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Guidebook on Learning Analytics and Dashboards

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Abbreviations

ALEs	Adaptive Learning Environments
API	Application Programming Interface
AWE	The Automatic Wellness Engine
BI	Business Intelligence
CAA	Cognitive Apprenticeship Approach
CFT	Cognitive Flexibility Theory
CLT	Cognitive Load Theory
CoP	Community of Practice
CMA	The Checks My Behaviour
CS	Course Signals
ECU	Edith Cowan University
EDM	Educational Data Mining
FoLA2	Fellowship of Learning Activities and Analytics
GDPR	General Data Protection Regulation
HE	Higher Education
HEI	Higher Education Institution
ICDE	International Council for Open and Distance Education
JEDM	The Journal of Educational Data Mining
JISC	The Joint Information Systems Committee
JRC	Joint Research Commission
LA	Learning Analytics
LAD	Learning Analytics Dashboard
LAK	International Conference on Learning Analytics and Knowledge
LAMS	Learning Activity Management System
LD	Learning Design
LMS	Learning Management System
NTU	Nottingham Trent University
NYIT	New York Institute of Technology
OAAI	Open Academic Analytics Initiative
OLI	Open Learning Initiative
OUA	Open Universities Australia
PASS	Personalised Adaptive Study Success
PBL	Problem-Based Learning
PLE	Personal Learning Environment
SAM	Student Activity Meter
SNAPP	Social Networks Adapting Pedagogical Practice
SIS	Student Information System
TEL	Technology-Enhanced Learning
TEP	Tertiary Enabling Program
UMBC	The University of Maryland, Baltimore County
VLE	Virtual Learning Environment

Introduction

About this Guidebook

This Guidebook is based on an analysis of the literature, materials from several institutions and organisations, and individual interviews and focus group interviews with academic staff at Tallinn University and Tallinn University of Technology (TalTech), which were further developed during discussions with the partners of the Erasmus+ TEACH4EDU4 project. This Guidebook focuses on how academic staff and management of higher education institutions (HEIs) can better use the significant amount of data found in various learning systems in their practical educational activities and develop actionable insights.

The aim of this Guidebook is to provide an overview of learning analytics (LA) and increase academic staff's knowledge, awareness and insights into how it can be used to enhance teaching and learning in higher education (HE). The Guidebook includes the following: an outline of learning analytics, its evolution and its practical applications; some considerations for HEIs as they aim to take an informed approach to LA; and a brief overview of the current landscape of LA internationally, The Guidebook helps educators of all levels design learning activities that include LA. The learning behaviour information gathered by LA solutions already put in place during the development of learning activities can lead to improved execution of learning designs and better-informed learning activities.

Defining Learning Analytics

Several definitions have been provided for the term 'learning analytics'. However, the most widely accepted definition comes from the conference organising committee of the *First International Conference on Learning Analytics and Knowledge* (LAK), who defined learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Long *et al.*, 2011).

The Development of Learning Analytics

The official formation of the field of LA is related to the organisation of the LAK in Banff, Alberta, Canada in 2011. The LAK conference was established as a response to the increased amount of data that surpassed the ability of organisations to make sense of it. In addition, the widespread emergence of online learning and political concerns about educational standards prompted the development of LA. Since 2011, LA has received much attention from researchers, practitioners, and administrators, resulting in numerous conferences, workshops, projects, journals, books and articles, PhD studies, professorships and organisations dedicated to LA.

The emerging field of LA is at the intersection of numerous academic disciplines, and therefore draws on a diversity of methodologies, theories and underpinning scientific assumptions. However, several other fields are dedicated to the study of data in education with somewhat different methodological perspectives. For example, Educational Data Mining (EDM) community was formally initiated earlier than LA community; the First International Conference on Educational Data Mining (EDM) was held in 2008 in Montreal and the *Journal of Educational Data Mining* (JEDM) was launched in 2009 following a series of workshops held at the major conferences starting in 2000. Two other communities with significant focus on data in education are centred around the [ACM Conference on Learning @ Scale]() that started in 2014 and the [International Conference on Quantitative Ethnography](), started in 2019. The Learning at Scale community investigates large-scale, technology-mediated learning environments that typically have many active learners and few experts on hand to guide their progress or respond to individual needs. The Quantitative Ethnography community supports and promotes research that unifies qualitative and quantitative analysis of human thought, behaviour, and interaction.

More recently, there has been a noticeable growth in autonomous areas of focus within the field of LA, for example, predictive analytics, social LA, multimodal LA and discourse analytics.

Importance and Impact of Learning Analytics

LA provides enormous benefits to learners, teachers, learning design, and the organisation itself. Since LA encompasses a wide range of analytics, LA activities can take place at the micro, meso-, or macro levels, depending on the granularity of the data and the actions taken as a result. Micro-level LA operates at the tracking and interpretation of individual/learner data, meso-level enables analytics at the institutional level and macro-level enables analytics within the cross-institutional level.

Benefits of Learning Analytics at the micro-, meso- and macro levels

At the micro level, LA enables better understanding and improvement of learners' learning experiences and leads to new insights and appropriate actions. It is possible to improve the achievement of learners, not just those who are considered to be at some level of risk and to provide high-quality personalised feedback to learners. The goal is to support learners in taking responsibility for their own learning by reflecting on and acting on their learning data. This provides great potential for optimising the learning process. Aggregate data will support measurement of impact of different pedagogical approaches, teaching, learning and assessment methods, and learning designs. Furthermore, aggregate information about programs and the wider learning experience can inform departmental, faculty or institutional priorities. According to Shum (2012), the breadth and depth at the macro and meso levels add power to micro-analytics. Effective LA demands mutual enrichments between the three layers of analytics.

Figure 1: Learning analytics by Buckingham Sun (2012)

The analyses of the data can provide various target groups and stakeholders with valuable insights into various aspects of the education process.

Table 1: Benefits of LA at micro-, meso- and macro-levels

Micro-level benefits:	**Meso-level benefits:**	**Macro-level benefits:**
• understand and predict students' learning behaviours, performance and achievements; • improve student academic success, learning outcomes, behaviour, performance and process; • enhance students' learning motivation, satisfaction, self-awareness and self-reflection; • improve engagement of students and student–teacher communication; • help students acquire self-directed learning behaviours and attributes such as self-reflection and management of their studies; • provide learners with insight into their own learning habits, progress and academic performance; • create personalised learning experiences that are customised for each learner, based on their behaviours and performance results; • provide personalised, timely, precise and actionable assistance/feedback regarding students' learning and personal interests; • monitor and assess the use of learning resources and suggest the appropriate level of sources (prerequisite or advanced subject matter material; • improve learning design, teaching strategy and excellence and instructor performance; • pinpoint the most effective techniques to enhance their courses accordingly and identify the success of their pedagogies. • identify at-risk learners, spot problems and discover patterns, and provide interventions before they suffer any negative consequences.	• improve data-informed and evidence-based decision making; • improve and optimise organisational resource allocation; • improve curriculum, programme and course design and development; • enrich personalization of learning experience and design the best learning environments; • predict student academic success/failure and performance, and find early indicators for success/failure; • prevent student drop out and increase retention rate; • increase and model student success; • improve student support and assessment services; • provide targeted course offerings; • analyse educational processes; • meet institutional standards; • compare units across programs and entities; • monitor educational processes; • evaluate educational resources; • track enrolments; • forecast educational processes; • identify gaps.	• transform the university system, academic models and pedagogical approaches; • more transparent data and analysis create a shared understanding of the institution's successes/challenges; • increase organisational productivity and the overall efficiency by providing up-to-date information and allowing rapid response to challenges; • apply cross-institutional comparisons; • develop benchmarks; • inform policy making; • inform quality assurance processes: • increase productivity; • apply rapid response to critical incidents; • provide expert help; • model impact of organisational decision making; • plan for change management.

The Importance of Learning Analytics for Learning Design

Learning design (LD) is a research field that has received increasing attention since the early 2000s due to the development of metadata standards. LD draws on knowledge from educational science, subject area content and context, and technology-enhanced learning (TEL). Educational designers can choose from a broad range of design models and methodologies, such as the four-component instructional design model (4C/ID), the cognitive apprenticeship approach (CAA), cognitive-flexibility theory (CFT), problem-based learning (PBL), community of practice (CoP), epistemic frames, design-inquiry of learning, cognitive load theory (CLT), and personal learning environment (PLE). Although evaluation is an essential component of these frequently used ADDIE-like design process models, the use of LA to support LD is uncommon.

However, possibilities to record, analyse, and visualise learning and teaching behaviour offer more opportunities to improve learning and teaching. In fully online educational settings, there are numerous examples of using possibilities of LA. There have been efforts to use LA as an instrument in LD processes to evaluate design choices and there are several frameworks available for connecting LA and LD. Although the urge to connect LA and LD has been rising, almost all frameworks and models are conceptual or difficult to operate in educational practice.

In the last decade, most examples of LA-LD connections are in online HE. A significant amount of technology-centred LA is applying a data science approach, also known as process data mining or a bottom-up approach, using data from the environment and trying to find meaningful patterns of learning. Several promising tools such as the Learning Activity Management System (LAMS) or instruments like Inspiration Cards and LA-Deck have been created focussing on what stakeholders want to analyse to improve learning processes and how to visualise them and connect LA and LD. It has been acknowledged that card games can provide some structure or procedural steps for LD: (a) facilitate creative combinations of information and ideas, (b) provide a common basis for understanding and communication in a team, (c) provide tangible external representations of design elements or information, (d) provide convenient summaries of helpful information or methods, and (e) are semi-structured tools between blank sticky notes and detailed instruction manuals. The card games range from general design cards to domain-specific games for domains like music and fur and sustainability.

Schmitz *et al.* (2022) have created a Fellowship of Learning Activities and Analytics (FoLA2) method to aid in the practical use of LA-supported LD. FoLA2 is a method of considering LA while designing curricula and learning activities for any subject. FoLA2 is available as a physical purchase (www.fola2.com) and an Attribution Non-Commercial Share Alike copyrighted free printable version. FoLA2 is actively used in the Netherlands and Germany in educational design, TEL, and LA development. The method enables several participants with different roles to interact with a set of card decks to collaboratively create an LA-supported LD. Using this method helps to design learning activities in a collaborative, practical way; it also raises awareness about the benefits of multidisciplinary co-design and connections between LA and LD. FoLA2 can be used to develop, capture, and systematise design elements and to systematically incorporate LA. FoLA2 has two aims: 1) on an individual level, it aims to increase knowledge about and awareness of LA, 2) on a group level, it facilitates shared terminology and understanding among team members to improve the co-creation of LA-supported learning activities.

Law and Liang (2020) recently provided a promising multilevel framework that combines LA and LD seamlessly by connecting LD curriculum elements to LA questions and LA solutions. There are also several literature reviews that try to provide a structured overview by reporting on common characteristics that link to the process of LD: sequence, learning activity flow, collaborative development, assessment, LA, meaningful context, technology adaptation, resources, tools, roles, environment, objectives, recall of prerequisite skills, and learner analysis. These characteristics only partly resonate in several other frameworks which try to give insight into how to design a set of learning activities. This diversity of frameworks is why researchers have lately noticed a lack of widespread practice in using LA-supported LD frameworks or instruments.

The Open University Learning Design Initiative (OULDI) is an approach developed and used by the British Open University (OU). It is described as a methodology for enabling teachers/ designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies. The OULDI approach defines seven basic learning design activities (Table 2).

Table 2. OULDI learning design activities

LD activity	**Details**	**Example**
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate
Interactive/adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate
Assessment	All forms of assessment (summative, formative and self-assessment)	Write, Present, Report, Demonstrate, Critique

The main focus of OULDI is on what students do as part of their learning, rather than on what teachers do or on what will be taught. After seventeen years of developing, testing, implementing and evaluating the evolving large-scale practice of learning design at the OU, the OULDI approach is now business as usual.

Another widely used model is the ABC Learning Design model. This is a collaborative program and module design method created at University College London (UCL) in 2015. It is now widely used across the sector to help develop new programs and review existing provision. The method enables program and module teams to rapidly develop a storyboard visualizing the learner journey based on their activities through the course of study. The method is non-prescriptive and builds from the participants' existing practice but can be used to identify opportunities for blended learning, to review assessment and feedback, and align the program to wider institutional priorities. At the heart of ABC is a 90-minute collaborative classroom-based or online workshop. As teaching teams build the storyboard, they reflect on the purpose, structure, and outcomes of their current or planned modules. In this process, teaching practice is discussed and opportunities to enhance the student journey may be identified and agreed.

ABC Learning Design is based on the pedagogic theory of Professor Diana Laurillard's Conversational Framework and her concept of "learning types". Her six learning types have proved to be a very effective method for helping teachers describe and discuss the student learning process. The six learning types are: Acquisition (i.e., to read/watch/listen), Investigation, Practice, Discussion, Collaboration, and Production. As operationalized in ABC, this straightforward taxonomy resonates well with mainstream classroom practice and always stimulates rich pedagogical discussion even for teachers with limited experience with (and sometimes enthusiasm for) educational theory.

Principles for Learning Analytics

The principles for LA are key to the way LA is developed and used within the university:

- LA should help all students achieve their learning goals and reach their full academic potential.
- Data collection, sharing, consent and responsibilities should be transparent.
- LA must adhere to ethical principles and the strategy, policies and values of the particular university and include all stakeholders, particularly students.
- Students have the right to access the data collected related to their learning, to act on it and, if necessary, to verify it.
- LA should be supported by focused staff and student development activities.
- LA should not be used to inform significant action at an individual level without human intervention.
- Universities must actively work to recognize and address the potential negative effects of LA.

