Best Practices for Using Data Analytics Tools in Universities: State-of-play

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Abstract
The large volumes of data used today have motivated research and development in various disciplines to extract valuable information for its analysis to solve problems. In recent years, data extraction and analysis at higher education institutions (HEIs) has become increasingly important. HEIs are looking for solutions that allow them to extract data from different information systems and convert them into knowledge that helps them to optimize their processes and improve process management (e.g. monitoring and forecasting learning outcomes, admission of students, ensuring equal access to education and career development in higher education, organization of research and project activities, etc.). Although the research in the field is still at a relatively early stage of development, there are a number of good practices in the literature for implementing data analytics tools. These practices show how innovative universities are finding solutions to improve and optimize their processes. The paper aims to present the best practices of higher education institutions for implementing data analytics tools to improve and optimize processes in training, research, student support and management.

Keywords
Data Analytics, Best Practices, Applications, Universities

1 Introduction

Nowadays, HEIs use a lot of software systems to automatize their activities. When users use these systems, they generate a large amount of data daily and leave a so-called "digital footprint". As a result, HEIs have the data sets needed to benefit from targeted data analytics. Data analytics has the potential to positively impact all the major areas that are of importance for HEIs, such as student enrolment and retention, integrated information management and reporting, operational cost management, regulatory compliance and research. Big Data and analytics in higher education can be transformative, altering the existing processes of administration, teaching, learning, academic work, and helping address contemporary challenges facing higher education [1]. Analysing and managing big data can bring accountability and transparency in the management of the education sector [2] and can assess institutional performance and progress in order to predict future performance and identify potential issues related to academic programming, research, teaching and learning [3]. Data analytic tools allow automatic extraction, analysis and classification of data (related to educational, scientific and other activities) and support governing bodies of the organization to make informed decisions.

The paper aims to investigate how Data analytics tools have been used in higher education institutions and to present the best practices of higher education institutions for implementing data analytics tools to improve and optimize processes in main areas (training, students support research and management).

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2 Using data analytics tools in universities

Each university has a number of typical processes that can be supported by data analytics tools. This section presents an overview of best practices for using data analytics tools to improve processes in 4 main areas – training, student support, research and management.

2.1 Training

One of the most common applications of data analytics tools is in the field of Training.

The data analytics tool for identifying at-risk students has been designed at the **New York Institute of TechnologNYy** [4]. The data analytics tool extracts data on student training and data for alumni, then performs analyzes and presents results in a suitable format for counselling staff. The main risk factors in the model include grades, student confidence in choosing a major and data on the payment of semester fees.

The **University of Derby** has a data analytic tool [5] that extract data for 29 indicators (including tracking student engagement, including attendance and activity during lessons and seminars, assessments, access to resources in the virtual learning environment, other commitments (e.g. childcare, work)). The tool allows stakeholders to identify units in which there are problems with students and such in which students have high achievements to disseminate best practices. The use of the tool proves the correlation between presence notifications, retention and results achieved. The changes made as a result of the analysis has led to an improvement in student achievement.

The main driver for implementing data analytics tools (called Automated Wellness Engine – **AWE**) at the **University of New England** is the opportunity for providing timely support to students who encounter difficulties. The AWE is based on the successful Emoticons identification activity embedded in the online student portal (myUNE) and other data in different university systems (e-Motion, e-reserve, LMS, SRM-student relationship management, SMS-student management system, unit discontinuation poll and the Vibe) related to students' interactions with the university and their teachers, use of facilities and their responsiveness to deadlines. The AWE helps teachers identify high-risk students who may struggle or drop out of their courses [6]. Based on the indicators, the AWE generates daily or weekly reports with detailed reasons for withdrawal and wellness-happiness ratings within individual schools and courses. Before its implementation, staff did not have timely and systematic evidence to assess when to support students. During instrument testing, the students' dropout rate was reduced from 18% to 12% [7].

The **Open University Australia** uses **Personalised Adaptive Study Success (PASS)** [4]**,** an early alert tool designed and built to enhance student engagement and retention in an online learning environment. Based on individual characteristics, social web, curriculum and physical data drawn from other systems, PASS helps teachers identify high-risk students who may be struggling or experiencing disengagement. Based on the various indicators used, the PASS generates visual signals, performance levels, self-assessment, predictive course mastery, highlight social interaction, recommends content and activities and provides a personalised environment.

