Data Analytics, Students' Academic Performance and Decision-Making in Higher Education

Silvia Gaftandzhieva, Rositsa Doneva, Milen Bliznakov

University of Plovdiv "Paisii Hilendarski", 24 Tzar Assen Str., Plovdiv, 4000, Bulgaria

Abstract

The success rate of students is an important indicator of the quality of the educational service offered in a higher education institution (HEI). University decision-makers need reliable data on the success rate of students in order to formulate specific and coherent decisions to further improve students' academic performance. This is where data analytics can be of invaluable help, as it supports a data-informed decision-making. For the needs of the most relevant decision making bodies in Bulgarian HEI (programme managers, deans and rector) this paper offers a data analytics software tool for monitoring student success in a timely manner and make timely data-driven decisions to increase retention rate and improve student success rate. The tool is based on three models with indicators for monitoring the student success correspondingly for each of the three types of decision-making bodies. The paper presents also the results of experimental tests with the models and the tool conducted on the basis of the information infrastructure of a Bulgarian university.

Keywords[1]

data analytics, software tools, big data, student success, data collection, monitoring, decision making, self-assessment reports, higher education institutions

1 Introduction

Nowadays, many higher education institutions (HEIs) receive funding based on the number of students, and their managers are looking for ways to reduce dropouts and provide a quality education that prepares students well for the labour market so that HEIs are attractive to prospective students. For this reason, the continuous monitoring of student success is among the main activities for each HEI.

Performing such monitoring by relying solely on traditional practices is no longer enough. On the one hand, data collection and analysis require human resources involvement and manually perusing endless data streams. On the other hand, the presented data are up-to-date at the time of the monitoring and do not provide information about the current state of HEI. Because of this, contemporary HEIs are increasingly looking for solutions which extract data from information systems and allow HEIs to optimize ongoing processes and make data-driven decisions.

Data analytics tools consolidate information from different sources to provide the big picture of trends and patterns that leadership teams can use to evaluate and streamline processes and create efficiencies [1].

Using data analytics tools, managers can find hidden patterns in educational information and collect evidence to support informed decision-making at each level in HEIs [2, 3, 4]. Some universities [4, 5] integrate analytics techniques with their decision support systems to help managers develop decision-making processes and collaterally improve student performance. These tools deepen the awareness of HEIs managers of students' success rates and allow them to track tuition trends over time and address program performance at an institutional level [6]. The governing bodies have access to aggregate data

Education and Research in the Information Society, October 13-14, 2022, Plovdiv, Bulgaria
EMAIL: sissiy88@uni-plovdiv.bg (A.1); rosi@uni-plovdiv.bg (A.2);milen@uni-plovdiv.bg (A. 3)
ORCID: 0000-0002-0569-9776 (A.1);0000-0003-0296-1297 (A.2)

for students' achievements [7], which they can analyse to improve the quality of education, students support and institution efficiency [8]. These data allow managers to monitor students' progress [4], identify at-risk and struggling students [9, 10, 11] and predict which students will or will not graduate [12, 13]. HEIs managers could use this information to identify the reasons for low grades and develop intervention plans that prevent a student from failing, stimulates students to achieve higher results [9], reduce the drop-out rate [14, 15, 16], improve students' completion rate [2, 10, 11, 17, 18]. Tools allow managers to identify the most effective programs and to gain a deeper understanding of what student success looks like in an institution.

All data can be disaggregated by different characteristics of students (e.g., age, income, gender) to understand better students' experiences, identify barriers and compare achievement gaps. Disaggregating student data enable HEIs to see trends in students' behaviour and achievement, compare performance from different student groups and study where aggregate data are masking discrepancies to reduce performance differences among groups while increasing excellence for all [19, 20]. For example, if student survey results show a gender divide in graduation rates, it might be efficient to have gender-specific targeted drop-out prevention.

In this way, data analytics tools can help strengthen the bond between students and the university, increase graduation rates [6, 21, 22], strengthen the social commitment of students to the university, overcome inequalities in learning progress and outcomes, and enhance the learning process to meet the students learning requirements [6, 23, 24].