Challenges of Learning Analytics

Several researchers have pointed out and categorised the challenges related to LA. The review of the literature revealed the LA challenges about data tracking, data collection, data analysis, scope and quality of data, evaluation of data, theoretical and educational foundations, a connection with learning sciences, learning environment optimization, emerging technology, and ethical concerns regarding legal and privacy issues. In the broadest sense, we can group the challenges associated with LA into educational, technological, management and research challenges.

Educational challenges include:

- weak theoretical and educational foundations;
- lack of connection between LA and learning sciences;
- a gap between theory and practice;
- ethical, privacy and legal issues related to monitoring learners;
- insufficient focus on learner perspectives;
- aligning LA with learning design;
- scope and quality of data (e.g., how much data should be collected and how much data should have variety; what type of data has value of learning and how much reliable prediction we could have by analysing these data).

Technological challenges include

- data tracking,
- data collection,
- data analysis,
- data evaluation,
- development of methods of working with a wide range of datasets in order to optimise learning environments.

Management challenges include:

- insufficient leadership in planning and monitoring LA implementation and the organisational change process;
- uneven understanding of and commitment to the initiative by stakeholders, namely, administrative, technical, and teaching staff;
- a lack of pedagogical concepts and general awareness about the organisation's learning culture driving the expected benefits for learning and teaching;
- insufficient professional training for teaching staff, student service staff, technical staff and the like on the benefits and limitations of LA or its technical infrastructure;
- insufficient rigorous empirical evidence on the effectiveness of LA to support organisational decision making;
- not enough policies, regulations, and codes of practice on privacy and ethics in LA.

Research challenges include:

- lack of geographical spread;
- gaps in knowledge (e.g., in terms informal learning and a lack of negative evidence);
- little evaluation of commercially available tools;
- little attention to ethics.

Why Do Learning Analytics Projects Often Fail?

The use of LA is complex, multifaceted and raises many issues for consideration in order to adopt it successfully. The review of the literature revealed the LA challenges about data tracking, data collection, data analysis, scope and quality of data, evaluation of data, limited theoretical and educational foundations and a connection with learning sciences, challenges related to learning environment optimization, emerging technology, and ethical concerns regarding legal and privacy issues. Collecting large amounts of data and drawing conclusions based on that data is often an overwhelming task.

The biggest and the most common mistakes made are:

- Lack of a consistent LA strategy, aligned with the strategic goals of the organisation**.** When developing a strategy, they usually treat the scope of the analytics as the starting point. In fact, the question is not "What do we want to analyse?" but rather "Why do we want to analyse this?" and "How are we going to use this data?".
- Lack of understanding and support from the organisation, including the top management, who think that development activities are not relevant for their organisational goals.
- Inadequate and incomplete tools are often fragmented across the organisation and managed by the IT departments that never treat them as a priority. Lack of a platform that could ensure quick, safe, and complex access to data is a real challenge. It can actually discourage the organisation from making practical use of analytics and limits its operation considerably.
- Limited budget that is not sufficient to cover the costs of buying adequate tools and employing analytics specialists to make full use of them**.**
- Skyrocketing expectations concerning quick return on investment and changes in all fields. The organisations that follow the trend of analytics-driven business wish to see immediate change and they focus on an excessively broad range of activities. Instead, they should select at most five initiatives that might bring the highest value in the shortest time. Failed expectations hinder future investment.
- Lack of experts with proper analytical qualifications concerning the extraction of relevant data from various sources, who are also able to analyse the collected information accurately and make conclusions based on that**.** Poor knowledge of basic and advanced tools is another problem.
- Lack of insightful analysis and understanding of the subject, both on the part of departments and the management. Expert knowledge is crucial here, as it makes it possible to discover the true objectives of the organisation and present them by means of appropriate data. Superficial knowledge gives superficial results. (https://hcmdeck.com/learning-analytics/)

Data Sources for Learning Analytics

LA uses a wide range of data from a vast array of sources about learners and their behaviours. For example, learning data captures everything a learner does online (e.g., logging into the virtual learning environment (VLE) or learning management system (LMS) or Student Information Systems, (SISs) browsing study materials, participating in online forums, submitting assessments online, digital library usage, Wi-Fi logs to eye movement and facial recognition data), making it possible to create smart algorithms that can detect when a student is struggling based on their behaviour. Every time a student interacts online with their university, they leave a digital footprint. The most widely-used source of data is student interactions within the VLE or LMS; every time a learner interacts with the learning environment, data is created and collected and recorded.

If you haven't used LA before, you may be wondering what data is the right data to track; for example: 1) what are the best sources of LA, 2) what data is the right data to be monitoring and how to figure out which ones to use? The key is to start with the right LA data - knowing exactly what we are collecting data for and what we want to know.

HEIs can use LA for a wide range of purposes, including:
- Prediction - to identify students at risk of dropout or failure of course.
- Personalization and adaptation - to give learners customised learning pathways, or assessment materials.
- Intervention – provision of information to instructors to support students.
- Information visualisation – to present overview of learning data visually on the LA dashboards.

Before you start analysing your data, it's important to understand what data you're collecting and why you're collecting it. You may be interested in:
- What exactly does the student do in the learning environment?
- How often do they log in, which pages, reading materials and videos do they click on and what do they contribute?
- How often do students respond to contributions from fellow students and are these responses focused on the content or not?
- What are areas for course or module improvement?
- How can you spot struggling learners early?
- What is the adoption rate of the learning modules?
- Is the course material appropriate for learners' competency levels?
- How are the online courses helping to reduce costs or increase revenue?

If you try to collect all the data you can find and try to sort it out later, you're likely to end up in chaos. Therefore, a strategic and goal-oriented approach helps to collect the right data, avoid collecting data you aren't going to use and keep it manageable. Depending on your goals, your most valuable data will be gathered from one or a combination of several contexts.

Engagement statistics can help assess learner engagement with the module. The sources for engagement insights are:
- statistics of site and logs, location/IP, statistics on quiz/course activity;
- logins;
- access to the course, time spent studying;
- session – metrics of the session, accessed resources and information, frequency;
- registration;
- learner access origin – home, school, workplace, etc.;
- access to the computer – desktop or mobile;
- correlation between exposure to course tools and assessment outcomes.

Performance statistics can help assess the quality of courses and the effectiveness of training modules:
- participation in discussions;
- participation in the course;
- gradebook scores – quizzes, exams, tests, homework submissions;
- self-assessments (graded and non-graded);
- learning journals;
- other course activities – webinars, classroom, collaborative exercises;

- resource use (video, pdf, etc.);
- course progress;
- frequency of access – how often and how long a resource or activity is accessed.
- online learner feedback on the course, the instructor, etc.

Various data can be used in powerful ways to improve learning and teaching and to make early predictions about long-term outcomes.

Learning Analytics Applications

There are four types of LA that HEIs can use to drive their decision making: 1) descriptive analytics, which tell us what has already happened; 2) diagnostic analytics which explain us why it happened; 3) predictive analytics, which show us what could happen, and finally, 4) prescriptive analytics, which inform us what should happen in the future.

In 2014, Gartner presented these four categories of analytics: descriptive, diagnostic, predictive, and prescriptive as shown on Figure 1. This provides insight into the raw data; as the complexity of the analysis increases, less additional input is needed.

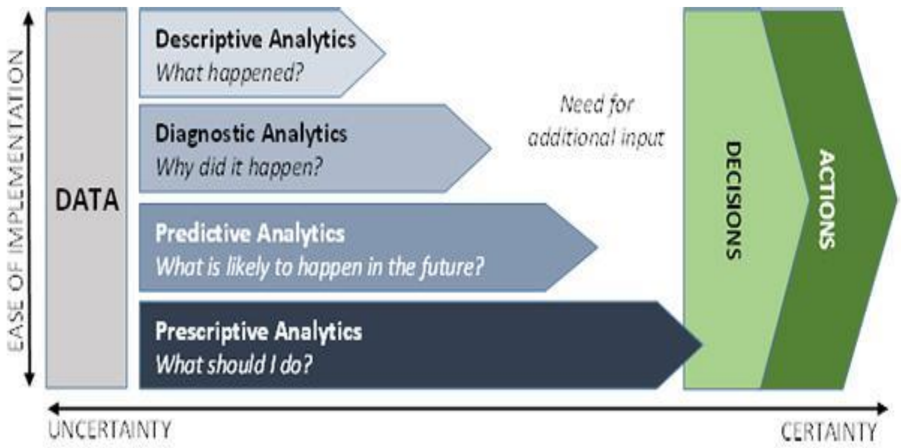

Figure 2: The four categories of analytics (Source: Gartner, 2014)

Descriptive analytics

The simplest and most basic form of analytics is descriptive analytics. Descriptive analytics process raw data from data sources to tell us what is happening or has happened in a specified period, providing greater insight into current or past events. They use visual representations or comparative aggregations to give a clearer understanding of the performance. They translate an abundance of coded, itemised data, akin to pieces of a jigsaw, into a coherent, informative picture. Descriptive analytics provide a hindsight view of performance. Although descriptive analytics usually require less complex data modelling than predictive or prescriptive outputs, an understanding of what is currently happening is crucial to informed action and decision-making. Implementing descriptive analytics in the LA dashboard would allow the educators to understand their students' performance trends and identify any issues.

Example of descriptive analytics in LA

The creation of teacher and student dashboards that convey information about students' learning behaviour and engagement relative to their peers. Nottingham Trent University's Student Dashboard is an example of such a platform which was developed in 2013 with the aims of improving student retention, increasing students' sense of belonging and improving academic attainment. The Dashboard is available to students and tutors via their VLE and shows students' engagement relative to their module peers across a wide range of activities. These include card swipes, VLE log-ins, VLE coursework submission, library loans, attendance, and e-book and e-journal use. It uses visualisations to show students their engagement relative to their peer group. This gives students valuable insights into whether they are maintaining an effective workload or need to increase their activity in the module. Some basic guidance for students in terms of increasing their overall engagement score is also included. The Student Dashboard also notifies tutors by email if any student shows no signs of engagement for fourteen days. This alerts tutors to engagement levels that may indicate a student is in need of more individualised support.

Diagnostic analytics

Diagnostic analytics is the next step of complexity in data analytics. While assessing the descriptive data, diagnostic, analytical tools allow the analyst to drill down and isolate the root cause of a problem. Diagnostic analytics gives in-depth insights into a particular problem on why the problem occurred. Diagnostic analytics provide the context needed in descriptive analytics. Whereas descriptive analytics is concerned with the count or average of a data set, diagnostic analytics is focused on identifying the significance of those events and where they stand in relation to similar events. This context can help HEIs identify what has happened, and it can also provide evidence to understand why it happened. Diagnostic analytics require more effort to complete. The common functions of diagnostic analytics are the distributions of outcomes, probabilities, and statistical likelihoods. Building on the work we've done in descriptive analytics, we can use diagnostic methodologies to find answers to more relevant questions. Diagnostic analysis can tell us what happened, and where that metric stands in relation to other metrics and the significance of that difference.

Predictive analytics

Predictive analytics is advanced analytics that brings many advantages, such as sophisticated analysis based on machine or deep learning. While the previous types of analytics were focused on what has already happened (and why), predictive analytics is focused on what is likely to happen. Predictive analytics is using previous conditions to make educated assumptions about what is likely to occur in the future. With predictive analytics, we make hypotheses or assumptions based on sets of quantitative data and how these sets interact with and affect one another. These hypotheses are tested using statistical tests that identify when the relationships between behaviours in different data sets are likely to affect one another. These behaviours are then characterised as "predictive." Predictive models also include a value that identifies the level of certainty of the prediction. However, no analytics can predict with 100 percent certainty, but every statistical test has a threshold that tells us when there is enough statistical evidence to consider the prediction "significant." Predictive analytics utilises descriptive and diagnostic analytics findings to detect clusters and exceptions and predict future trends. Predictive analytics is a valuable tool for forecasting.

Examples of predictive analytics used by HEIs include regression models, classification models, and Bayesian analyses. These examples require some advanced analytics tests to complete them: t-statistics, AIC (Akaike information criterion), confidence intervals, KS (Kolmogorov-Smirnov) test statistics, p-values, etc. While these tests can all be calculated manually, they are made much easier by available business intelligence (BI) tools, many of which will not only calculate these models but also translate them into plain language. The use of predictive analytics is LA's most significant application to date to proactively identify students who may need targeted support. Research in this area has enabled the development of early alert systems that assess students' quantifiable levels of engagement with services such as the VLE and eLibrary, often in combination with other sources of data such as high-level demographic or attendance data, to develop a profile of their activity.

Example of predictive analytics in LA

Course Signals (CS), developed at Purdue University, is arguably LA's most famous early alert system and has garnered much attention for LA since 2012. CS operates at a module level and draws data from multiple sources including the student's academic history, their engagement with the VLE and some demographic information. It feeds this information through an algorithm which identifies the 'risk level' for that student. This information is fed back to both the module coordinator and the student using a traffic light system. A red light indicates a low likelihood of passing the module, an amber light indicates the student may potentially have difficulty in passing the module and a green light denotes that a student is on track to successfully complete the module. Use of CS has been associated with improved student grades and student retention.

Prescriptive analytics

Prescriptive analytics is sophisticated analytics that utilises machine learning and algorithms to prescribe a possible action that can be taken to eliminate a future problem. Prescriptive analytics is the extension of predictive analytics. If predictive analytics tells us what is likely to happen by finding relationships in the data with very little uncertainty, prescriptive analytics finds the most significant of those events and recommends automated future actions. Prescriptive analytics takes the detailed statistical work of the predictive models and provides guidance around discrete decisions that can be made to ensure positive results.