Among the goals of the data analytics tool used at **Marist College** [4] are to create predictive models and study the effectiveness of interventions with at-risk students. The data used include the number of visits to online courses, read and published discussions in a forum, submitted assignments and tests, student assessments. By using the created forecast model, lists of students at risk have been prepared. The students are divided into three groups, two of which are supported. The results of the conducted experiments show that 6% of students who received support increased their grade, 25.6% of students who did not receive support dropped out, and 14.1% of the students who received support have interrupted their training.

The **University of Wollongong** uses the Social Networks Adapting Pedagogical Practice tool (**SNAPP**) [8] to generate visual representations (social network diagrams) of user interactions and activity and patterns of behaviour on discussion forum posts and replies. SNAPP illustrates users' level of engagement and helps stakeholders identify students at risk of underperforming due to lower levels of participation than these of other students.

The **University of Bedfordshire** [5] is developing a tool for tracking student engagement during training, which makes it possible to identify patterns of student engagement and present them in an appropriate format to faculty. The university also is planning to develop a university strategy for Business Intelligence that includes various types of analysis. Students have increased their attendance at the university and the library since they became aware of the monitoring of visits.

Rio Salado College [9] implements data analytics tools to predict students' risk behaviour based on activities (such as login or site activity). The tool allows teachers to quickly understand what students' needs are and take steps to retain them.

The data analytics tools implemented at **Nottingham Trent University** [10] provide teachers with information on student activity and progress, enabling them to support students to increase their success and retention. After using the tool, 27% of students have changed their behaviour after reviewing their data on the dashboard. Some students begin to perform additional academic activities, while others compete for the highest activity score during their studies. The implemented tools allow decision-making based on data. The data analytics tool is also used for making predictions for dropping out of students in the next academic year. The results show that less than 25% of students with low average activity scores increased their success from the first to the second school year. Over 90% of students with good or high average activity scores achieved higher results.

The **Edith Cowan University** uses the early intervention tool (called **Connect for Success – C4S**) to improve student success, retention and graduation rates. The C4S automatically flag students who are likely to require extra support to complete their studies. When the C4S team identify, it refers them to the appropriate services in the university. In addition to daily reports, consolidated reports are sent to support services and faculties in the university [11].

Grinnell College [12] combines data analytics tools with intelligent grids to increase retention and graduation rates. Various social and psychological factors which can be linked to learning data to calculate the probability of success of each student play the role for student success.

Bowie State University [13] has implemented the data analytics system **SSMS** to improve the retention and success of at-risk students. The system enhances the performance of all retention agents, including faculty staff, advisers, counsellors, retention coordinators, etc. The SSMS behaves like a support social network, creating connections and linkages among support staff and student support functions.

Researchers at **Harvard University** proposed a machine learning prediction model that can learn from unstructured text to predict which students will complete an online course. The results demonstrate the potential for natural language processing to contribute to predicting student success in MOOCs and other forms of open online learning [14].

Northern Arizona University uses an academic early alert tool for increasing instructor feedback and facilitating instructor-student interactions – **Grade Performance Status (GPS)**. GPS duplicates the course roster with online submission forms for each student in the class. From the Campus Solutions faculty page, instructors can access the GPS interface and select automated comments of general concern for attendance and grade. They can also type in personalized comments, academic concerns, and positive feedback. As a result of using GPS, student-instructor interaction was increased, personal interventions were given, and students showed better academic performance, retention and graduation rates [15].

To solve significant retention and student success challenges **Paul Smith's College** developed a Comprehensive Student Support Program [16]. Paul Smith's implemented two technological solutions: **Rapid Insight's Veera and Analytics programs** and **Starfish Retention Solutions EARLY ALERT and CONNECT programs**. First, Rapid Insight's Veera, a data intelligence program, and Analytics, a statistical and predictive modelling program, allow the college to combine different file types and data formats into a single file for analysis, automate routine reports and analyses, use predictive modelling to identify at-risk students before their enrolment, automate the distribution of the results to those who need them. The Starfish EARLY ALERT and CONNECT technologies allow the college to automate much of our data collection, use analytics to increase our identification of at-risk students, automate the process to prioritize students for intervention and outreach and automate communications with the support offices, students, and faculty in real-time.