Some researchers view data analytics as a tool for providing awareness to improve the curricula and increase the quality of study programs and educational practice in general [25, 26, 27]. HEIs managers can be alerted when a specific course is experiencing larger-than-normal dropouts, allowing them to investigate the cause and identify whether it is a problem with the standard of teaching, the lecturer or something else. Tools extract knowledge from educational data and help HEIs managers identify courses and programmes that more closely meet the needs and preferences of students [12], determine the most effective teaching techniques, and provide insights into how teachers can reflect on their teaching practice to affect learning outcomes [28, 29]. Such tools help managers to improve the teaching staff selection [18] and evaluate the work of teachers (incl. assessment methods and feedback [9]) and take measures to improve the quality of the training and teaching methods [30, 21, 22], update the curricula and organize learning resources more efficiently, and thus to provide students with a better studying environment [13]. HEIs managers can use data analytics tools to examine whether the most recent curriculum and instruction adjustments improve the performance of weak students. In addition, they can use data analytics tools to improve cost reduction [18], address the desire for accountability for the various institutional stakeholders [31, 32], and achievement of the HEIs' strategic goals [18].

Data analytics tools can be used as a planning and monitoring tool [33], e.g. for modelling the number of students' plans and monitoring the year outcomes. Tools allow managers to track the current performance against the strategic goals, examine trends in student lifecycle, make forecasts, and evaluate facts and figures for an efficient ROI. Leadership must assess performance against plans to take action and be prepared to act on predictive findings, develop risk reduction plans and implement targeted interventions or other support. Data analytics tools provide capabilities for generating and distributing different reports, including HEIs annual performance reports. Results from the annual reports unlock and provide meaningful summarised historical data to assist HEIs managers answer tactical questions for making timely data-driven decisions across all departments and divisions [6, 28, 34] and determine whether the measures taken to retain students and improve the quality of education are effective and sustainable. Data analytics tools help HEIs make benchmark comparisons across HEIs and student groups. From the institutional perspective, the results allowed for establishing a competitive strategy to improve the HEIs rank among other universities and enhance its reputation [35].

Worldwide, HEIs leaderships have expanded data-driven decision-making to many aspects of their activities and continue extending them [1]. They are applying data analytics tools to identify at-risk students and reduce drop-out rate (New York Institute of Technology [9], Marist College [9], University of New England [36], University of Wollongong [37], Rio Salado College [38], Bowie State University [39], Strayer University [40], University of South Australia [41]), provide better feedback and facilitate teacher-student interactions (Northern Arizona [42], University of Edinburgh [38]), identify effective teaching strategy (University of Maryland Baltimore County [9]), track student outcome (Oxford Brookes University [9]), track student engagement and predict student success (Open University

Australia [9], University of Bedfordshire [43], California State University [44], Harvard University [45], Purdue University [9], University of East London [43], University of Edinburgh [38], University of Adelaide [46]), improve student success and graduation rate (University of Derby [43], Nottingham Trent University [47], Edith Cowan University [48], Grinnell College [49], Bowie State University [39], Paul Smith's College [50], Charles Darwin University [51], Open University [43]), advise learners on the best possible completion options (University of North Bengal [52]), improve HEI evaluation results (Manchester Metropolitan University [43]). In Bulgaria, research in using data analytics tools in universities is at a very early stage. Some experiments for using data analytics tools to increase the effectiveness of monitoring, management, quality assurance and evaluation of training delivered to all management groups which make decisions in universities have been done at the University of Plovdiv [53] and the University of National and World Economy [33].

All this motivates the development of data analytics tools for monitoring students' success that will extract and analyse data about academic staff and allow different stakeholders (e.g. programme managers, deans and vice-deans, rector and vice-rector) to monitor the student success and make timely data-driven decisions to increase retention rate and improve institutional processes in many aspects. The paper presents three models for monitoring the student success and a correspondent software tool designed for the needs of decision making bodies in Bulgarian HEI (programme managers, deans and rector). The tool allows them to monitor student success in a timely manner and make timely data-driven decisions to increase retention rate and improve student success rate. In addition, the tool can also significantly assist in the preparation of self-assessment reports with data for student for the need for external quality assessment in HE. Research and experiments with the models and the tool are conducted on the basis of the information infrastructure of the University of Plovdiv "Paisii Hilendarski".