By reviewing the historic actions of students, LA can be used to provide students with evidence-based information on tailored actions and resources that have the greatest likelihood of helping them to improve their understanding and performance. Recommender systems and adaptive learning environments (ALEs) are examples of how this approach can be used to support student success.

Recommender systems

Recommendation has become one of LA's most important goals. This approach goes beyond describing the current state or predicting outcomes, but suggests how the user can increase the possibility of improving learning outcomes. Recommender systems are automated programmes that construct a profile of the user and use the historic actions and choices of previous users with a similar profile to recommend resources or courses of action which may be of benefit or interest to the current user. Benefits of recommender systems include the following:

- Because they are automated, costs are reduced. This means that a greater number of students can be assisted at a higher level, leaving HEI staff more time to engage with students who require more in-depth support.
- Because recommendations are based upon evidence from previous users, it gives a quantifiable likelihood of achieving the desired outcome.

Example of prescriptive analytics in LA

Degree Compass was developed at Austin Peay State University to assist students in navigating the complexities of the enrolment process. It reviews each student's module history and previous grades and, by referencing the data of previous students with a similar profile, it recommends modules that best fit the student's programme of study and individual strengths. The system most strongly recommends modules that are necessary for the student to graduate, that are core to the university curriculum and the student's major, and within which the student has a high chance of success. In addition to helping students to make informed, evidence-based choices, the system has an advisor-facing platform that enables advisors to offer more personalised support. It also uses the data it analyses to identify at-risk students, enabling the institution to offer further, tailored supports if required. The potential power of recommender systems is most clearly demonstrated by the accuracy of Degree Compass's predictive capabilities; initial exploration found the system's predictions of modules in which students were likely to achieve an A or B grade proved accurate in 90% of instances.

Adaptive learning environments

Some authors have argued that the current VLE functionality does not adequately meet the individual learning needs of 21st century learners. Adaptive Learning Environments (ALEs) have been proposed as a means of allowing students to engage in more self-directed and tailored learning. ALEs are intelligent systems that support individualised student learning by adapting to the understanding and progress of each learner. They are digital platforms that provide lessons, formative assessment and immediate, personalised feedback and/or guide students to the resources that will benefit them most. The researchers describe the benefits of ALE as follows:

- *Instant feedback:* given the importance of immediacy and frequency of feedback to learning performance, ALEs can enable embedded mechanisms that provide instant feedback.
- *Personalised learning*: ALEs can identify students' learning behaviour and current depth of understanding to tailor an individualised learning path.
- *Self-paced learning*: a well-structured ALE should enable students to direct their own rate of learning. Confident students can skip units that they understand well, while students who are less familiar with the subject matter can work at their own pace without fear of slowing down their peers.

Example of Adaptive Learning Environments

The Open Learning Initiative (OLI), an ALE developed at Carnegie Mellon University, is an example of a highly effective learning tool that effectively utilises LA. OLI is a platform that hosts online courses and was designed to provide students with an optimal learning environment. Lessons are provided through multiple media and are interspersed with opportunities for students to practise what they have learnt. Students are provided with immediate and tailored feedback. The platform was designed to enable instructor-free online teaching that would mirror the learning that occurs in the classroom, but it is also used as a teaching aid by lecturers who combine it with face- to-face teaching. By improving preparation and engagement, this hybrid approach has been shown to reduce by half the time taken for students to learn course content. Another key feature of OLI is its reporting dashboard, which allows lecturers to review students' progress against the learning outcomes of the module. Class plans can thus be focused upon areas that the evidence suggests will be of greatest benefit to the class.

Learning Analytics Dashboards

Learning analytics dashboards (LADs) are "single displays that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualisations" (Schwendimann *et al*., 2016). LADs have gained increased attention due to their potential to support teaching and learning. LA dashboards involve the measurement, collection, analysis, and reporting of learners' data and their environments to support understanding and optimization of learning. Usually arranged on a single screen, LADs are useful analytics applications because they help to convey quantitative information in a more digestible and actionable manner for the user.

Development of Learning Analytics Dashboards

In the past decade, an increasing number of LADs have been developed. However, this growth took mostly place in European, Australian, and American HEIs. Other regions such as great parts of Latin-America lacked the local capacity to gather, manage, process, or visualise the data. Many LADs have been developed that use a variety of data sources to support sense-making and decision-making. For example, Student Activity Meter (SAM) was one of the early LADs developed on top of data from students and visualises time spent and resource use by students to support awareness for students and teachers. Other early examples include SNAPP that visualises the evolution of social interactions among learners in online forums to enable timely interventions by teachers. Step-up! visualises social media data of students to increase student engagement. Course Signals visualises predicted learning outcomes as a traffic light, based on grades in the course so far, time on task and past performance. SLICE visualises annotations of students on slides during face-to-face lectures. In addition, several LADs focussed on the facilitation of group work.

These early examples demonstrated the rich potential of LADs in a very broad range of applications, including raising awareness and self-reflection in blended learning settings for both students and teachers, improving engagement of, and interaction with students in face-to-face lectures, predicting study outcomes and identifying at risk students, facilitating group work, and enabling social comparison. Most of these early examples relied on interaction data from learners with their learning environment captured from application logs. In addition, the early examples typically supported either students or teachers, but other stakeholders were not often supported.

The Objectives of Learning Analytics Dashboards

LADs are designed with different purposes, functionalities and types of data in an attempt to influence learners' behaviour, achievement and skills, and to give relevant information to students and other stakeholders to inform potential next steps in the learning process. LADs are particularly helpful in the reporting of data because they function as data visualisation scaffolds to facilitate the comprehension of the information being presented. More specifically, by revealing patterns in educational data that are difficult to detect otherwise, LADs are useful analytics applications that convey quantitative information into more 'digestible' and actionable items.

LADs aggregate different indicators about learners, learning processes and learning contexts collected in various online environments and apply information visualisation techniques to help teachers, learners, and other stakeholders to improve learning. The objectives of the LADs include providing feedback on learning activities, supporting reflection and decision making, increasing engagement and motivation, and reducing dropout. LADs can show data through different visualisations, such as bar and pie charts, line and network graphs, tables, gauges, dials, and maps.

LADs can have the following goals, affecting metacognitive and cognitive skills, behavioural and emotional competencies, performance, online social and help-seeking behaviour, retention or engagement, supporting awareness and reflection, planning, achieving goals, improving self-regulation, deactivating negative emotions, providing navigation support, monitoring progress and increasing motivation.

LADs can support teachers in giving advice to students on their learning trajectories. The LAD presents the likelihood of the particular student failing a course in which she/he is interested. The LAD can use colour cues (e.g., green, yellow, red) to indicate whether the risk of failure, based on past performance, is low, medium, or high.

Types of Target Users

LADs can support:

a) teachers/educators in developing their own practice and in targeting their support at individual student needs;
b) students/learners to gain insight into their learning actions and the effects these have their learning;
c) administrators in understanding how cohorts are developing and their organisational needs, and
d) researchers to discover patterns in large data sets of user traces and to communicate these data to their peers.

Teacher dashboards are a specific application of LA in which visual displays provide teachers with information and insight about their students' behaviour (e.g., concerning student abilities, progress and performance during lectures) and can play a significant role in identification of LD elements which may be important for enhancing learning processes and performance.

Student LADs are collecting student data and reporting the data back to students. The goal of student LADs is to provide feedback to learners to improve teaching and learning; student-facing reporting systems close the feedback loop and in best case scenarios, give students real-time access to their data to increase student awareness, reflection, and achievement. In addition, student LADs can contribute to the increasing awareness among students for self-monitoring and self-reflection, and could be used as powerful metacognitive tools for learners that could support learners to self-regulate when learning online.

Millecamp *et al.* (2019) arranged a workshop in Ecuador and asked the participants to list the problems of education that they would solve with a LADs and to categorise them based on the stakeholders of this dashboard.

Table 3: Dashboards according to the stakeholders

Learners	Teachers	Institution	Other
Decision support	Detect students at risk	Optimise physical space and resources	Opening up data for community
Tracing improvements	Monitor use of technology	Decision support based on failure rates	Ranking universities
Make learners more responsible	Time management	Making data more transparent	Regulatory compliance
Showing different courses	Detect need for own knowledge upgrade	Graphical instrument for research	Helping communities
Detect difficulties inside course	Detect difficulties inside course	Moving people across areas	Demographic information
Coaching/feedback from teachers	Optimise teaching strategy	Measuring results vs money	
Detect learning deficiencies	Cluster students for feedback		

This workshop resulted in seven possible dashboards for learners, seven possible dashboards for teachers, six dashboards with the institution as stakeholders, and five with other stakeholders, as shown in Table 2.

Types of Learning Analytics Dashboards

There are various types of dashboards:

- for traditional face-to-face lectures to enable the teacher to adapt the teaching, or to engage students during lecture sessions;
- for face-to-face group work and classroom orchestration, for instance by visualising activities of both individual learners and groups of learners, or
- awareness, reflection, sense-making and behaviour change in online or blended learning.

It is also possible to distinguish dashboard according to their purpose:

- self-monitoring,
- monitoring others,
- administrative monitoring,
- content recommender dashboard, and
- skills recommender dashboard.

The content recommender helps students identify gaps in their content knowledge and the skills recommender helps students improve their metacognitive strategies.

It is also possible to divide LADs according to purpose of analytics:
- predictive dashboards and
- descriptive dashboards.

Although LADs have been developed for a broad range of stakeholders, including learners, teachers, researchers or administrative staff, the majority of dashboards support teachers and not as much attention has been put into developing dashboards for learners.

Components of Learning Analytics Dashboards

LADs involve the following four components:
- measurement,
- collection,
- analysis and
- reporting of learners' data and their environments to support understanding and optimisation of learning.

LADs are particularly helpful in the reporting of data because they function as data visualisation scaffolds to facilitate the comprehension of the information being presented. More specifically, by revealing patterns in educational data that are difficult to detect otherwise, LADs are useful analytics applications that convey quantitative information into more 'digestible' and actionable items.

Key Characteristics of Learning Analytics Dashboards

Key characteristics of data dashboards include:
- all visualisations fit on a single screen;
- displays the most important indicators to be monitored over time;
- regular updates of data (ideally automatically);
- easy to understand; can be understood and used by anyone with access;
- often includes filtering and 'drill down' functions which enables users to view the data of most interest to them (e.g., filtering by location, age or gender). The visualisations then update to display only data that meet the characteristics chosen.

Learning Analytics Dashboard Indicators

LADs are designed with different purposes and functionalities and can provide instructors with crucial hints for dynamic intervention and assessment, displaying students' learning status, patterns, performance, and interactions in the form of visual elements and making it possible for instructors to identify at-risk students or groups. Schwendimann *et al*. (2016) identified over 200 different LAD indicators which were categorised into six broad groups, depending on the questions they aim to answer. However, an indicator may belong to more than one group.
1) *Learner-related indicators* present information describing the learner(s) - who are the learners?
2) *Action-related indicators* present information about the actions performed by the learner(s), usually in an aggregated form - what do they do while learning?
3) *Content-related indicators* provide information about the content that the learner(s) interacted with or produced - what is the content involved in their learning?

4) *Result-related indicators* give information about the outcome of learners' activities - what is the result of their learning?
5) *Context-related indicators* provide information about the context where the learning took place - in which context does the learning take place?
6) *Social-related indicators* show how learners interact with others.

It is also possible to divide the main statistical indicators into two main groups:

- *Engagement statistics* (e.g., site statistics and logs, location/IP; quiz/course activity statistics (question assessment), logins, course access, time spent learning, session (sessions metrics, tools and content accessed, frequency), learner origin of access (home, office), etc.
- *Performance statistics* (participation in discussions, participation in the course, gradebook scores (quizzes, exams, homework submissions), self-assessments (graded and non-graded), journals, webinars, classroom, collaborative exercises, use of resources (video, PDF, etc.), course progress, leaderboard, frequency of access – how often a resource or activity is accessed and how long, online learner feedback - on the course, the instructor, etc.

Engagement statistics can help assess learner engagement with the module. Performance statistics can help assess the quality of courses and the effectiveness of training modules.

Valle *et al.* (2021) refer to:

- *cognitive measures* that include learning performance (e.g., scores), uses of learning strategies and achievement of goals set by the learner;
- *affective measures* that refer to motivation and other affective outcomes (e.g., anxiety and satisfaction) as well as learners' perceptions of learning and their learning experience. Thus, all self-reported perceptions;
- *behavioural measures* that refer to measures related to learners' behaviours such as time spent in an activity, number of clicks on a given resource and help-seeking behaviour (e.g., number of questions posted in a discussion board).

Theoretical Models

There are several theoretical frameworks or models that are used to guide the design and development of LADs. For example, the model by Molenaar and Knoop-van Campen (2019) consists of:

- an *awareness stage* (which data is available),
- a *reflection stage* (which question can the teacher answer based on the data),
- a *sense-making stage* (answering the question based on the data), and
- the *impact stage*, in which a decision for pedagogical action is made.

Comparing LA theoretical models, Van Leeuwen *et al*. (2021) found several recurring elements which they summarised into three overarching phases:

1) All models contain an initial stage of *awareness*, meaning that teachers know there is data available and they look at the information shown on the dashboard. Teachers can be looking for information, or driven by the analytics themselves, when the teacher notices or is alerted to a deviant situation and decides to inspect the dashboard in more detail.