At **Strayer University**, contact with students at risk leads to a 5% increase in attendance, a 12% increase in enrolment and an 8% decrease in dropout – compared to a control group which is not supported [17].

At **Youngstown State University**, three years after introducing data analytics tools, the graduation rate has increased from 81.1% to 86.8% [18].

At the **University of South Australia**, 730 at-risk students from different courses have been identified. Of the 549 contacted, 66% passed with an average score of 4.29. 52% of students who were not supported completed the course with 3.14 GPA [19].

Data analytics tools are also widely used for tracking student achievement and predicting student success. **California State University** [20] uses some demographic variables, data from the learning management system and the student information system to predict student success. The conducted experiments have shown that students activity in the learning management system has a 25% lower impact on the final assessment of at-risk students than the impact it has on the assessments of these students who are not at risk of drop out.

The data analytics system of **Purdue University** [4PUR] evaluates the success of students based on their grades and activity in the learning management system. After using the system in some courses, the percentage of students with B and C grades is higher than that of students with D and F final grades. In one of the courses, there is a 10% increase of A and B final grades compared to student results from the previous year when the system was not used. In one of the courses at the beginning of testing the system, 20.25% of students are at high risk. By the end of the course, only 10.6% of students were in the high-risk group, and 69% of all students moved from the medium-risk group to the low-risk student group. The results of a survey of students show that 89% of students find it beneficially to have access to data on their progress during their studies, and 74% say that using the system has increased their motivation.

Institutions such as **Purdue** or **Rio Salado** that have performance dashboards in their learning management system, students can constantly monitor their progress and determine how they are performing, so there are benefits at the student level as well [21].

University of East London [5] applies data analytics tools to study the way students learn and combine different activities, such as work, study and parenting. The university introduces an automated attendance system, and students receive warnings and are removed from their studies if they do not improve their attendance. The experiments show a correlation between attendance and students' success in the modules – students do well if they are above the attendance threshold (over 75%). After implementing the system, the attendance of students increases and there is an increase in their success.

The **University of Maryland Baltimore County** [4] applies data analytics tools to identify an effective teaching strategy using the learning management system. The tool allows students to compare their activities in the learning management system in a selected course with these of other students and activities of students who receive the same, higher or lower grades. Students who receive D or F final grades use the learning management system by about 40% less than those with C or higher final results. The conducted analysis shows that the tool can improve students results not only in the specific course but also in subsequent courses.

Carnegie Mellon University in Pittsburgh uses the **Open Learning Initiative** [22] learning platform, which creates and hosts web-based modules designed by a team of experts in teaching, learning, practice and software development. The platform gives students access to learning materials through different media elements (e.g. text, animations and audio recordings), provides opportunities for them to practice what they have learned and generates personalized information based on how students had done and had mistaken. In addition, it provides the lecturer with a board that gives real-time data on how students are doing, where they may have problems, and so on. This intelligence allows them to tailor their lectures to ensure they cover topics that are difficult for students. Teachers found that students could learn the content of an entire semester just as well in half the time when using the platform.

The **University of Edinburgh** [9] uses data analytics tools to provide better student feedback, identify learning problems, improve ways to provide information to students and help monitor student attendance. Teachers can monitor the student progress against the goals set in the curriculum and make decisions for each student. If a student attendance is low or an assignment deadline is missed, the system sends emails to the student and/or parents.

Faculty staff at the **Technical University of Madrid** use data analytics tools for evaluating and monitoring individual progress within teamwork. The information provided by the tool system and timely information extraction allows preventing problems, carrying out corrective measures and making informed decisions to improve the learning process of teamwork [23].