2 Indicators for data collection

On the basis of a literature review in the field [1-53] and available data in potential data sources are proposed 3 models for monitoring students' success with a set of indicators that serve as a business logic basis of the developed data analytics tool (see Section 3). The three models are developed correspondingly for the needs of three different levels of the university decision making bodies – programme managers (PM), deans (D) and rector (R) – called bellow stakeholder groups. Those models define what type of data should be collected from the institutional information infrastructure that decision making bodies of the institution will be able to use to track data for students results for different purposes, e.g. monitoring, analysis, intervention, etc., but finally to improve the quality of training in HEI and graduation rates.

Each model includes indicators of two levels. Indicators from Level 1 represent the subject to which the collected and aggregated data relate – student success during training, student success in graduation, gender gap. These indicators group together a set of Level 2 quantitative indicators whose values are extracting from the university information systems. Table 1 presents the three models and their indicators of Level 1 and Level 2. Those indicators of Level 2 that are part of the model for the relevant stakeholder group are indicated with "+".

Table 1: Model for monitoring student success

Indicator – Level 1	Indicator – Level 2	PM	D	R
1. Student success during the training	Number/ratio of students who have successfully completed the academic year and have passed to the upper course per faculty		+	+
	Number/ratio of students who have successfully completed the academic year and have passed to the upper course per study programme	+	+	+
	Number/ratio of students who have successfully completed the academic year and have passed to the upper course per professional field			+
	Number/ratio of dropped out students per faculty		+	+
	Number/ratio of dropped out students per study programme	+	+	+
	Number/ratio of dropped out students per professional field			+

Indicator – Level 1	Indicator – Level 2	PM	D	R
	Average grade of students at the end of each academic year per faculty		+	+
	Average grade of students at the end of each academic year per study programme	+	+	+
	Average grade of students in current academic year per subject	+		
	Number/ratio of students with average grade Excellent, Very good, Good, Satisfactory and Poor per study programme	+	+	
	Number/ratio of students with average grade Excellent 6.00 per study programme	+	+	
	Number/ratio of students with grades Excellent, Very good, Good, Satisfactory and Poor in current academic year per subject	+		
	Number/ratio of students who took the final exam with grades Excellent, Very good, Good, Satisfactory and Poor per study programme	+	+	
2.Student success in graduation	Number/ratio of graduate students per faculty		+	+
	Number/ratio of graduate students per study programme	+	+	+
	Number/ratio of graduate students per professional field			+
	Average grade of students in graduation per study programme	+	+	+
	Maximum success of students in graduation per study programme	+	+	
	Minimum success of students in graduation per study programme	+	+	
	Number/ratio of graduate students with grade Excellent 6.00 per study programme	+	+	+
	Number/ratio of graduate students with grade Excellent 6.00 per faculty		+	+
	Number/ratio of graduate students with grades Excellent, Very good, Good and Satisfactory per study programme	+	+	
	Number/ratio of graduate students with grades Excellent, Very good, Good and Satisfactory per faculty		+	+
	Number/ratio of graduate students with grades Excellent, Very good, Good and Satisfactory per professional field			+
3. Gender Gap	Number/ratio of women and men among students who have completed the academic year and have passed to the upper course per faculty		+	+
	Number/ratio of women and men among students who have completed the academic year and have passed to the upper course per study programme	+	+	
	Number/ratio of women and men among dropped out students per faculty		+	+
	Number/ratio of women and men among dropped out students per study programme	+	+	
	Number/ratio of women and men with average grade Excellent, Very good, Good, Satisfactory and Poor per study programme	+	+	
	Number/ratio of women and men with average grade Excellent 6.00 per study programme	+	+	
	Number/ratio of women and men with grades Excellent, Very Good, Good, Satisfactory and Poor in current academic year per subject	+		
	Number/ratio of women and men who took the final exam with grades Excellent, Very good, Good, Satisfactory and Poor per study programme	+	+	
	Number/ratio of women and men among graduate students per faculty		+	+
	Number/ratio of women and men among graduate students per study programme	+	+	+
	Number/ratio of women and men among graduate students per professional field			+
	Average success of women and men in graduation per study programme	+	+	+
	Maximum success of women and men in graduation per study programme	+	+	
	Minimum success of women and men in graduation per study programme	+	+	
	Number/ratio of graduate women and men with grade Excellent 6.00 per study programme	+	+	
	Number/ratio of graduate women and men with grade Excellent 6.00 per faculty		+	+
	Number/ratio of graduate women and men with grades Excellent, Very good, Good and Satisfactory per study programme	+	+	+
	Number/ratio of graduate women and men with grades Excellent, Very good, Good and Satisfactory per faculty		+	+