2) The second stage is *interpretation*, in which the teacher engages in making sense of the analytics shown, and arrives at an answer to the following question: What are the analytics telling me?
3) The final stage is *enactment*, in which interpretation is translated into pedagogical action. This could entail a support action for students, but a teacher can also decide not to undertake an action, or to reflect on their own actions instead of student behaviours.

One of the most common theoretical frameworks that are used to guide the design of LADs, when learning theories are adopted, is self-regulated learning.

In the MULAS model by Matcha *et al.* (2019), it is suggested that LADs add a goal-setting functionality (like the so-called S.M.A.R.T goals that are specific, measurable, achievable, relevant, and time-bound) and a recommendation feature that provides learning tactics based on data mining results. In addition, it is recommended that developers and designers explore various forms of communications and representations, and not assume that one style of representation or visualisation would work for all learners. However, several researchers note that although research has investigated LADs, yet none have explored the theoretical foundation that should inform the design and evaluation of such interventions. There is a rich variety of indicators being used to build current LADs. However, there is comparatively little work on comparing which indicators (and which visualisations) are most suitable for the different user data literacy levels.

Design of Learning Analytics Dashboards

There is a growing need to understand how to design LADs to help educators support learning experiences by providing real-time formative feedback. The process to design and evaluate dashboards has received very little attention from the LA research community, usually focused on research level visualisations of data or new analytical methods. However, LADs are the main representation of LA and as such their correct design and evaluation should be an important component in the LA research agenda. Designing meaningful LADs is still a complex process that requires an explicit understanding of the user's needs.

There have been several approaches to the design of LADs, such as

- the person-oriented approach,
- the process-oriented approach, and
- the cloud-based approach.

In order to start the dashboard's design the following questions need to be answered:

- *Why:* What is the goal of the visualisation? What questions about the data should it answer?
- *For whom:* For whom is the visualisation intended? Are the people involved specialists in the domain, or in visualisation?
- *What:* What data will the visualisation display? Do these data exhibit a specific internal structure, like time, a hierarchy, or a network?
- *How:* How will the visualisation support the goal? How will people be able to interact with the visualisation? What is the intended output device? (Klerkx *et al.*, 2017).

Having these questions in mind can be useful when acquiring and filtering data for the LAD. For example, considering a data set that contains the following learner traces: access to learning resources, time on page in digital textbooks, contributions to discussion for a, and time spent on assignments; from these traces, designers can define several relevant questions as a starting point in the design process. A teacher might ask questions like these:

- When did students start looking at the course material?
- What is the average time that a student spends reading the textbook?
- How many hours did the student work on this assignment?
- How often did the student ask a question on the discussion forum?

A student might ask similar questions:

- How much time do I spend on an assignment, compared to other students?
- How much do I contribute to the discussion forum, compared to other students?

The specific, direct "what," "when," "how much," and "how often" questions can be directly mapped in a data set. Questions like "Why did this student have to enrol twice in this course?" or "Are students more eager to work on assignment 1 or assignment 2?" are more difficult to answer as these are more exploratory in nature. Therefore, it is often advisable to focus on direct, specific questions, especially in the early phase of design (Dabbebi *et al.*, 2019).

Building a visual dashboard typically entails a data-gathering and pre-processing step. Visualisation experts claim that this step takes 80% of the time and effort compared to all other steps. McDonnel and Elmqvist (2009) identify the following intermediary steps:

- *Acquiring raw data:* It is important to have a clear idea of where the data will come from (e.g., the log files of the LMS, assessment results, etc.), and when the data will be updated (continuously, not at all, at specific intervals). Will the data be available through an Application Programming Interface (API), an export file, or some other source?
- *Analysing raw data:* Data may need to be cleaned if some values are missing or erroneous, or pre-processed to compute aggregate values (mean, minimum, maximum). In data analysis, distribution can also be an issue: are there apparent outliers, clusters, etc.?
- *Preparing and filtering data:* Using the initial questions from step 1, choose the relevant data from the pool of analysed raw data (Klerkx *et al.*, 2017).

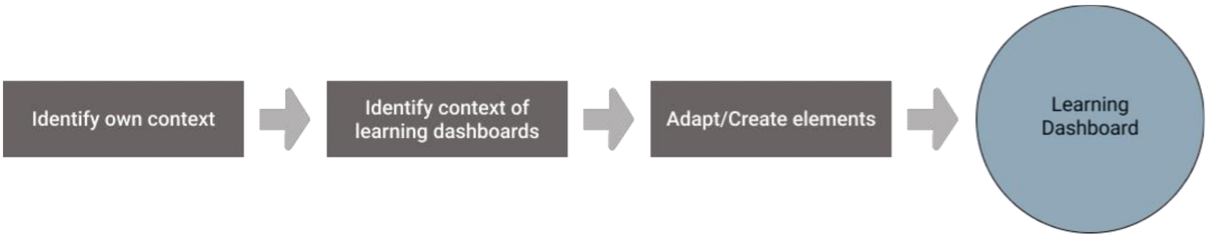

Figure 3: Steps creating LADs (Millecamp *et al.*, 2019).

The different steps of developing LADS are shown in Figure 3: 1) Identify the context of the new LAD. 2) Identify the context of existing LADs to find similar LADs 3) Adapt these existing LADs to the new context.

Important in the visual mapping design is to choose a representation that best answers the questions you want users to be able to answer, i.e., that serves your visualisation goal for the intended target audience. After selecting a visual encoding, high-fidelity prototypes can be built using visualisation tools (like Tableau) or existing visualisation libraries (like D3.js).

There is no best way to visualise a data set, but some techniques have been proven to work better than others, for example:

- Pie charts are usually a bad idea.
- Bar charts can be quite powerful.
- Coordinated graphs enable rich exploration.
- 3-D graphics often do not convey any additional information and force the reader to deal with redundant and extraneous cues.
- Scatterplots and parallel coordinates are good representations for depicting correlations. In addition, it is found that among the stacked chart variants, the stacked bar significantly outperformed both the stacked area and stacked line.

The visualisations facilitate identification of trends and patterns, and ideally, the information presented in a dashboard is used to guide decision making and action. However, there are many questions that need to be answered:

- What are the challenges to visualise the data, to clean up the data, to perform usability tests, to implement the technical design, etc.?
- What are the challenges of using different visualisation techniques?
- Which interaction techniques are applied and what are their strengths and pitfalls?
- What are the commonly encountered challenges and pitfalls during the visualisation process?
- What workflows and recipes can be used to develop the visualisation?
- Which are the challenges when evaluating a LA visualisation?

A recurrent topic related to the development of visualisations is the need to involve stakeholders in the design process as early as possible through participatory design process, including in early needs analysis, concept generation, and concept validation. Focus groups, pilot studies, eye tracking, stimulated recall, and interviews are possible strategies to achieve this goal. Other good practices include the assessment of users' data analytics skills prior to development, replication of results through open anonymised datasets, open source code, the use of standards, and learning from successful visualisations. Pitfalls in the design process include starting from the visualisation instead of a research question and building visualisations without conducting any validation analysis on the data. Another important pitfall is the lack of actionability of current LADs: often users need to be explained how to enact upon the information given (Verbert *et al*., 2020).

The one-size-does-not-fit-all principle should be considered. For example, a dashboard that works in Europe does not necessarily work in other cultures; or a dashboard that is designed for learners is not always useful for teachers and its subdomain of personalisation. There is a consensus that it is important to clearly outline who will be the end-user of a LAD, as different user groups have different needs. There is no consensus on whether visualisations should be tailored to the user's data literacy level or not. It is also mentioned that we should consider the impact of visualisations on users of different ages, genders, races, etc. It is also noted that many dashboards are overwhelming, presenting too much data and options (Verbert *et al*., 2020).

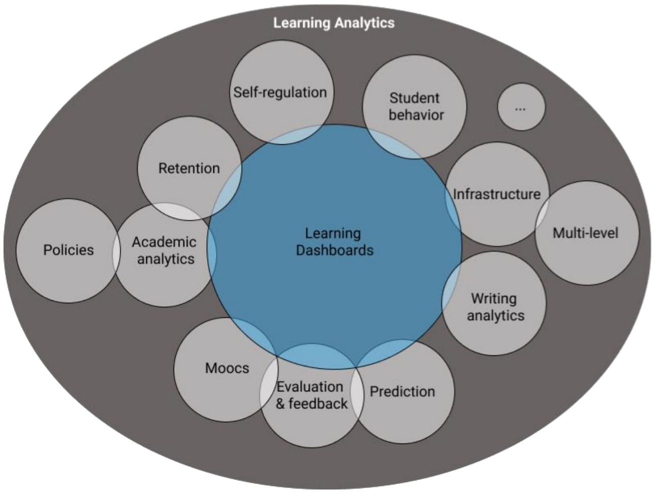

Figure 4: Learning Analytics Dashboards with different subdomains (Millecamp *et al.*, 2019).

Millecamp *et al.* (2019) presented the field of LA with different subdomains. The subdomain of LADs overlaps with a lot of different other subdomains of which it can visualise the data (Figure 4).

Most of the proposed LADs still follow the traditional paradigm in which the teacher is the main user monitoring students. LADs have been studied mostly in formal, HE contexts. However, more and more studies are starting to experiment with providing dashboards to students. Dashboard solutions are still heavily based on log analysis, often using a single platform as their source of data. However, the fact that learning is becoming more blended and more distributed across different tools and contexts, more and more dashboards are experimenting with multiple kinds of data sources and platforms to get a complete view of learning processes.

Criticism of Learning Analytics Dashboards

Several authors note that existing LADs are rarely grounded in learning theory, cannot be suggested to support metacognition, do not offer any information about effective learning tactics and strategies, and have significant limitations in how their evaluation is conducted and reported. In addition, a common criticism of LADs is that they don't provide adequate space for narrative explanation or reflection which may be critical to understanding the data presented. Some critical voices have also raised concerns about the lack of acceptance, uptake and adoption.

Nowadays, existing LAD instruments mostly target performance visualisation often in the form of outcome feedback, rather than process-oriented feedback, and without providing support mechanisms to facilitate their interpretation and suggestion. The data are more used in summative assessment, hardly noticed process assessment, or the existing LADs which are based on formative assessment are focused on evaluating the "usefulness" and "usability," and lack of attention to the impact of LADs used on instructional effects and learning performance. In addition, current dashboard solutions are mostly based on performance indicators of learners, leading to decreased mastery orientation without considering the learners' goals. In addition, the interpretability of data visualisations is often neglected in their design. Analytical approaches based on which learner feedback is proposed are limited to statistical and data mining techniques. Such techniques neglect the procedural and sequential aspects of learning processes and may thus provide product-oriented, rather than process-oriented, guidance.

Tools for Learning Analytics

Schwendimann *et al*. (2016) identified 51 platforms used for LA of which Moodle was the single most popular platform for retrieving data. The most commonly used LA tools are:

- LADs, which visually represent indicators of student progress and academic performance;
- communication tools that support LA;
- diagnostic instruments that provide teachers with visualisations to help them identify patterns and trends in e-learning environments (e.g. SNAPP tool that essentially serves as a diagnostic instrument, allowing teaching staff to evaluate student behavioural patterns against LA activity design objectives and intervene as required in a timely manner; LOCO-Analyst, which is an educational tool aimed at providing teachers with feedback on the relevant aspects of the learning process taking place in a web-based learning environment, and thus helps them improve the content and the structure of their web-based courses).

Learning Analytics as Moodle Plugins

- *SmartKlass* is a LA plugin that can be incorporated with Moodle using a simple and easy dashboard, added directly as a new tab in the control panel. xAPI 1.0 is used to gather user interactions with the platform. Some of SmartKlass's advantages are: 1) Moodle 2.6, 2.7, 2.8, 2.9 and 3.0 are compatible. It supports the Tin Can API as well. 2) It highlights students with difficulties and provides information such as individual and collaborative work, 3) It can be used in business, school, and university learning.
- *MOCLog Moodle Analytics* is a monitoring program to evaluate Moodle LMS log files more effectively and efficiently, thereby enhancing teaching and learning efficiency. This also provides benefits like: 1) Relevant log file analysis interpretation schemes, 2) Easier and quicker log file review in Moodle online courses, 3) Feedback from various stakeholders, 4) Serving all primary LMS users, 5) Monitor all log files status
- *GISMO* is an interactive graphical monitoring plugin that provides online visualisation of student activity. This is a Moodle LMS plugin tracking student attendance, content reading, submission of documents.
- *Analytical Graph* plugin includes five separate graphs for the description of the learner profile. This is a plugin for Moodle LMS. This helps the administrative officer to send messages to users in a course based on their behaviour. The diagrams show: 1) Grade chart, 2) Content access chart, 3) Number of active users chart, 4) Assignment submissions chart, 5) Hits distribution chart.
- *The Heatmap* plugin overlays a heatmap onto a course to show events with more or less activity to help teachers develop their course. It was inspired by a device called Moodle Activity Viewer (MAV), and it is a Moodle LMS plugin. It also provides information on the number of visits and unique users for each operation. It can even be turned off if it is not necessary.

Learning Analytics as a Part of Learning Management Systems

- *SumTotal Systems* provides an interactive software kit focused on the technology of Microsoft Reporting & Analysis. SumTotal LMS provides regular reports that cover virtually all the daily reporting requirements. You may use these reports as the starting point for any further reports to be produced. You can create customised real-time dashboards to help managers decide. Every report has its Amount Total LMS.