The **University of Adelaide** has developed a data analytics module for **Canvas** [24, 25] learning management system that tracks the activity of students and teachers in all courses. The module allows tracking the access to the training courses, the interaction and the duration of student interactions with the educational content, publications in the training courses (including publications in forums, magazines and blogs). Based on data analysis, teachers can identify students who need support. Administrators can use the module to track the activity of students, faculty staff, observers and/or designers in courses. In addition, they can generate reports on the total number of courses, teachers, students, assignments, presentations, discussion and response files, files, and media records. The module allows teachers to anticipate how students respond to course exercises, provide a quick overview of student achievement, identify students at risk of learning interruption, and evaluate the effectiveness of teaching strategies.

In Bulgaria, research in the field of using data analytics tools in universities is at a very early stage. However, some examples could be mentioned.

The developed mobile applications at the **University of Plovdiv** [26, 27] allow students and teachers to trace out the values of the indicators (students' activity, success rate, adherence to the learning schedule). The set of indicators for both applications is based on an analysis of the data generated by participants in the learning process (students and lecturers) in Moodle. Using the mobile application students [27] can track their activity and success rate during the training, and can compare their average level of activity and success rate with the other students, to increase their success, as well as to track whether they adhere to the learning schedule. The developed mobile application allows teachers [26] to identify the opportunities for improvements the quality of courses, and enhancing the performance of their students. Teachers can use the application to keep track of the activity and progress of their students, adherence to the learning schedule, as well as to quickly identify students who are at risk of failing or dropping out at an earlier stage than it otherwise would be possible.

At the **University of National and World Economy** [28] data mining models for predicting student performance, based on their personal, pre-university and university-performance characteristics have been developed. The dataset used for the research purposes includes data about students admitted to the university in three consecutive years. Several well-known data mining classification algorithms are applied to the dataset. The data attributes related to the students' university admission score and the number of failures at the first-year university exams is among the factors influencing most of the classification process.

2.2 Student Support

Data analytics tools provide institutions with a higher impact on the training, teaching and support of students.

Open Universities Australia [4] has implemented a data analytics tool that helps students choose the appropriate training module. The models combine numerical and qualitative data to create a complete picture of student learning. The semantically rich data from the discussion forums and the answers to open questions allow a better understanding of the knowledge and needs of the students.

Charles Darwin University [29] uses data analytics tools to provide student support and improve the quality of education, teaching and retention. The tool generates reports that provide information to teachers about the need for student intervention and support, which is submitted to evaluate the program. The tool also informs and support academic ranking decisions in situations where a student is on the border between two grades. The combination of the student activity report, the scoreboard, and the records of the early progression warnings provide reliable evidence to support consistent and fair decisions.

Austin Peay University uses the **Degree Compass** system [30] to help students choose to study modules. The system analyzes the available information about the curriculum of each user, the history of the modules and previous degrees, referring to the data of previous students with a similar profile, recommends modules that may be most suitable for the student.

Counsellors and faculty members at the **University of North Bengal** are provided with inputs to advise learners on the best possible completion options [31]. Demographic and academic variables of students, such as gender, marital and employment status, selected subjects, social status, age and income status, are taken as independent or explanatory variables for predicting the response variables. Data analysis showed that the pattern of student attrition is strongly biased towards a relatively disadvantaged category of learners. It also indicated that employed men or married women are more likely to leave due to factors, such as pregnancy or relocation and remoteness of location of residence contributed to a high dropout rate.

At **Oxford Brookes University**, some problems with ethnic minority students in particular courses were identified [4].

The **University of Gloucestershire** uses personal tutors to support students with their studies and remote learning adds more complexity to how they carry out their role. By using Jisc's Analytics service, tutors already have access to VLE (virtual learning environment) engagement, library and assessments data facilitating better conversations with their students. **Checkin+** adds another critical analytics stream for them to use with attendance data that is fully integrated with The University of Gloucestershire's timetabling system and most importantly – caters for all types of learning. Checkin+ uses a 4-digit code for students to log their attendance which can be done both in a classroom or remotely online. There is no attendance monitoring hardware located at the institution which means the system genuinely caters for blended learning. the Students experience of learning at university isn't solely governed by their timetabled modules. For many, libraries and careers exploration also play an important role. Checkin+ combined with core analytics service provides data on these areas which are used by both personal tutors and careers advisors to strengthen their guidance [32].