3 Data analytics tool

Following the proposed model (Section 2), a corresponding data analytics tool for monitoring student success StudAnalyst is designed, developed and implemented.

Based on an analytical review of software solutions for extracting, analyzing and visualizing data from various information sources, software tools developed by TIBCO Software (*JasperReport Server, Jaspersoft ETL and JasperSoft Studio*, https://www.tibco.com/) and the *Dynamic Presentation Framework* (DPF) developed by a team working at the University of Plovdiv are selected for software development. The *JasperSoft Studio* provides a rich set of tools for design report templates that can be filled out with data retrieved from different sources. *JasperReport Server* allows users to organize structured repositories, access data collections and use them as data sources for the needs of *JasperSoft Studio* when generating, storing reports and presenting them in the preferred form. The server also propose integration with software applications through web services. *DPF* visualizes dynamic user-driven views of objects in a web browser and allows connection to external sources through web services.

The architecture of the StudAnalyst (see Fig. 1) has three layers – Presentation, Application and Data layers.

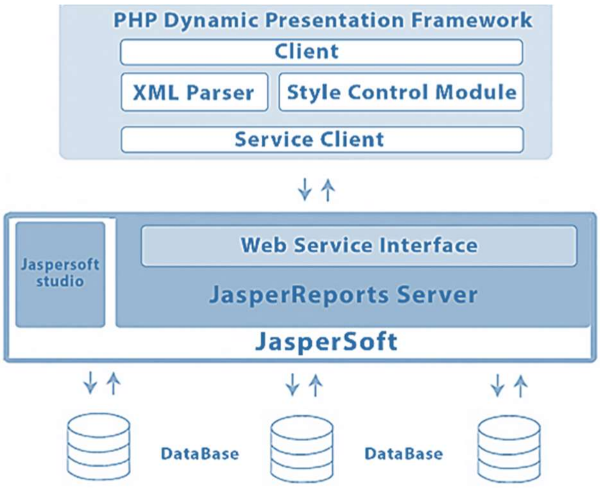

Figure 1. StudAnalyst Architecture

DPF is in the basis of the StudAnalyst *Presentation Layer*. DPF allows user to choose template, request the generation of a report and view the result (visualized report). By using XML Parser and Style Control Module functionalities users can modify some view attributes such as color, font size, etc., to visualize the report in the web browser in a user-friendly way. There are currently three separate user roles: Programme managers (PM), Dean/Vice-dean (D), Rector/Vice-rector (R).

The core functionality of the *Application Layer* of StudAnalyst and its business logic are implemented through JasperSoft Studio. Important tasks from this functionality are modelling the three models for the needs of each stakeholder group (see Section 2) and extracting values for indicators from the university information systems. Solving these tasks requires an in-depth analysis of the institutional information infrastructure (in the case of the University of Plovdiv) that aims to determine the **appropriate data sources**, which of the stored data and how they can be extracted and analyzed to be used for forming values of the indicators from the proposed models. As a result of this analysis student information system in which results from all taken exams are stored is defined as a potential data source of the designed data analytic tool. Then, JasperSoft Studio is used for design and development of templates of reports that will **collect appropriate data** for the proposed indicators (see Table 1) for the needs of each user (Programme manager, Dean/Vice-dean, Rector/Vice-rector). Templates have been stored on the JasperReport Server that plays an intermediate role between the architectural layers. Firstly, the Client Application requests the REST services of JasperReports Server to run a chosen template and generate a report through the Service Client. Then the JasperReports Server Web Service interface responds to HTTP requests from the DPF.