- *Saba* has developed algorithms for machine learning that intelligently recommends appropriate course material based on user interests, expectations, and web-based activities. Saba has Saba analytics, which is meant to promote knowledge gathering and assessment in various learning systems. Reporting in Saba takes less time than the user's review. It gives a full training summary with a button press.
- *Docebo* offers an overall image of organisational learning, helping you understand more about learning habits and introducing tailored learning initiatives.
- *Talent LMS* has a comprehensive reporting feature that reports on everything in the e-learning world. A timeline is documented for all device acts. Accurate reports are generated to obtain accurate details. You can generate reports according to your requirements.
- *Absorb LMS* assists directly from the reports. You can conveniently register users directly from the report interface. You can also display or cover the corresponding columns and arrange them in any order. You can also configure and save dynamic date filters. The Business Intelligence Module facilitates your team to gather valuable information from your LMS.
- *Cornerstone Suite* builds visually rich executive dashboards to complete data management and visibility for all reporting forms.
- *Litmos* gives you full access to real-time results that allow you to keep an easy track of individual trainee progress or compare team results within your institution. You may also export the document as a PDF or a CSV file.

Top Learning Analytics Tools

The five top LA tools that optimise the learner's learning experience and progress are:

- *Wooclap* is an audience response tool that helps improve the engagement of in-class learners. It is an app that improves learning by a playful mechanism of in-class questionnaires. This app is also excellent in LA since it provides instructors with analytics. The instructors can assess who answered at what time and how long they needed to answer. The analytical software has a feedback wall so that students can interact with their teachers and chat about their problems.
- *YET analytics* is one of the most extensive LA and visualisation tools. Built upon Xapi, YET analytics offers a wide range of visual analytics that improve the content of learning and the understanding of learners. It also provides valuable insights into role readiness, career path, talent development, and advanced engagement analytics on various learning ecosystems. It also provides precise predictive analytical solutions to meet the needs of various learners.
- *Bright Bytes* is an analytical tool that analyses how teachers and students use technology for learning, studies devices' availability and internet access, assess teachers' and learners' level of expertise through multimedia, and analyses learning culture, professional development, and technology needs.
- *Knewton* is an innovative US-based platform for personalised learning through data analysis. By analysing student performance data in real-time, Knewton Alta, its higher-end version, allows teachers to adapt their learning and education content to every student and track their progress. The platform also has its online courses, which are checked and automatically adjusted to the students' progress.
- *Clever* is one of the fastest-growing U.S. LA in Edtech. Clever released its advanced app, called Goals, providing teachers and students with a single sign-on platform for

communicating between all software and learning resources. Firstly, the Goals Tool allows teachers to set targets for each learner, such as what to do, how to use, and so on. This then allows them to monitor the progress of the students accurately. The students are also able to track their progress. Clever is a handy analytical tool for students to learn and track their contribution to the learning environment.

Checklist to Choose a Learning Analytics Tool

This section presents the checklist for your institution's choice of the right LA tool. The first step in product choices is the needs analysis.

1. *Needs Analysis*

Through understanding the answers to the following questions, you can identify your needs:

- What does your organisation need? Do you want to track learners or do you want to track their performance according to any tracking parameter?
- What sort of learning programs do you analyse?
- What is the foundation of the student, and what is the geographical distribution of the students?
- Is the big tool data compatible?
- Is it compatible with other LMS and tools?
- What is the data delivery mode?
- Is it possible to export it to various formats, including PDF, Excel, or Word?
- Does it provide management automated data sharing?

2. *Assess Options*

You should compare the resources available on the market according to the following parameters after you have met your requirements:

- To learn if the organisation is a startup or well known.
- What is the seller's sort of technical support?
- Could it work efficiently with the current LMS?
- Can the tool be scaled?
- Can it perform data cleaning, data auditing, and data cross-validation?
- Is it a desktop tool or a cloud-based tool?
- What are pros and cons of the tool?
- What kind of protections does the data protection tool offer?
- What is the technical know-how needed to incorporate the tool with your LMS systems?

You may also shortlist the standard tools on the market that meet your requirements based on these criteria.

3. *Hands-on Experience*

Some tools provide a free trial. So, you can know the tool's usability, report production capabilities, etc. before you invest in a particular tool. You should also read reviews of the tool from independent blogs, take the opinions of both the internal IT experts and external consultants, and even get information from current customers.

These are some of the things you have to note when selecting a tool for LA. There are several key features that you need to test before selecting a LA tool:

- *Ease of Use.* One of the most critical aspects of buying of LA tool is a quick user interface, commonly known as a dashboard or a scorecard.

- *Functions for Data Sharing.* Look for a solution that will allow you to prepare a saved analysis report that is automatically retrofitted and sent to a designated user set at a given time.
- *Scalable Architecture.* Since any analytics system's key benefits are the ability to distil vast volumes of data into usable information, a practical LA system needs to be scalable at an organisational level. It should be noted that this scalability should not be too costly.
- *Analysis and Reports.* In addition to a straightforward user interface, consider the tool's versatility to produce reports based on your organisation's processes. Some solutions offer out-of-box reports and give users integrated reports specific to their learning system software. Nevertheless, bear in mind that a one-size-fits-all solution cannot be an empirical method.

Integrating Learning Analytics into the Organisation

Realising LA capability will require an institutional shift in how we think about enhancing learning and teaching activities that facilitate this. We must involve learners as active agents in this process, and as collaborators and co-interpreters, not simply as passive recipients. We must seek out potential efficiency gains that can be realised as a result of insights gained from analysis of learning data. Above all, we must ensure all aspects of LA activity are pursued in a manner that is sensitive to the ethical and privacy concerns inherent in the collection, analysis and retention of this data.

Culture and Vision

The culture of the institution will influence how staff and students perceive LA. LA is likely to be a better fit if the institution puts a strong emphasis on providing the best possible learning experience to students. In some institutions, there is a close partnership between the institution and its students. Involving them in the roll-out of LA, seeking their input in defining the benefits for them and dealing with issues such as ethics, can be helpful.

There may be initiative fatigue in the institution and already overstretched staff may resist the introduction of LA tools if they feel these will increase their workload. It will be helpful to show case studies from other institutions where there are positive benefits from providing LA. It should also be emphasised that LA aims to help students through their learning journey – and that student data will be subject to rigorous protection in compliance with the General Data Protection Regulation (GDPR) and clearly defined policies.

LA is not an end in itself but can help to meet institutional priorities such as improved retention, progression, achievement and student support. There should be a vision that clearly shows how LA aims to assist in meeting overall institutional objectives. It may also be helpful to see LA as part of a broader move across all areas of institutional activity to use data to support better decision-making.

Senior Management Sponsorship

Some universities report that having a senior leader with a vision for LA has been critical to the success of LA institutional projects. The importance of senior management approval and promotion of a move towards more data informed decision-making processes in general – and specifically in the area of learning and teaching – cannot be overstated. If stakeholders across the institution know there is a strong commitment from the top management they are more likely to take LA and the necessary changes to their working practices seriously.

Usually senior management will not have specific expertise in LA and, while a familiarity with the concepts and what is involved will be important, they will devolve day to day management of LA to someone who has or can develop more in-depth knowledge of the area. There will inevitably be other institutional priorities and competition for scarce resources. LA will not necessarily demonstrate quick wins and, while appearing novel and innovative, it takes long-term commitment to embed use of the tools effectively into working processes. It may be several years before LA shows benefits. Ongoing interest in LA from senior management and a commitment to its deployment are therefore key.

Policy Framework

LA will require the institution to adapt existing policies or develop new ones. It should fit with existing strategies and policies in areas such as teaching and learning, student support and IT. Institutions may decide to develop specific new policies in areas relating to the ethical and legal handling of student data. It is also suggested to develop policy in the area of handling interventions with students resulting from the analytics.

Staff Capabilities and Capacity

IT/student records systems staff will need specific expertise in integrating existing data sources. However, capacity issues should be seriously considered. Widespread, effective staff use of the tools will depend on staff being convinced of their benefits and feeling that they have the time to fit using them into already busy schedules. Delivering the tools as part of an existing programme of activity in an area such as personal tutoring is likely to have greater impact than simply making the tools available to all.

Change Management Strategy in order to Implement Actionable Learning Analytics

Several authors suggest change management strategy in order to implement actionable LA in organisation (see Figure 5):

- definition of the LA vision and objectives and align them with the organisation's mission and learning culture;
- identification of organisational, political, or technological factors that will affect the implementation;
- involvement and continuous information of all stakeholders including students, teachers, administrators, etc.;
- development of and continuously update a strategic plan focussing on short-term and long-term wins, including a needs and risk analysis as well as a clear timeline outlining responsibilities of involved stakeholders;
- allocation of resources and identification of expertise (inside and outside of the organisation) for achieving the LA objectives;
- undertaking a robust formative and summative evaluation of the LA initiative to further refine the overall implementation and organisational change process.

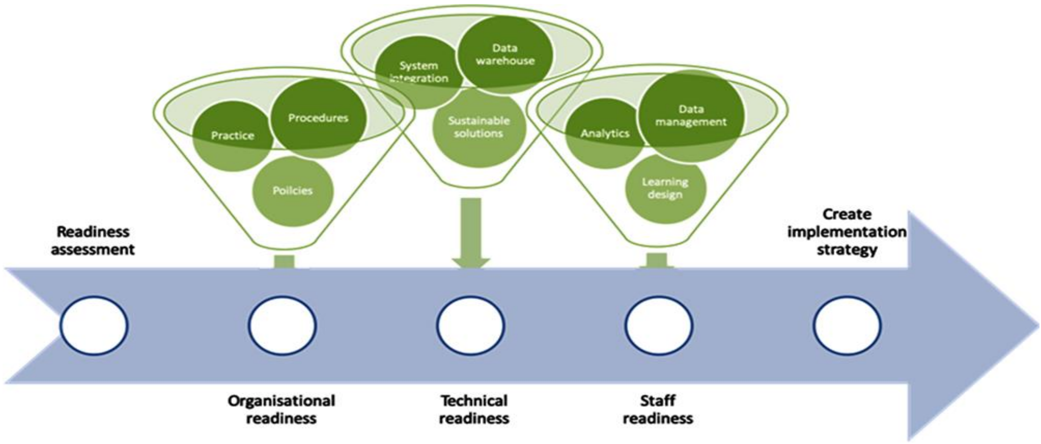

Figure 5. Change management strategy for implementing actionable LA.
Source: Ifenthaler (2020)

The following major steps are suggested:

- develop flexible systems that can adapt to the needs of individual organisations, i.e., their learning culture, requirements of specific study programmes, student and teacher preferences, technical and administrative specifications;
- define requirements for data and algorithms;
- involve all stakeholders in developing a LA strategy and implementation;
- establish organisational, technological and pedagogical structures and process for the application of LA systems as well as providing support for all involved stakeholders for a sustainable operation;
- inform all stakeholders with regard to ethical issues and data privacy regulations including professional learning opportunities (e.g., educational data literacy);
- build a robust process for ensuring the validity and veracity of the system, data, algorithms and interventions;
- fund research on LA;
- constitute local, regional and national LA committees including stakeholders from science, economics and politics with a focus on adequate development and implementation (and accreditation) of LA systems.

Ethical Implications of Learning Analytics

LA provides tremendous opportunities to assist learners, but it also poses ethical questions you shouldn’t ignore. Collecting and analysing data often means processing personal data - data which, directly or indirectly, contains information about individuals such as students and teachers. When an educational institution processes personal data, the General Data Protection Regulation (GDPR) applies. The GDPR places strict criteria on the basis for using LA. The use of LA requires careful consideration of the risks for individuals, and suitable measures to be taken. It is not as simple as asking for consent once and including a privacy statement on the website.

In 2019, the International Council for Open and Distance Education (ICDE) published a report on global guidelines regarding ethically-informed practice in LA. The report includes a number of issues that are important ethical considerations regarding the use and development of LA. These issues include transparency, data ownership and control, accessibility of data, validity and reliability of data, institutional responsibility and obligation to act, communications, cultural values, inclusion, consent, and student agency and responsibility. A brief overview of the ethical guidelines surrounding these core issues is below.

Data Ownership and Control

- The issue of data ownership will be impacted to some extent by relevant national and international legislation (i.e., GDPR, 2018).
- Institutions should be aware of and make transparent issues around third party sharing, especially since sharing might include student data.
- There is lack of clarity around who owns the data (institutions vs. students) and this can make principles surrounding meaningful consent complicated.
- A suggestion surrounding the aforementioned issue is to have the institution see their role as having temporary stewardship over the data, and not owning the data.
- For data that may be personal and/or sensitive, students should have some say as to how data can be used and who may be able to access the data.
- HEIs should grant students the ability to correct and add context to their raw data.

Transparency

- Institutional transparency might best begin by making clear to students and to other stakeholders the purpose of learning analytics.
- The core issue of transparency here relates primarily to how student data is collected and analysed and used to impact students' learning. Making students and stakeholders more aware of the uses of data brings about challenges, but also allows for greater insight and involvement. However, it is not always possible to be completely transparent, and it is not in the best interest of students to communicate a predicted poor outcome.

Accessibility of Data

- This core issue relates to the determination of who has access to the raw and analysed data, as well as the ability of the students to access and correct their own data. It could also include making clear which data would be included within a learning analytics application, and what data might be out of scope.
- Some individuals will have access to some categories of personal student data (i.e., income, academic history, etc.). Within a learning analytics context, data may be accessed on a 'need-to-know' basis in order to facilitate the provision of academic and other support services.

Validity and Reliability of Data

- The institution needs to ensure that data collected and analysed is accurate and representative of the issue being measured.
- Proxy measures should be used with caution.
- It is important to make sure that datasets are complete and sufficient to enable predictive calculations to be made. When learning analytics are communicated to stakeholders and students, the results should be transparent (where possible) and clearly understood.

