Sinclair Community College	Student Success Plan (SSP)-Project	Provides a holistic case management system used by teachers and support staff in helping students to complete college	[38]
25.	Georgia State University	Predictive Analytics	Eliminating the gap in graduation rates between low-income and minority students and the rest of the student body	[39]
26.	University of Kentucky	SAP's HANA	Provide real-time insight into student's behavior and success	[40]
27.	University of Lynchburg, Virginia	Student Retention Predictor (SRP)	Identifies and priorities group of at-risk students	[41]
28.	Harvard University	Learning Catalytics	To provide learners with customized support to boost the efficient collaboration between learners and enabling the instructors to fine-tune instructional practices	[42-43]
29.	Capella University	Fully Embedded Assessment Model (FEAM)	Learning and Career outcomes	[44]

2.2 Implementation of Learning Analytics in the UK

Numerous institutions in the UK are deploying learning analytics in diverse ways and for various reasons. In the United Kingdom, the work of Jisc (formerly the Joint Information Systems Committee) has made considerable progress in LA with the establishment of a national learning analytics service for higher and further education. Working and collaborating with 50 universities, Jisc has developed a suite of resources, tools, and guides to support the implementation of LA in the UK [45]. The research concluded that those who have earlier adopted this for enhancing the learning experience of students are due to several reasons. Those reasons include improving the chances for achievement, providing better feedback, and boosting students so that they may become brilliant learners. Retention may be a significant issue for some institutions, and they use learning analytics for identifying the students who are at risk of dropout. However, retention is not a significant problem for others. One of the crucial drivers mentioned is providing students better information about their progress. As per the current scenario internationally and in the UK also, Jisc anticipates that LA can make a significant contribution for; quality assurance and quality improvement, boosting retention rates, assessing and acting on differential outcomes for students, and as an enabler for the introduction of adaptive learning.

Table 2: List of Universities implementing LA in the UK

Sr. No.	Institute	Projects/ Case Studies/ Tools/Pilots	Purpose	Reference No.
1.	The Open University	a). OU Analyses Project b). Analytics4Action Evaluation Framework , c). OpenEssayist	a). Provide early prediction of 'at-risk' students so that meaningful and 'cost-effective' intervention can be provided. b). Translate the insights from learning analytics into actionable interventions. c). tool for learner support, analytics for assessment, provide description and summary for visualization	[46-48]
2.	University of Edinburgh	Learning Analytics Report Card (LARC) (Project)	Presents a summary of student's academic progress in textual and visual form	[49]
3.	University of Derby	D2L's Brightspace VLE, Student Experience Traffic Lighting (SETL)-Project	Easy to learn Provide invaluable insight through data analytics capabilities, Automates the delivery of courses, Track learners progress, Tailored to each learner's lifestyle	[50-51]
4.	University of Nebraska-Lincoln	Hobsons Starfish Early Alert	Identify Struggling students, Support at-risk students.	[52]
5.	Nottingham Trent	Dashboard	Send e-mail alert to instructors when student	[53]

	University		engagement stops for two weeks	
6.	University of Bedfordshire	"Strategic ICT for Managing Student Engagement (SIMSE) project JICS's Strategic Toolkit Improved Student Engagement System (SES)"	Students progression and retention, Tailored guidance	[54]
7.	Bridgwater College	ProMonitor, ProSolution	Attendance reports and retention at the level of individual, program and college, e-mails/letters sent to students/parents if the deadline has been missed or attendance is unsatisfactory	[55]
8.	The University of East London	QlikView	Automated e-mails sent to students every month showing their attendance	[55]
9.	Lancaster University	Tableau	Interactive Transcript help instructors to give better advice to students	[55]
10.	Loughborough University	Co-Tutor	"Software creates dashboards and exactly alerts for different tutoring roles and provides an audit trail of their interaction with students, to escalate issues, automatic messages and notifications are passed."	[55]
11.	Manchester Metropolitan University	Enhance Quality and Assessment for learning (EQAL) program, Programme leader dashboard	Personalized information to students, "Continuous Monitoring and Improvement (CMI) system, Student Engagement Monitoring (SEM)"	[55]
12.	Oxford Brookes University	Academic Performance Tracking Tools, Dashboard, Qlikview	The tool used for module program and faculty review and overall operational plan for university	[55]
13.	University of Wolverhampton	Tribal's Student Insights	Predict student risk, focus on retention and academic performance risk	[56]
14.	University of Northampton	Projects –LEARN (Learner Engagement Attendance & Retention at Northampton) Student Analytic dashboard Active Blended Learning ChANGE (Changemaker Attributes at Northampton for Graduate Employability)	Track student's engagement in the course, help instructors to support student success	[57-60]
15.	Swansea University	Unitu	Provide online space where students, instructors and supporting staff talk and resolve academic and non-academic issues, improve student's engagement	[61]
16.	Coventry University	EdTech startup: Aula Learning Analytics Dashboards (LAD) Learning and study strategies Inventory (LASSI)	Student engagement through social learning	[62]