Data Layer of the StudAnalyst includes the student information system which JasperReport Server addresses them to retrieve the necessary data when generating reports and the JasperReports Server repository itself.

The data analytics tool fills the developed templates with data directly retrieved from the student information system or obtained through calculations and then generates reports depending on the user's role. This is because indicators from Level 1 and 2 are the same for different stakeholder groups, but they differ in lower levels and this is embedded in the designed report templates, e.g. for the ***Indicator 2.7. Number/ratio of graduate students with grade Excellent 6.00 per study programme*** the related data sources for acquisition of values of the indicators of Level 3 and the indicators/values themselves for each user role will be different (see Table 2). Therefore, the generated reports for different stakeholder groups contain different data retrieved from the information systems depending on the user's role.

Table 2. Indicators of Level 3 according to user role for Indicator 2.7.

User role	Input data	Output Values
PM (Programme manager)	Study programme	Study programme Year of Graduation Number of students graduated with Excellent 6.00
D (Faculty Managers: Dean, Vice Deans)	Without input data for the entire faculty Study programme	Study programme Professional field Year of Graduation Number of students graduated with Excellent 6.00
R (University Managers: Rector/Vice-Rector)	Without input data for the entire university Faculty Professional Field Study programme	Faculty Professional field Study programme Year of Graduation Number of students graduated with Excellent 6.00

StudAnalyst allows users to generate reports for each indicator of the proposed models with retrieved values s/he wants to see the current situation in the faculty/university depending on its user role. The reports can also be automatically generated by the tool following the predetermined schedule and stored in its repository. Such automatically generated reports can be accessed by users who have access rights.

Reports contain data presented in the form of tables and diagrams and allow users to perform various analyses, e.g. StudAnalyst allows vice-rectors to:

- monitor how many students have completed the academic year and have passed to the upper course per faculty, study programme and professional field;
- monitor how many students have dropped out per faculty, study programme and professional field;
- track average grade of students at the end of each academic year per faculty and study programme;
- monitor how many students have graduated per faculty, study programme and professional field;
- track average grade of students in graduation per study programme;
- monitor how many students have graduated with Excellent 6.00 per study programme and faculty;
- monitor the number of graduate students with Excellent, Very Good, Good and Satisfactory grades per faculty and professional field;
- monitor student success in terms of equality between women and men;
- generate annual reports for students' success;
- track trends by comparing monitoring results from different periods and make data-informed decisions to enhance students' success.

Figure 2. presents a part of report generated through the StudAnalyst tool for *Indicator 3.9. Number/ratio of women and men among graduate students per faculty* by Vice-rector. The report shows the number of graduated men and women and their ration in each faculty.

VISUAL EDITOR

Repository | Settings | **Login:** Vice-rector

STORAGE FOR PU "PAISII HILENDARSKI"

Number/ratio of women and men among graduate students per faculty

Faculty	Women	Men	Total	%women	%men
Biology	192	57	249	77.11	22.89
Pedagogy	1148	197	1345	85.35	14.65
Economics and Social Sciences	560	183	743	75.37	24.63
History and Philosophy	72	59	131	54.96	45.04
Mathematics and Informatics	308	315	623	49.44	50.56
Physics and Technology	72	143	215	33.49	66.51
Philology	283	56	339	83.48	16.52
Chemistry	138	21	159	86.79	13.21
Law	121	60	181	66.85	33.15