2.3 Research

Walden University [33, 34] applies the Faculty Insight tool to aggregate and match data of individual faculty members in six areas of scholarly activity (book publications; journal article publications; journal article citations; published conference proceedings; federal research grants; and professional honorific awards). The data analytics tool is available to academic leaders and faculty members. This tool displays the scholarly activity and products for individual faculty members and provides them with possible funding sources, honorific award opportunities, and research collaborators based on this data. Faculty can use the Faculty Insight tool to examine their scholarly data in the Academic Analytics Database, request/report corrections to that data, and edit their research profiles to include additional scholar data.

University of Colorado [35] use academic analytics to track the research activity of the faculty staff. Academic analytics collects data for all publications, grants, awards and books of the faculty staff. The tool allows users to generate reports on all the people who have received a specified award, people in a department/school/institute have no publications/high publications/high h-indices/ high citations, or another specified criterion, work of people in a unit (e.g., number of books in 10 recent years) relative to others in the same discipline, etc.

2.4 Management

In some universities, the use of data analysis tools is part of the university strategies. **Manchester Metropolitan University** [5] is investing funds in the implementation of data analytics tools to improve its external evaluation results, learning platforms and curricula. The reorganization of the curricula carried out after analysis of data on the implementation of the programs brings significant benefits to the university. According to statistics, improvements in the university are related to overall satisfaction, which increased by 6% in 2012 and another 3% in 2013.

The data analytics tool developed at **Oxford Brookes University** [4] allows tracking student outcomes. The faculty staff uses the tool for reviewing modules and programs, and the data influence the overall operational plan of the university. The tool allows them to view estimates and progress data. Academic advisors use an internal module of the learning management system to track activity and communicate with students. The tool also allows users to view bachelor programmes portfolios.

Among the main goals for implementing data analytics tools at **Open University** [5] are developing an "analytical way of thinking" in the institution, making evidence-based decision-making and increasing student success. An original solution is that the university deliberately does not compare the measures taken with student success. For example, if students have not submitted an assignment, their expected behaviour after the intervention may be that they will present their solution or call their teacher. After such cases, the system continues to track students' behaviour instead of the success rate that depends on many more factors.

Intelligent data analytics tools are also part of the strategy of **Flinders University** [29]. As part of the excrement conducted in 2016, the teaching staff measured the activity of students with video resources in the learning management system, analyzed the data and compared them with the final grades by topic. The results show that the ratings obtained correlate with the reviews of the video resources. The activity of students is also measured by the frequency of their physical visits and comparisons with their final grades – the increase in attendance led to higher final results.

The successful implementation of the data analytics tools is one of the main strategic goals of the **University of Adelaide** [24]. It requires the continued commitment of all stakeholders – from students to managers. The system tracks students' activity and success. The collected data serve to support and improve teaching and learning. The tool allows stakeholders to analyze courses and generate reports to provide information about the activities in the course. Teachers can use the system to identify students who are at risk of dropping out or those who are achieving excellent results.

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 are conducted in Bulgaria. The software prototype **LATCh** [36] designed for the needs of decision making bodies in Bulgarian HEI (programme managers, deans and rector) allows them to monitor the learning process and make timely data-driven decisions to improve institutional processes in many aspects. Research and experiments with LATCh are conducted based on the information infrastructure of a typical Bulgarian university – University of Plovdiv "Paisii Hilendarski". Experiments for applying data analytics tools for analyzing the available data and extracting useful information for decision making have also been done at the **University of National and World Economy** [37]. Researchers from **Sofia University** explore how learning analytics can improve the results of e-Learning. They propose a method for cross-system data collection [38] that uses collected data to reveal students' behaviours and regularities during the educational process.

3 Conclusion

The paper presents the first stage of the study devoted to the implementation of data analytics tools at the University of Plovdiv. In the next stage of the study, based on the analysis of best practices and the used university system, data analytics tools will be designed and developed to allow different stakeholders (students, teachers, managers at different levels, etc.) to carry out tracking, monitoring and making informed decisions in the management of the selected processes taking place in the HEI in real-time, and hence their improvement and optimization.

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