Institutional Responsibility and Obligation to Act

- It is important to reflect on if access to knowing and understanding more about how students learn in turn brings about a moral obligation to act. Due to scarce resources, it is not always possible to provide the interventions that may be necessary. However, it is important for the institution to consider its policy for identifying where support resources are focused.

Communications

- Care should be taken when communicating directly with students on the basis of their analytics. It is important that predictive analytics are truly predictions, and may be useful, it is also important to look for additional context. When communicating with students, it may be most effective to use general support terms (i.e., ‘we’re just checking in with you to see how your studies are going’).
- Regular communications with staff should be encouraged, in order to help ensure that the staff understand the values, anticipated benefits for students, as well as guidelines for ethical practice.

Cultural Values

- In multicultural contexts, understanding and interpreting data are more complex. It is important to remember that measures used are likely to differ in different cultures. Care should be taken if purchasing analytics from developers to make sure that the approach is accurate for its purpose and can be adapted if appropriate.

Inclusion

- With LA, there is a danger that certain categories of students will be identified negatively as being particularly at risk. There are ethical issues relating to inclusion and exclusion if the institution communicates a desire to protect its success rate. LA should be primarily used to support students.

Consent

- Consent to collect student data should be sought at the point of registration. However, consent at this point is less meaningful for students, who may not know how learning analytics can be used to help them. If consent is sought at registration, it should include transparency and potentially with a later option to withdraw consent.
- There have been conflicting responses and opinions regarding consent surrounding non-sensitive data. An alternative approach to considering consent in this way includes differentiating between initial consent for the collection of data and specific consent when data are used to intervene in the choices students have and in adapting their learning experiences.
- Other approaches include providing opportunities for students to provide or withdraw consent where an intervention might significantly alter their experience. Consent should not be considered in binary terms, but should be presented to students as a menu of options.
- Generally, this principle should be built around a minimum of informed consent.

Student agency and responsibility

- Where possible, it is recommended that institutions seek to engage students in applications of learning analytics. In this way, students should be treated as equal participants in the uses of their data. Students can be more actively involved in creating and designing the interventions that will support them.

Best Practice of Learning Analytics: Case Studies

In the global landscape, the USA can clearly be identified as a leader in research publications about LA, followed by Spain, the UK, Australia, Germany, Canada, India, the Netherlands, Japan, and China. Review studies have looked into the trends and perspectives of educational technology on a national level in five countries around the world (China, Germany, Japan, Italy, and the USA) as well as the efforts for data-driven improvement of education in seven European countries (Austria, Denmark, Finland, Germany, Norway, Spain, and Sweden). While some studies have investigated a nation-wide LA deployment, e.g., the USA, Australia, New Zealand, and the UK, the systematic adoption of LA in higher education is embryonic.

Learning Analytics in the US

The US has been noted as a leader in LA research and practice, with LA being driven at national policy level for a number of years. Federal LA structures aiming to enhance the use of LA in elementary and high schools have filtered through to state and district levels. It is difficult to capture a comprehensive picture of the extent to which LA has permeated US higher education, although anecdotal evidence suggests that the US for-profit sector has produced some of the most successful LA projects to date. Many of the major software packages and suppliers that cater for LA are US-based. These include Ellucian Course Signals, Civitas Learning and Blackboard Analytics. Companies such as these are very active in their home marketplace. Civitas Learning, for example, is used by over 70 institutions across the US.

A number of US HEIs have been at the forefront of LA developments internationally. These include Arizona State University, Curtin University, Georgia State University, Marist College, Michigan State University, Purdue University, University of Central Florida, the University of Maryland Baltimore County and the University of Tennessee. US higher education students also report positively on the use of LA at their institutions, with 87% of 2,657 surveyed students reporting that having access to analytics related to their academic performance can have a positive impact on their learning experience (McGraw-Hill Education, 2015).

1. Traffic Lights and Interventions: Signals at Purdue University

At Purdue University, Indiana, the institutional goal was to use business intelligence to increase student performance at the course level, thus increasing retention and graduation rates. The Signals system attempts to help students advance rapidly enough to seek help and improve their likelihood of grade or pursue a different path.

Signals mines SIS, VLE, and grade book details to create an indicator of the "traffic light" that indicates how each student is considered at risk. The teacher will then take a variety of interventions. The predictive algorithm is based on student success (points earned so far), effort (VLE interaction), previous academic background, and student attributes (e.g., age or credits attempted). These components are weighed and incorporated into the algorithm that produces the required traffic signal. Red suggests a high probability of ineffective yellow possible problems and green a high likelihood of success. Potential issues in the second week of the semester are reported. Teachers can therefore decide to interfere in different ways, for instance, by posting the signal on the student's home page, e-mailing, or arranging a meeting. Positive feedback is sent as a green light, which a positive message will be reinforced by the teacher.

An alert message will give negative feedback. Student performance, final-grade measurements, and behaviour, and VLE and aid search behaviour interactions have been evaluated with signals. Two semesters of data showed that in those courses using Signals, Cs and Ds were consistently higher than Ds and Fs. Meanwhile, students who received automatic interventions sought assistance faster and more often than those who did not.

Two years of results have been tracked and seemed encouraging. In biology, the pilot signals produced 12% more grades of B and C than among non-pilot students and 14% lower grades of D and F. There was also a 14% rise in students withdrawing early enough to avoid impacting their overall grade point (GPA) grades. When they realised their degree of risk, it also seemed that students appeared to alter their behaviour, thus enhancing their efficiency. Students in pilot groups requested support sooner and more often than not. And after the interventions ended, these students were 30% more likely than those in the control group to seek help.

Signals had a significant advantage in that students who used Signals used the subject support desks and extra tutoring sessions, mostly poorly attended. Signals were also shown to enhance contact between students and teachers. Meanwhile, teachers accepted that students appeared to display progress in commitment and thought about their tasks earlier by using cues.

The opinions of Learners on Signals were also sought. In five semesters, more than 1500 students were surveyed anonymously to collect feedback on their use of signals. Most felt that the automated notifications and alerts they received were a form of personal interaction with their teacher, which reduced the feeling of "just a number." They considered the messages and the lighting details beneficial and useful to alter their behaviour and wished for even more specific information about improving them.

2. Analysing the Use of the VLE at the University of Maryland

The University of Maryland, Baltimore County (UMBC) a public research university with 12,000 students has had rising VLE use but no evidence that it enhances learning. In an educational research project, the associations between VLE data and final grades were examined and how the predictions are best used to help students. It also examined possible approaches and how effective data-based teaching activities can be identified.

As a first move, students with C grades or higher used VLE 39% more than those with lower scoring. The Checks My Behavior (CMA) method was developed to help students equate their VLE activities in a course with a synthesis of the entire cohort. After a pilot, the tool was deployed across the institution with an advertisement campaign and a VLE gradebook link. In 1 year, 45,000 visits were made to the CMA tool page. In a cohort of new UMBC students, 92% used the VLE, while 91.5% used the CMA method. Those that used the tool were 1.92 times more likely than those who didn't use a C grade or higher. The students can pay attention to input from the CMA tool that a staff member cannot hear or acknowledge. The tool could also draw on "obsessive status-checking tendencies" of students to provide regular feedback which is not cost-effective if employees are involved. As a precaution, successful students prefer to embrace new tools in more significant measure than hard-working students.

A more thorough review of the VLE log files showed that one teacher had an exceptionally high student involvement level. He used the 'adaptive release' feature of Blackboard, so the students had to take questions about course material before accessing the assignments. Usually, students in the adaptive release sections were 20% higher than in other sections. They did better than those who had not used adaptive releases when those students went to their next course. Therefore, analytics revealed efficient learning design and a general conclusion: efficient implementation of a VLE tool in a pre-conditional course will lead to better results in this course and subsequent courses. It was also proposed that specific VLE operation types may promote better participation, which in turn contributes to better levels.

Future improvements have been proposed, in particular, a consent mechanism for resolving privacy issues by adding two checkboxes to the tool: ‘It’s ok to track my usage of this site’ and ‘It’s ok to follow up with me for an informational interview.’ Additional scheduled changes provide an analysis of the frequency and length of VLE use as opposed to other devices and warnings sent to individuals when their VLE operation falls below the target level (model from the rest of the cohort). It also aims to provide the students with a facility to exchange information with staff and encourage them to intervene when their VLE behaviour falls below a certain amount.

3. Identifying at-risk Students at the New York Institute of Technology

New York Institute of Technology (NYIT) is a private university with 13,000 students in the United States and abroad. By creating their predictive model, NYIT has been able to classify at- risk students with a high level of precision in partnership with counselling staff. In the first year of their research, the goal was to improve students’ retention by developing a model for recognizing the most in need of support individuals and providing information on each student’s condition to assist support counsellors in their work. The process included collecting data, the analytical process, and the output processing in a beneficial format for the counselling staff. There are two explanations for this approach: however accurate the predictive model could be if the counselling staff were not willing and able to integrate it into their daily work, and without time-consuming manual intervention, the model had to work quickly and automatically.

The problem definition came from the users: the student support consultants. An external supplier of IT solutions worked with NYIT personnel to define, deploy, and analyse the required data. The design process was an iterative loop, with NYIT consultants at every point involved. The model was designed within the NYIT so that the database, forecast model, and front end of the consultants were all on the same platform.

The model used four data sources: admission application data, registration/placement test data, all students’ surveys, and financial data. The latter was included because the rate of completion was known to affect the student. The model has been educated on a variety of records of previous students in NYIT. A total of 372 variants of four mathematical approaches were compared to see which modelling of the risk best depends on the other characteristics (coming grades, finance, etc.).

The models have been tested for precision and recall to assess the match between student conduct. The model’s best edition had a recall of 74% and a precision of 55%. This is very strong compared with a similar model, independently developed at Western Kentucky University (WKU). The WKU model was based on pre- registration data only. Therefore, the increased recall of the NYIT model is considered because of the inclusion of financial and student survey data and the type of model used. It means that three of those students were correctly projected to be at risk for every four students not returning to study in the following year. The results were displayed on a dashboard with and for student support staff. A simple table showing whether they are to return to study the following year, the percentage trust in that model prediction, and, most importantly, the reasons for the prediction, is a simple one-line for each student. The counsellor then has the basis to discuss his condition and future plans with each student.

4. A Fine-Grained Analysis of Student Data at California State University

The PhD project of John Whitmer has observed student behaviour at California State University, Chico. This is a medium-sized campus in the northwest of the state with a full-time population of 14,640 students. Whitmer studied the entire community of 377 students on a new course designed to view a much more profound use of learning technologies. His study sought to tackle factors contributing to student achievement more extensively than the more complex approaches taken by some other researchers. He assumed that most of the VLE data in current LA programs had been overlooked, and there was no reason for the inclusion of certain variables and not others. He divided VLE interventions into broader categories, e.g., listed posting as an interaction practice for a debate. He also considered nine traditional student variables, including sex, whether in a minority racial/ethnic group, revenues, high school grades, and whether the student was the first in a family to study.

Whitmer points out that earlier studies have consistently shown a much more significant association between student characteristics and student performance than single demographic variables. If the student's race, income, and gender are used, predictions should be much stronger than using one of these variables. Seven of the nine student variables were statistically important. VLE use, however, was a better indicator of student progress than commonly used demographic and registration data to classify students at risk. It has also been found that the use of individual VLE resources varies widely between students but is less widely used within the specified categories, i.e. administration, evaluation, content, and involvement. Whitmer therefore advises that predictive analytics should not be carried out at the level of individual instruments.

Total Hits is the most important indicator of student performance and Assessment Activity Hits are near seconds. Whitmer points out in his results that total VLE hits are an excellent starting point for predictive modelling and early warning systems. All of the above variables except Total Hits have been used to perform a multivariate regression. It was found that 25% of the final grade variance was clarified. Another 10% applied the predictive relation to the degree to all the student characteristic variables in the study.

Overall, Whitmer concluded that the use of VLE is connected with student achievement. What his research does, however, is to measure the difference between the different types of VLE use and thus allow teachers to track their students' efforts and to have risky students flagged them. He found that more than four times the VLE variables were as closely correlated with achievement as demographic variables. The use of VLE is a proxy for student effort and therefore a good indicator of the last degree. It indicates that students do more than their histories or past performance on a course. A further finding was that use of VLE is less successful for risk students: the impact of VLE use by risky students (based on minority status and income), relative to non-risk students, has dropped by 25%.

5. Transferring Predictive Models to Other Institutions from Marist College

The Marist College (New York State Liberal Arts Institution) led the Open Academic Analytics Initiative (OAAI), which developed an open-source early warning solution for higher education. The predictive model was moved to multiple institutions effectively and intervention methods were tested to support at-risk students. The technologies are now being used as part of JISC's LA architecture in UK universities. The first predictive models were based on Marist College results. Based on the Purdue approach, data sources included demographic information such as gender and age, aptitude information, such as high school scores, and different aspects of VLE use. The models were used in two community colleges and two state universities with a significant number of low-retention ethnic minors to research the models' portability and the efficacy of interventions with risky students.

Researchers found that the three most critical indicators to predict student progress were scores, the grade point average as well as the current academic status. The model was trained using Marist College data and was distributed to partner colleges and universities. It has been found to be transferring well, with about 75% of at-risk students in three of the four institutions. The researchers predicted a much greater disparity between institutions and Marist because of the disparity between student cohorts, type of institution and teaching practices. They believe that it was their first project to recognize partial contributions to students' final grade, as entered in the VLE Gradebook method, as the primary indicator to assess students at risk. This encourages teachers to take action much earlier than before in the semester.