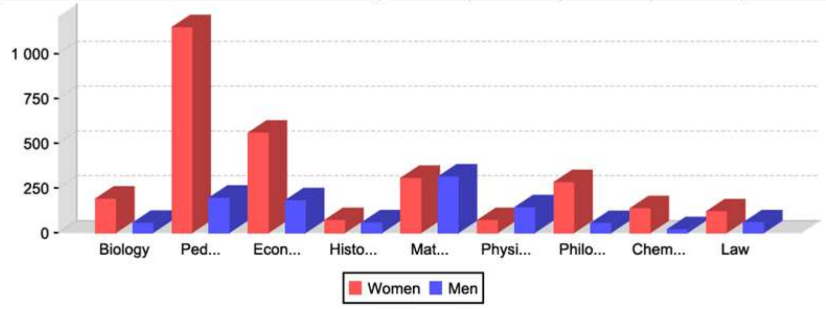

Figure 2. Generated report

Once the data analytics tool generates the reports, users can **analyse** them to make data-informed decisions to stimulate students to improve their success. The data in the generated report (see Figure 2) show that more than 75% of all graduate students in 5 faculties are women (e.g. Faculty of Chemistry, Faculty of Pedagogy, Faculty of Philology, Faculty of Biology, Faculty of Economics and Social Science) and 66.51% of students graduated in the Faculty of Physics and Technology are men. Only in the Faculty of Mathematics and Informatics and the Faculty of History and Philosophy the number of male and female graduates is approximately equal. The latter shows that the senior management of faculties in which the share of a certain gender is low can take measures to stimulate admission and graduation of the respective gender. When entering parameter values (faculty name), the generated reference contains only data for each study programme in the respective faculty.

The data analytics tool automatically generates **annual monitoring reports** for each indicator with summary data for each faculty and the university. These annual monitoring reports can be viewed and downloaded by users who have the right to access them. The leadership can review the monitoring reports to identify where activities are having an impact and compare the results with those from the previous year to show the progress or lack of progress made.

4 Conclusions

The developed StudAnalyst tool allows users to monitor student success in a timely manner and make timely data-driven decisions to increase retention rate and improve student success rate. In addition, the tool can also significantly assist in the preparation of self-assessment reports with data for student for the need for external quality assessment in HE.

Currently, the StudAnalyst tool is provided for real-time testing at the University of Plovdiv. Representatives of all stakeholder groups are invited to use the tool to generate reports needed for the monitoring student success, internal and external quality evaluation and annual reports. Their feedback will be taken into account in the development of the final version. In the future, the functionality of the tool will be expanded to allow data extraction for other quantitative indicators. The next version of StudAnalyst will have dashboards that will allow users to participate and understand the analytics process by compiling data and visualising trends and occurrences. These dashboards will display data visualisations in a way that is immediately understood and can serve as an effective foundation for further dialogue.

The tool can be adapted for the needs of each HEI, regardless of the type of the relevant university information systems. For this purpose, it needs to identify data analytics purposes and map the context at the university.

5 Acknowledgements

The paper is partly supported within the project MU21-FTF-018 "Application of big data analysis methods in higher education" of the Scientific Research Fund at the University of Plovdiv “Paisii Hilendarski”.

6 References

[1] M. Krawitz, J. Law, S. Litman, How higher-education institutions can transform themselves using advanced analytics, 2018, URL: https://www.mckinsey.com/industries/public-and-social-sector/our-insights/how-higher-education-institutions-can-transform-themselves-using-advanced-analytics

[2] P. Long, G. Siemens, Penetrating the Fog: Analytics in Learning and Education, EDUCAUSE Review, 2011 (46), pp. 31-40.

[3] N. Patwa et al., Learning Analytics: Enhancing the Quality of Higher Education, Res J Econ 2:2, 2018.

[4] Y. Nieto et al., Academic decision making model for higher education institutions using learning analytics, 2016 4th International Symposium on Computational and Business Intelligence, Olten, 2016, pp. 27-32.

[5] Y. Acevedo et al., A proposal to a decision support system with learning analytics, 2018 IEEE Global Engineering Education Conference, Tenerife, 2018, pp. 161-168.

[6] B. Daniel, Big Data and Analytics in Higher Education: Opportunities and Challenges. British Journal of Educational Technology, 2015, URL: http://onlinelibrary.wiley.com/doi/10.1111/bjet.12230/full

[7] T. Laet, E. Foster, The ABLE project: How do we put what we have learnt from learning analytics into practice, 2018, URL: https://www.ntu.ac.uk/__data/assets/pdf_file/0032/365873/foster.pdf

[8] M. Ekowo, I. Palmer, Predictive Analytics in Higher Education, 2016, URL: https://www.newamerica.org/education-policy/reports/predictive-analytics-in-higher-education/

[9] N. Sclater et al., Learning Analytics in Higher Education: A review of UK and international practice Full report, Jisc, 2016.