2.3 Implementation of Learning Analytics in Australia

Australian people do some of the most interesting innovations. They have carried out extensive work on learning analytics. Interesting largescale practices are described in a report called "Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement" [63]. One of the project 'Loop' targeted the practical problem of how to better support effective teaching and student learning online and understand the needs and perceptions of teachers in higher education to ensure that learning analytics can be genuinely useful in teaching and learning practice [70]. To enhance the teaching and learning at Wollongong [69], various studies are there which are related to the usage of social network analysis. The role of analytics is examined to help in planning by students through their modules at "Open Universities Australia (OUA)" [68].

Table 3: List of Universities implementing LA in Australia

Sr. No.	Institute	Projects/ Case Studies/ Tools/Pilots	Purpose	Reference No.
1.	Edith Cowan University	Tool: C4S	Improve student engagement, Enhancing retention	[64]
2.	University of New England	Automated Wellness Engine (AWE) Dashboards-- e-Motion, The Vibe	For identification of high-risk learners, an Evidence-based system of retention is used. For enhancing the learner retention and engagement and early alert, the engine is designed	[65]
3.	The University of Adelaide	Teamwork DashBoard	Monitoring teams in real-time for CS students for their role in problem-solving is done by the educators, team projects. Feedback about team interactions is provided by educators using Teamwork Dashboard, Identify problematic team.	[66]
4.	University of Sydney	Tool developed -PASTA	Provide instant feedback for students and auto-grading for teachers	[67]
5.	Open Universities, Australia	Personalized Adaptive Study Success (PASS)	Identify student at risk, Personalization of the study experience for each student, suggest alternative modules to struggling students	[68]
6.	University of Wollongong	SNAPP (The Social Networks Adapting Pedagogical Practice)	Evaluate students' behavioral pattern and provide the best practice	[69]
7.	University of Melbourne	Loop Tool	Enable teachers to articulate their learning, and Data is represented via visual representations from the LMS	[70]
8.	Macquaire University	Loop Tool	Enable teachers to articulate their learning, and Data is represented via visual representations from the LMS	[70]
9.	University of South Australia	Loop Tool	Enable teachers to articulate their learning, and Data is represented via visual representations from the LMS	[70]

2.4 Implementation of Learning Analytics in European Countries

Europe has seen an enormous surge in the research being conducted in learning analytics, especially from countries such as Netherlands, UK, Germany, Spain, Austria. Additionally, several European countries, such as the Netherlands, Norway, and Denmark, are developing nationwide learning analytics strategies that include national policies, infrastructure, and competence centers. Many ongoing European-funded projects are given below:

FP7-funded projects: "LACE (Learning analytics community exchange)" [71], "LEA's Box (Learning analytics toolbox)" [72], "PELARS (Practice-based experiential learning analytics research and support)" [73], "PERICLES (Promoting and Enhancing Reuse of Information throughout the Content Lifecycle taking account of Evolving Semantics)" [74].

Erasmus+funded projects: "PBL3.0 (Integrating learning analytics and semantics in problem-based learning)" [75], "SHEILA (Supporting higher education to incorporate learning analytics)" [76], "STELA (Successful transition from secondary to higher education through learning analytics)" [77].