Students who were then exposed to one of two separate intervening techniques were officially considered to be at risk. The first group got a message saying they are in danger of not finishing the course and giving advice on how to boost their chances. The second was targeted at the online support community with open educational tools in fields like studying skills, time management, stress reduction, algebra, statistics, writing, and research. Colleagues and support staff also provided opportunities. Both interventions included structured text, which with each message becomes more serious.

In 2012, two separate cohorts, 1739 and 696, were split into three groups: Students who received a call, those targeted at the support environment and a control group that did not receive interventions. There were no variations between the two treatment groups overall, but the final level increased by 6% for those who were exposed to control intervention in one course. Another result was that in the intervention community the withdrawal rates were higher than among control subjects. Students who choose to leave early rather than risk later should clarify the differences. The Marist researchers conclude that the predictive model enables students to have earlier input on their progress and resolve problems in advance. They also note that some students seem "immune" to interventions. They found that very few students who did not respond to the first treatment improved after the second or third intervention.

Learning Analytics in Australia

In 2013, the Australian Government commissioned a report focused on enabling its higher education sector to take full advantage of the potential of LA. A subsequent 2016 report providing an overview of LA practices in Australia included interviews with senior managers from 32 Australian universities and, although none described instances of full, strategic implementation at institution level, approximately half reported having implemented an LA programme at their institution. The surveyed universities included 17 that utilised LA primarily to support retention activities and 15 that supplemented their retention activities with resources and supports aimed at enhancing teaching and learning more broadly. The way in which LA was understood or approached at a given institution was shown to be affected by dimensions such as leadership, strategy, readiness, conceptualisation and technology. The rapid development of the LA culture in Australian higher education is evidenced by national-level investment in LA projects, such as Loop, an open source analytics tool being piloted across three Australian universities with a view to wider expansion.

1. **Enhancing Retention at Edith Cowan University**

In Perth, Western Australia, Edith Cowan University (ECU) has a diverse community of students, primarily from non-traditional backgrounds. The strategic priorities are maintaining strong teaching quality records and helping students improve retention through Connect for Success (C4S), an institution-wide predictive LA initiative. The C4S technology automatically detects students who may need assistance. The organisational structure allows support personnel to contact a wide range of students and perform many interventions for each. Governance, control systems, organisation, coordination and risk management involved a staggered program over 2–3 years. This offered time for technology advancement and a framework for changing management in order to help staff and create new positions in the student-facing teams.

The University has invested heavily to determine which student variables are better suited to predicting attrition. Although the research review identified some common factors (including grades, university entrance scores and linguistic skills) in students' attrition in other institutions, students' departure or absence are different and the factors that depend on one another. Therefore, ECU agreed that the compilation and review of institutional data were necessary to classify the students most likely to need help accurately. For the first three semesters of an ECU student's period, statistical models were developed based on more than 200 student variables. The models used ECU SIS data, including details on population and development, divided into undergraduate and postgraduate courses. Six models have been developed in total to predict retention. As a consequence, for every new and continuing student registered in an undergraduate course, ECU has a probability ranking.

In a regular report, the predictive model recognizes students who may need assistance. This is checked by two staff who make sure no student is approached twice or too often. Personalised emails are then sent to the students who provide support. If students do not answer the initial email, a similar message is contacted by telephone. A dashboard helps support staff to record and track each student's contacts and support. They may develop an action plan that agrees with the student which could include appointments or interventions to specialist support services.

Critical success factors included: training and professional support staff, collaborations with institutional stakeholders, awareness of consistent responsibilities and boundaries with other ECU facilities, workflow processes on a regular basis and good support from the management. The challenges included: data integrity (manual selection in the early stages, understanding of it was an issue), re-sourcing at peak periods (for example, during orientation), systemic integration of information systems and 'student suspicions.'

Roughly 700 students were approached via e-mail and/or telephone and were offered the chance to opt for an initiative to support their studies. The institution estimates 20% of students opted in to meet the take-up rates for similar programs at other universities.

2. Early Alert at the University of New England

There are about 18,000 students at the University of New England, New South Wales, Australia with a high number of part-time and external or mixed-graduates. The socio-economic status of 20% of students is poor. The key driver was the need to recognize students who struggled so that they could get help promptly. In the past students who were at-risk appeared to be found after they had not submitted the assignment or attended a class. Many students who were off-campus were also difficult to observe. The goal was to establish a "dynamic, systematic and automated mechanism to achieve the learning well-being of every student". Three strands were there:

e-motion: Each student has a collection of emoticons and a text box on their website. They may choose to record how you feel every day (happy, neutral, unhappy, very unhappy) connected with their current module. The Student Support Team contacts all students with a negative emotion within 24 hours. 17–20% of students who record “unhappy” or “very unhappy” are the team’s case. Thirty three percent of these require several contacts.

The Vibe: Students’ statements are added into a word cloud, which is updated every 10 minutes, in the text box alongside the emoticons, so the entire student cohort can see what their peers are thinking. This word cloud serves as a barometer for students’ welfare and normalises student experience, since the larger the word, the higher the number of students. The text entries on each student’s portal page also give the support team a regular update on student problems and concerns.

The Automatic Wellness Engine (AWE): Every night, analyses data from seven systems and runs a model based on 34 triggers which indicate risky behaviour. These metrics are based on actions, not demographics. The data sources include e-motion student entries, class attendance, previous study history, previous results, career applications and online student portal access trends, and other University websites. Also included are previous AWE ratings. Time series and trend analysis are used to determine the intervention ranking. The AWE can still run the model, even when a student doesn’t provide direct feedback through e-motion. The student support staff dashboard is updated every morning to determine increasing students need support. An automated email, accompanied by phone calls and additional support, is used in the first instance.

Initial AWE trials lowered the attrition from 18% to 12%. Qualitative feedback from students shows that Early Warning has effectively strengthened students’ sense of community and increased the incentive to share their study expertise. Students’ feedback was “overwhelmingly optimistic,” suggesting they appreciate constructive support. Other aspects of the method are effective when automatic input on the cohort motivates students instead of the personnel’s direct interference. Another essential aspect of Early Warning is the importance of LA in a broader social media strategy. Multiple channels establish a sense of community and the support staff’s participation as a routine (not only in times of crisis). The staff use Facebook, Instagram and a blog to connect daily with students and interfere with the AWE if needed. Students are more open to the process because they know the staff by name.

3. Analysing Social Networks at the University of Wollongong

The University of Wollongong, New South Wales, Australia is a public university with more than 30,000 students. The central premise of the Social Networks Adapting Pedagogical Practice (SNAPP) initiative is that collaborative learning is necessary to foster students’ comprehension. SNAPP analyses interactions in on-line forums to display trends and relationships as social network diagrams in real time.

The teacher usually moderates these forums while students deal with specific learning tasks or have general discussions about the topic or administrative issues. The timing and consistency of the lecturer’s interventions will significantly affect the learning experience of the student. There are hundreds of participants in some of these forums which makes it difficult for a teacher to control the action.

Teachers can track relationship evolution by comparing diagrams over time. The software SNAPP is used as a diagnostic method to help instructors identify students who are separated from the main discussion or to understand how the overall trend progresses. Instructor visualisation may also be used to focus on learning design and even redefine the role for a potential cohort.

While primarily intended to encourage interaction in real-time, teachers mostly used SNAPP after completion of their courses for reflection. This was useful for professional growth, as network patterns imply different moderation modes, e.g. if a teacher responds to individual students and does not promote broader debate. SNAPP was felt to be helpful in real-time in identifying isolated students, especially in broad forums during busy times. Some teachers showed their student groups SNAPP network diagrams as part of a discussion of how to contribute to an online platform.

SNAPP was suggested to be marketed as a reflective teaching tool and to highlight the value of learning design in professional development. It was felt that there was a need to increase understanding of common patterns of interaction among staff and to understand how, as a facilitator, one can participate in a conversation that shows unwanted patterns of social interaction. The SNAPP project showed a clear correlation between students' learning orientations and the platforms they often use. For example, people with a strong emphasis on learning preferred learning discussions and resource sharing. Students with a success orientation focused on the discussion of administrative and appraisal forums. SNAPP software is a web browser extension that collects data from the selected forum automatically and shows the relationships as social networking maps. SNAPP targets student engagement data as a commitment measure and develops a visualisation framework that operates through many third parties' platforms and variants. This approach can be used to add other features to a VLE.

4. Learning Analytics Practice at the Flinders University

The Learning Analytics Community of Practice (LA CoP) has played an important role since its creation in bringing together key university people with an interest in the area. Since the Flinders University has declared LA as a key strategic direction and is beginning to invest more in the field, the LA CoP is expected to continue to play a significant continuous role in shaping future LA developments at Flinders.

Application of learning analytics in a flipped classroom. Since the unit started in 2008, live lectures have been given to a gradually diminishing audience each week. In 2016, the teaching team agreed to revamp the subject to increase overall student participation and give students an opportunity to discuss classroom challenges while teachers were present. Therefore, the standard lectures were replaced by a "flipped class." The LMS teaching team assessed the LMS students through the study of LA and the contrast with final topic grades. As anticipated, unit grade increases were seen with increased video access. Student involvement was also assessed by the frequency of physical attendance and an increase in last grade was also observed in contrast with the final subject grades as physical attendance improved. Unfortunately, however, in final subject ratings or test scores, no overall improvement was seen compared to the previous year following completion of the flipped classroom.

Learning Analytics for a First-Year Psychology Research Methods Topic. In this unit, the professor carefully structures formational tests and recognizes concepts in which students seem to struggle by the use of LA. A study workshop will be held at the end of each semester to study these areas and propose new revisions and procedures to explicitly resolve these problems. Also, with the method changing from year to year, the instructor was able to use various methods to teach the identified problem areas and then use LA to compare the relative benefit of these various approaches.

5. Learning Analytics Practice at Murdoch University

Murdoch University has built and implemented LA at a relatively early level. The key focus to date was investigating students' attrition, but a Student Analytics Committee was created to investigate more widely in the field of LA. So far, it has established and instigated many projects involving the use of existing LMS instruments and functions. It also establishes a long-term strategy on LA within the educational technology context that includes the steps taken by other universities and the evolving LA innovations in the landscape of education technology. Aspects of this long-term strategy should be:

- push the use of established resources in LA and related 'know- how' inside schools ('quick wins');
- provide the necessary information and perspectives on the function of the broader Student Analytics and Student Success Initiative;
- investigate and/or contribute to the development of LMS and related educational technology capabilities for LA. LA in a Multi-mode IT Unit. This unit is available at campuses, off campuses (external/distance/online), and international campuses in Singapore and Dubai. It was planned to be available in mixed mode from the ground up. Students have preparatory materials that include readings, lectures for all students, a short video series, and a pre-workshop quiz. On-campus students and international campus students will be given workshops consisting of a computer laboratory session followed by a group discussion/tutorial session. Off-campus students engage in the same computer lab session and in an online discussion forum. Students then have to complete post-workshop tasks. Due to the diversity of modes of distribution, it was determined that it would be necessary to understand items and events to research when used (in the timeline of the offering of the unit) and what forms were more used (e.g., videos, online quizzes).

6. Learning Analytics Practice at Charles Darwin University

Institutional Development. The Charles Darwin University is a dual sector institution that utilises the power of education technology to provide students across the Northern Territory and beyond with and sustain learning opportunities. The combination of the education technology suite with a large external cohort of students means that a large part of teaching is digitally recorded in the systems. This is a good example of how LA are used for a range of reasons, including improved learning and education and retention.

Charles Darwin University has done extensive work in the creation and implementation of LA in the organisation. The main focus of the work was on LMS and SIS data integration. The two programs provide a significant part of the knowledge about learning and teaching and the types of questions that teaching staff want to answer. The result was that a wide range of reports was adapted, both for vocational education and training and teachers of higher education and several classes, faculty and university reports, which could be used for several different purposes.

Tertiary Enabling Program. Given the high attrition rate in the TEP and the supporting programs across Australia, this project aims to identify possible factors contributing to attrition rates and key periods when attrition-occur. The aim is to use this information to help students if they need it to complete their program successfully.

This project builds on research on the relationship between LMS access frequencies and timelines and academic success to recognize crucial time points. This offers valuable information to enable teachers to intervene efficiently and to serve students better. This information is also applied to ongoing program assessments and is used to advise ongoing curriculum development and teaching practice. Although work began in one TEP unit, this project has been extended into other units in the program.

Use analytics for grade boundary decision-making. This case study discusses the use of LA to support students during the semester and inform and promote academic decisions on degree levels while a student is on a grade level. This nursing unit, entirely external through LMS, has a consistent sequential frame- work including weekly self-assessment quizzes and adaptive releases, ensuring that several data points can be readily viewed as historical student progress and performance record. To provide early warning emails to students and guide students at information sources of assistance to help them get on track (or help them to cope with life-related issues), the success dashboard (showing the various types of user activities) and the retention centre are used to locate students who are deemed to be at risk based on a set of configurable guidelines. A combination of the Student Snapshot report, the grade centre's download, and early progress warnings are uncommon and effective in promoting transparent and reasonable decision-making.

7. Personalised pathway planning at Open Universities Australia

Open Universities Australia (OUA) is a distance education consortium owned by seven Australian universities. Study materials are entirely or partly online, or with a mix of print, CD and DVD. Qualifications are offered as modular courses. Students can choose how many units they study at the same time but planning a route through the modules necessary for a qualification can be difficult. Personalised Adaptive Study Success (PASS) enables personalisation of the study experience for each student, especially in terms of their path through the curriculum. It aims to support struggling students by suggesting alternative modules, more appropriate to their needs, as well as offering support. Students at risk are also identified.