[10] A. Boyer, G. Bonnin, Higher Education and the Revolution of Learning Analytics, International Council For Open And Distance Education, 2017, URL: https://hal.archives-ouvertes.fr/hal-03012475/document

[11] J. Reyes, The skinny on big data in education: Learning analytics simplified, TechTrends, 2015 (69), 75–80.

[12] A. Oztekin, A hybrid data analytic approach to predict college graduation status and its determinative factors, Industrial Management and Data Systems, 2016 (116), 1678-1699.

[13] R. Asif, A. Merceron, S. Ali, N. Haider, Analyzing Undergraduate Students’ Performance using Educational Data Mining. Computers & Education, 2017 (113), 177–194.

[14] J. Rastrollo-Guerrero, J. Gómez-Pulido, A. Durán-Domínguez, Analyzing and Predicting Students' Performance by Means of Machine Learning: A Review, Appl. Sci., 2020(10), 1042

[15] F. Alshareef, H. Alhakami, T. Alsubait, A. Baz, Educational Data Mining Applications and Techniques, (IJACSA) International Journal of Advanced Computer Science and Applications, 2020 (11), pp. 729-734

[16] S. Sivakumar, S. Venkataraman, R. Selvaraj, Predictive modeling of student dropout indicators in educational data mining using improved decision tree, Indian Journal of Science and Technology, 2016 (9), 1–5.

[17] C. Lawson et al., Identification of 'at risk' students using learning analytics: the ethical dilemmas of intervention strategies in a higher education institution. EduTechResDev, 2016 (64), 957–968.

[18] I. Giacumo, J. Bremen, Emerging evidence on the use of big data and analytics in workplace learning: a systematic literature review, Quarterly Review of Distance Education, 2016 (17), 21p.

[19] Education New York, The Importance of Disaggregating Student Data, 2012, URL: http://www.educationnewyork.com/files/The%20importance%20of%20disaggregating_0.pdf

[20] K. Bannan, Universities Use Data Analytics Tools to Support Academic Advising, 2019, URL: https://edtechmagazine.com/higher/article/2019/05/universities-use-data-analytics-tools-support-academic-advising

[21] C. Romero, S. Ventura, Data mining in education. WIREs Data Mining and Knowledge Discovery, 2013 (3), 12-27

[22] M. Attaran, J. Stark, D. Stotler, Opportunities and challenges for big data analytics in US higher education: A conceptual model for implementation. Industry and Higher Education, 2018 (32), 169–182.

[23] B. Daniel, R. Butson, Technology Enhanced Analytics (TEA) in Higher Education. In Proceedings of the International Association for Development of the Information Society, Fort Worth, TX, USA, 2013, pp. 22–24.

[24] A. Pena-Ayala, Educational data mining: A survey and a data mining- ˜ based analysis of recent works, Expert systems with applications, 2014 (41), 1432–1462.

[25] S. Gupta, J. Choudhary, Academic Analytics: Actionable Intelligence in Teaching and Learning for Higher Education in Indian Institutions. In Proceedings of the International Conference on Skill Development & Technological Innovations for Economic Growth, vol. 3, 2015.

[26] C. Silva, J. Fonseca, Educational Data Mining: a literature review, Chapter in Advances in Intelligent Systems and Computing, volume 520, 2017, 87-94.

[27] A. Zorić, Benefits of Educational Data Mining. Journal of International Business Research and Marketing, 2020 (6), 12-16.

[28] A. Nguyen, L. Gardner, D. Sheridan, Data Analytics in Higher Education: An Integrated View, Journal of Information Systems Education, 2020 (31), 61-71.

[29] K. Avramides, J. Hunter, K. Oliver, R. Luckin, A method for teacher inquiry in cross-curricular projects: Lessons from a case study. Br. J. Educ. Technol, 2015 (46), 249–264.

[30] S. Suhirman, T. Herawan, H. Chiroma, J. Zain, Data Mining for Education Decision Support: A Review, iJet, 2014 (9), 4-19.

[31] S. Saranya, R. Ayyappan, N. Kumar, Student Progress Analysis and Educational Institutional Growth Prognosis Using Data Mining, International Journal Of Engineering Sciences & Research Technology, 2014 (3), 1982-1987.