JRC Funded "LAEP (Implications and opportunities for learning analytics for European educational policy)" [78].

H2020 funded Project: "RAGE (Realizing an applied gaming ecosystem)" [79].

Innovation Fund Denmark funded projects: GBL21 (Game-based Learning in the 21st Century) [80]. ATEL (Automatically Tracking Early Stage Literacy Skills) [81].

Table 4: List of Universities implementing LA in European Countries

Sr. No.	Institute	Projects/ Case Studies/ Tools/Pilots	Purpose	Reference No.
1.	University of Salamanca (Spain)	Virtual e-Learning Analytics System (study)	Facilitate Visualization, help in decision making, Improve education processes	[82]
2.	Open University of Catalonia (Spain)	Automated System for Inferring Relevant Topics for Each Subject	"Used for analyzing the suitability of materials to subjects, Allows better understanding of subjects Enrich and contextualize other analytical processes."	[83]
3.	Dublin City University, Ireland (Europe)	PredictED	Uses past and present log data to predict outcomes weekly basis, Generate automated personalized e-mails to students at-risk	[84]
4.	KU Leuven, Belgium	a. LASSI b. REX	a. Provide actionable feedback about five learning skills accessed by LASSI concentration, anxiety, motivation, test strategies, time management b. Provide Feedback on academic achievement	[85]
5.	TU Delft, Netherland	a. LASSI b. REX	a. Provide actionable feedback about five learning skills accessed by LASSI concentration, anxiety, motivation, test strategies, time management b. Provide Feedback on academic achievement	[86]
6.	Ulster University, Northern Ireland	Blackboard Predict	To help identify students at-risk	[87]
7	RWTH Aachen University (Germany)	eLAT (a Learning Analytics Toolkit)	Support faculty evaluation, Indicator, and visualization of specific data	

Table 5: List of other Universities implementing LA

Sr. No.	Institute	Projects/ Case Studies/ Tools/Pilots	Purpose	Reference No.
1.	University of North Bengal (India)(study)	Determine the predictors of dropouts	Provide valuable guidance for counselors and faculty members to educate learners for the best possible completion options.	[88]
2.	University of British Columbia (Canada)	a. OnTask b. VizIT c. Threadz	a.Provide timely personalized and actionable feedback to learners b.helps instructors stay informed about learner activity in edX c.Allows instructors to visualize the social dynamics of discussion forums	[89]
3.	University of South Pacific, Fiji	Framework for development of an open textbooks analytics system	Enables the recording, analysis, and presentation of interactional data that is generated by student interactions with open textbooks	[90]

3. CONCLUSION

Learning analytics (LA) has enabled providers to develop new ways of achieving excellence in teaching and learning. It has helped students to make the best choice about their education. LA will aid in developing more student-focused programs of higher education. It also provides tools and data to the institutions which may be required for making continuous improvements. The usage of digital tools enhances the learning process. Various projects/case studies from LA revealed how, with the usage of these tools,' student's learning is optimized and has proven to be beneficial for institutions, teachers, and students. After going through the available literature, this study observes that there is a positive response to the usage of LA. In this paper, the evidence on the implementation of LA in higher education across the world is gathered. It can be seen from the study that proper research and practice in the field of LA has been seen in the USA, Australia, UK, and other European countries. Most of the work has been limited to the use of prediction and data models to identify student's at- risk so that timely support can be provided. LA could play a significant role in supporting other essential areas like wellbeing, innovation, and employability. There are various emergent aspects as well, such as developing an open education system, lifelong learning, and spreading of education internationally. Owing to the prevailing trend of digitalization, LA supports the emergence of the online education system. LA has addressed various challenges faced by higher education institutions. Within an institution, LA is not just a technological/development or a research issue but an organizational issue as well. Various challenges, privacy, and ethical issues are faced while collecting the data of the students. They are thus considered carefully and addressed according to the institution and cultural context. This study has summarized the findings on LA for different projects/case studies that are going on in different countries and institutions. Implementation of LA in higher education can be seen as promising. Although the field of LA is still in its infancy. Various unexplored and underexplored areas exist in the projects/case studies, and the researchers in the future could explore them.

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