In a traditional linear path through the curriculum, poor performance on one module impacts upon student outcomes for subsequent modules, and a struggling student may not have an opportunity to catch up with the rest of the cohort. In contrast, PASS supports a personalised and adaptive learning path. A student with a weakness in a particular topic can study extra modules to strengthen that area before re-taking the original module. PASS can recommend an alternative study path at any point where the student is deemed to require help.

PASS draws upon data from a wide range of sources, including customer relationship management systems at OUA and partner universities, the learning management system and the curriculum profiles for each unit and program. In essence, the analysis is based upon three profiles: the student profile (location, socio-demographic factors, prior knowledge etc.), the learning profile (use of online content, assessment, online forums etc.) and the curriculum profile (requirements of the module and program, alternative paths etc.) A combination of statistical and qualitative data is analysed by the LA engine, which feeds into the reporting engine and into the personalisation and adaptation engine (producing recommendations and other feedback for students and tutors). This is intended to enable intervention at the micro, meso and macro level, for example, suggesting an extra mathematics module to a student or providing evidence for redesigning a section of the curriculum.

PASS uses the output from a LA engine to inform a personalisation and adaptation engine, and a reporting engine. The personalisation and adaptation engine feeds recommendations for content and activities to the student dashboard in the online learning environment. Dashboards are provided for students, facilitators and instructional designers. These can be customised by adding and moving tiles with different functions, such as summaries, recommendations and alerts.

One of the conclusions of the project is that the preparation of stakeholders for applying insights from LA in meaningful ways is vital. A major challenge for this project was the interaction and fragmentation of information as well as its contextual idiosyncrasies. The models combined numerical and qualitative data to build a more rounded picture of the learner's situation. In particular, semantically rich data from discussion forums and responses to open- ended assessments, for example, enable a better understanding of learners' knowledge and needs.

Learning Analytics in Europe

A study by the EU Joint Research Commission (JRC) identified the Netherlands, Denmark and Norway in 2016 as being among the more advanced European countries with regard to the development of national approaches and the establishment of an LA infrastructure.

1. Developing an 'Analytics Mind-Set' at the Open University

Open University, UK, has more than 200,000 students studying part-time degree, postgraduate and sub-degree qualifications. It invests extensively in a strategic LA program to improve student achievement through the incorporation of evidence-based decision-making on all levels. Due to funding changes, the retention of qualifications is now a strategic challenge for the institution; retention of students is particularly demanding if they are locally distributed, are part-time students, and generally have several years to graduate.

In ten main fields, the University strengthens its institutional capacity to improve the foundations for the productive use of LA. These are grouped into three main strands: data availability, research and insight development, and processes that influence the performance of the student. At the macro level, incorporating details on the student learning experience offers strategic goals to consistently improve student experience, retention and development. At the micro-level, analytics are used in student, module and certification levels to perform short, medium and long-term interventions. One of the goals is to establish an 'analytical mindset' around the university such that staff integrate evidence-based decision making into their regular activities.

Understanding the effects of initiatives is an essential objective. There are a wide number of interventions within the University. Earlier, it was difficult to decide how a single action influenced students' performance and so a more cohesive image was created with the LA approach. Data from SIS, VLE and other platforms is collected. Many dashboards, reports and software are being created for a variety of users, including senior management, school support staff, academics and students, to access analytical outputs easily. For example, the dashboard support staff helps staff to handle a standardised intervention program. A student dashboard helps students to track the progress of their study paths and make informed choices. Predictive analysis is being developed to model students' development at the individual and institutional module levels and based on previous cohorts in similar modules.

At the curriculum stage, faculty use analytics to inform the design changes and evaluation of the learning modules. Analytics may also recognize effective learning designs that enable best practice to be shared. LA was seen by the University as an ethical method, with an emphasis on the student as an active participant. The Policy for the Ethical use of Student Data for LA' goes beyond legal requirements. This approach also acknowledges that, however good the models, a student is more than a data collection, and that elements of student experience will still be beyond the area of LA. Key factors influencing student performance are now adequately well known to guide strategic planning priorities.

The British Open University's Institute of Educational Technology (IET) has a world-leading research program on Learning Analytics and Learning Design that aims to advance the way teachers design blended and online courses to enhance student behaviour and success. The program investigates, develops, and establishes new ways that students can improve their engagement, satisfaction, and success within learning. It collaborates with educators across the globe to implement learning techniques that have been grounded by teachers and distance learning module designers of The Open University. Technological developments have allowed for teachers and researchers to capture and understand the digital traces of learning activities in Virtual Learning Environments (VLEs). The capability to capture rich data about learner behaviour enhances the insight that educators have into how their students react to different learning designs. The IET's recent research has explored the impacts that different learning designs have on learners and teachers, how different learning designs can support the learner journey to create a balanced workload, and how to provide effective support for diverse groups of learners

2. Predictive Analytics at Nottingham Trent University

Nottingham Trent University (NTU) has launched an institution-wide dashboard to improve its 28,000 students' academic experience by fostering dialogue between students and staff, one of the most influential LA projects in the UK. The main goals were: enhancing retention, growing the sense of belonging to a community and improving attainment.

Previous institutional research has shown that somewhere in the first year up to a third of the students have considered leaving at some point during their first year. These doubters were less confident, less engaged, developed poorer ties with col- leagues and tutors, and were more likely to retreat early in the final analysis. Instead of "doubters," who most wanted it, students who asked for guidance were helped by tutors but did not ask. There are four main dashboard features designed to accomplish these goals. Students and staff can see exactly the same details, the dashboard sends an email warning when student involvement ends for 2 weeks, the dashboard enables students to write down accepted activities when they interact with students. The tool itself is simple to use with a low effect on academic time for training and use.

Demographic data have not been used in the model intentionally because a student can only alter their actions and not their context, and there is the dashboard to inspire students. One in five commitment ratings is issued to each student: High, Good, Partial, Low and Not Fully Enrolled. The dashboard helps students verify their participation and tutors to address the students' success with them. Two graphs showing progress that indicates engagement, contrasts individual students with the rest of the cohort and indicates the student's engagement level. In order to obtain a deeper understanding of the recent commitment, the tutor should train down to the stage below the grade.

The pilot showed that a greater effort was positively connected to success and achievement in four courses. Examining a much wider dataset for students of the first year found that a student's dedication was much more important than data such as history or entry qualifications. In the final year, there has been a strong correlation between the commitment and the final qualification: 81% of students have a high average degree with an honours degree of 2:1 or the highest award, while only 42% of students have a low average degree.

In a first-year student survey, 27% said their behaviour had changed in response to dashboard results. Some students have done more academic tasks, for example, independent study, but these are not calculated in the dashboard. Others fought for the highest ranking. However, there is a risk of partiality here because the dashboard will help students express and express themselves. In the coming years, NTU will discuss these concerns in far more depth.

Another effect is that tutors adjust the way they interact with students due to analytics. They conclude that enhanced knowledge on individuals enables them to more accurately tailor their interventions. Most tutors in the first pilot once a week used the dashboard with a marginal effect on their workload; one third of the tutors contacted students because of their engagement details.

Conclusion

The official formation of the field of Learning Analytics is related to the organisation of the *First International Conference on Learning Analytics and Knowledge* (LAK) in Banff, Alberta, Canada in 2011. The LAK conference was established as a response to the increased amount of data that surpassed the ability of organisations to make sense of it. Since 2011, LA has received much attention from educational researchers, practitioners, and administrators, resulting in numerous conferences, workshops, journals, books and journal articles, PhD studies, professorships and organisations dedicated to LA. The emerging field of LA is at the intersection of numerous academic disciplines, and therefore draws on a diversity of methodologies, theories and underpinning scientific assumptions.

The USA has been identified as the leading research hub based on publication outputs followed by Spain, the United Kingdom, Australia, Germany, Canada, India, the Netherlands, Japan, and China. Although the level of adoption of LA at the institutional level is still low, many higher education institutions (HEIs) are either in the preparation phase of implementing LA or in the process of piloting LA solutions to be adopted by the whole institution later on. Adoption of LA is mostly found to be small in scale and isolated at the instructor level. Few institutions have a dedicated strategy, policy or evaluation framework for LA. Several HEIs such as Purdue University in Indiana, Austin Peay State College, and University of Michigan's Rio Salado Community College in the United Sates, and the University of Wollongong in Australia have implemented significant LA initiatives. The forerunners in Europe are Nottingham Trent, Dublin City and The Open University. The European Commission, Australian and UK governments have funded a number of LA projects. However, overall adoption is still low.

There are many objectives for LA initiatives. Some can help students acquire self-directed learning behaviours and attributes, provide feedback to students about their learning activities, progress and performance in order to support the development of self-regulation skills. It promises to provide insights helpful for enhancing teaching practice, learning decisions, and educational management. To successfully introduce LA initiatives, providers need policies aligned with organisational strategic goals and objectives, the necessary infrastructure, skilled staff and an appropriate organisational culture including leadership support. The major barriers and challenges to LA are an unsupportive organisational culture, a lack of leadership support, a lack of staff and insufficient time to undertake the necessary work, and staff resistance. In addition, many of the available tools are immature and not sufficiently user friendly and implementing LA can also be expensive because of staff training costs, support costs, and system costs. Not addressing the voice of the students and teachers in the design process of LA solutions, could be one of the major implications in successful implementation of LA in the institutional and instructional practice. Issues that might potentially undermine the progress of LA include unclear goals for LA, unequal data literacy among academics, lack of actionable data and concerns of ethics and privacy.

Over the years, several frameworks, models and approaches have been proposed to assist LA adoption at an institutional or instructor level. The most commonly used LA tools are learning analytics dashboards, which visually represent indicators of student progress and academic performance. The main type of LA systems are early alert or warning ones that provide personalised and timely interventions for struggling or underperforming students. Some of the common methods used are data visualisation techniques, social network analysis, semantic and educational data mining including prediction, classification, clustering, regression, text mining, association rule mining, process and sequencing mining, relationship mining, structure discovery and discovery with models, gamification and separation/distillation of data for human judgement and outlier detection.

There is a rich variety of indicators being used to build current LADs. However, there is comparatively little work on comparing which indicators (and which visualisations) are most suitable for the different user data literacy levels. In terms of evaluation, many of the papers are still exploratory, but this area is slowly veering towards more evaluations in real courses and other authentic settings. There is a general acknowledgement of the importance of authentic data to make a meaningful dashboard proposal. Very few studies look directly into student learning gains or learning-related constructs. Although the very nature of dashboards and how they are used (normally designed either to support the teaching process or to facilitate reflection and motivation) makes it difficult to isolate the impact of dashboards on learning, this is a limitation of most existing studies that should be addressed in the future.

There is still little evidence that shows improvements in students’ learning outcomes, learning support and teaching, wide deployment and ethical use. Despite the fact that the identified potential for improving learner practice is high, we cannot currently see much transfer of the suggested potential into higher educational practice over the years. However, the analysis of the existing evidence for LA indicates that there is a shift towards a deeper understanding of students’ learning experiences for the last few years. LA has been a developing research field for a decade, yet evidence of impact remains scarce; LA research has failed to fully deliver on its promise to impact education and educational institutions. The weaknesses of the research include lack of geographical spread, gaps in knowledge (e.g., in terms of informal learning and a lack of negative evidence), little evaluation of commercially available tools, and little attention to ethics.

Learning analytics have informed learning design and collaborative course development by providing insights into how students react to different learning designs. With the development of learning technology, learning analytics has been used to analyse data about learners to improve learning performance and inform learning design. A collaborative learning analysis framework can be developed to illuminate how to analyse collaborative learning. The proposed framework can include six elements: analysis of cognitions, metacognitions, behaviours, emotions, social network relationships, and alignment. The analysis of alignment focuses on the alignment between collaborative learning design and enactment. The purpose of alignment analysis is to analyse the deficiency of collaborative learning design, advance technological knowledge about design, and improve learning performance. By analysing data generated during online collaborative learning, such as log frequency, discussion transcripts, and group products, educators can gain insights into how online collaborative learning occurs and evolves over time.

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Glossary

Big Data	A huge amount of structured or unstructured data, gathered from a wide variety of sources, often interpreted through data analytics/data mining.
Data Abuse	Misuse of data.
Data Analytics	The process of examining large data sets to uncover hidden patterns, unknown correlations, trends, customer preferences and other useful insights.
Data Mining	Finding meaningful patterns and deriving insights in large sets of data using sophisticated pattern recognition techniques. To derive meaningful patterns, data miners use statistics, machine learning algorithms and artificial intelligence.
Dataset	A collection of data, very often in tabular form.
Learning Analytics	the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs. It covers a range of methods that includes machine learning, dashboard design, social network analysis, writing analytics, and natural language processing.
Learning Analytics Dashboard	A collection of widgets that provide the user with an overview of the reports and metrics needed to achieve one or more objectives. In learning analytics, they're primarily intended for faculty, administrators, and other professionals, but students can also benefit from specific dashboards.
Machine Learning	The science of getting computers to learn and act like humans do, and improve their learning over time in autonomous fashion, by feeding them data and information in the form of observations and real-world interaction.12 Predictive analytics is an example of machine learning application in education.
Metadata	A set of data that describes other data, providing a structured reference that helps to sort and identify attributes of the information it describes.
Virtual Learning Environment	A collection of integrated tools enabling the management of online learning, providing a delivery mechanism, student tracking, assessment, and access to resources. It is also sometimes referred to as a learning management system (LMS).
Visualisation	A visual abstraction of data designed for the purpose of deriving meaning or communicating information more effectively. Visuals created are usually complex, but understandable in order to convey the message of data.