[32] K. Arnold, Signals: Applying academic analytics, Educ. Q., 2010 (33)

[33] D. Kabakchieva, Business Intelligence Systems for Analyzing University Students Data, Cybernetics and Information Technologies, 2015 (15), 104-115.

[34] Y. Nieto, V. Gacía-Díaz, C. Montenegro, C. González, R. Crespo, Usage of Machine Learning for Strategic Decision Making at Higher Educational Institutions. IEEE Access, 2019 (7), 75007-75017

[35] F. Swiontek, A. Lawson-Body, L. Lawson-Body, The Use of Machine Learning in Higher Education, Issues in Information Systems, 2015 (20), 56-61.

[36] D. Davis, Altis Consulting: HE Information Management Specialists. Presentation to the UK Learning Analytics Network, Edinburgh, UK, 2015.

[37] A. Atif, D. Richards, A. Bilgin, M. Marrone, Learning analytics in higher education: a summary of tools and approaches. In ASCILITE-Australian Society for Computers in Learning in Tertiary Education Annual Conference, Australasian Society for Computers in Learning in Tertiary Education, 2013, 68-72.

[38] Universities UK, 2016, Analytics in Higher Education, ISBN: 978-1-84036-370-8

[39] F. Chacon, D. Spicer, A. Valbuena, Analytics in support of student retention and success, 2012, URL: https://library.educause.edu/resources/2012/4/analytics-in-support-of-student-retention-and-success

[40] Civitas Learning, 2016, URL: http://ji.sc/civitas-learning-space

[41] Siemens et al., Improving the quality and productivity of the higher education sector: Policy and strategy for systems-level deployment of learning analytics, 2013, 20p.

[42] M. Star, L. Collette, GPS: shaping student success one conversation at a time, EDUCAUSE, 2010, URL: : http://er.educause.edu/articles/2010/12/gps-shaping-student-successone-conversation-at-a-time

[43] N. Sclater, Learning Analytics: The current state of play in UK higher and further education, Jisc, 2014

[44] J. Whitmer, Logging On to Improve Achievement: Evaluating the Relationship between Use of the Learning Management System, Student Characteristics, and Academic Achievement in a Hybrid Large Enrolment Undergraduate Course, University of California, Davis, 2012, 90p.

[45] C. Robinson, M. Yeomans, J. Reich, C. Hulleman, H. Gehlbach, Forecasting student achievement in MOOCs with natural language processing, The 6th International Conference on Learning Analytics & Knowledge, Edinburgh, 2016, pp. 383-387.

[46] University of Adelaide Learning Analytics Project,
URL: https://www.adelaide.edu.au/learning/teaching/learning-analytics/project/

[47] Foster, What have we learnt from implementing learning analytics at NTU? Jisc Learning Analytics Network, Nottingham Trent University, 2015, URL: http://bit.ly/Foster-Ed-2015

[48] AUTCAS, Edith Cowan University Case Study Summary – AUTCAS. Australian University Teaching Criteria and Standards Framework, 2014, URL: http://uniteachingcriteria.edu.au/.

[49] R. Stiles, K. Wilcox, Blending Human Intelligence and Analytics for Student Success, EDUCAUSE, 2016, URL: https://library.educause.edu/-/media/files/library/2016/8/elib1605.pdf

[50] Y. McAleese, L. Taylor, Beyond retention: using targeted analytics to improve student success, EDUCAUSE, 2012, URL: http://er.educause.edu/articles/2012/7/beyondretention-using-targeted-analytics-to-improve-student-success

[51] D. West et al., The Use of Learning Analytics to Support Improvements in Teaching Practice. Innovative Research Universities. Melbourne, Australia, 2018, ISBN-13: 978-0-646-98756-9, 41p.

[52] D. Yasmine, Application of the classification tree model in predicting learner dropout behaviour in open and distance learning, Distance Education, 2013 (34), 218-231.

[53] R. Doneva, S. Gaftandzhieva, M. Bliznakov, S. Bandeva. Learning Analytics Software Tool Supporting Decision Making in Higher Education., International Journal on Information Technologies and Security, 2020 (12), 37-46.