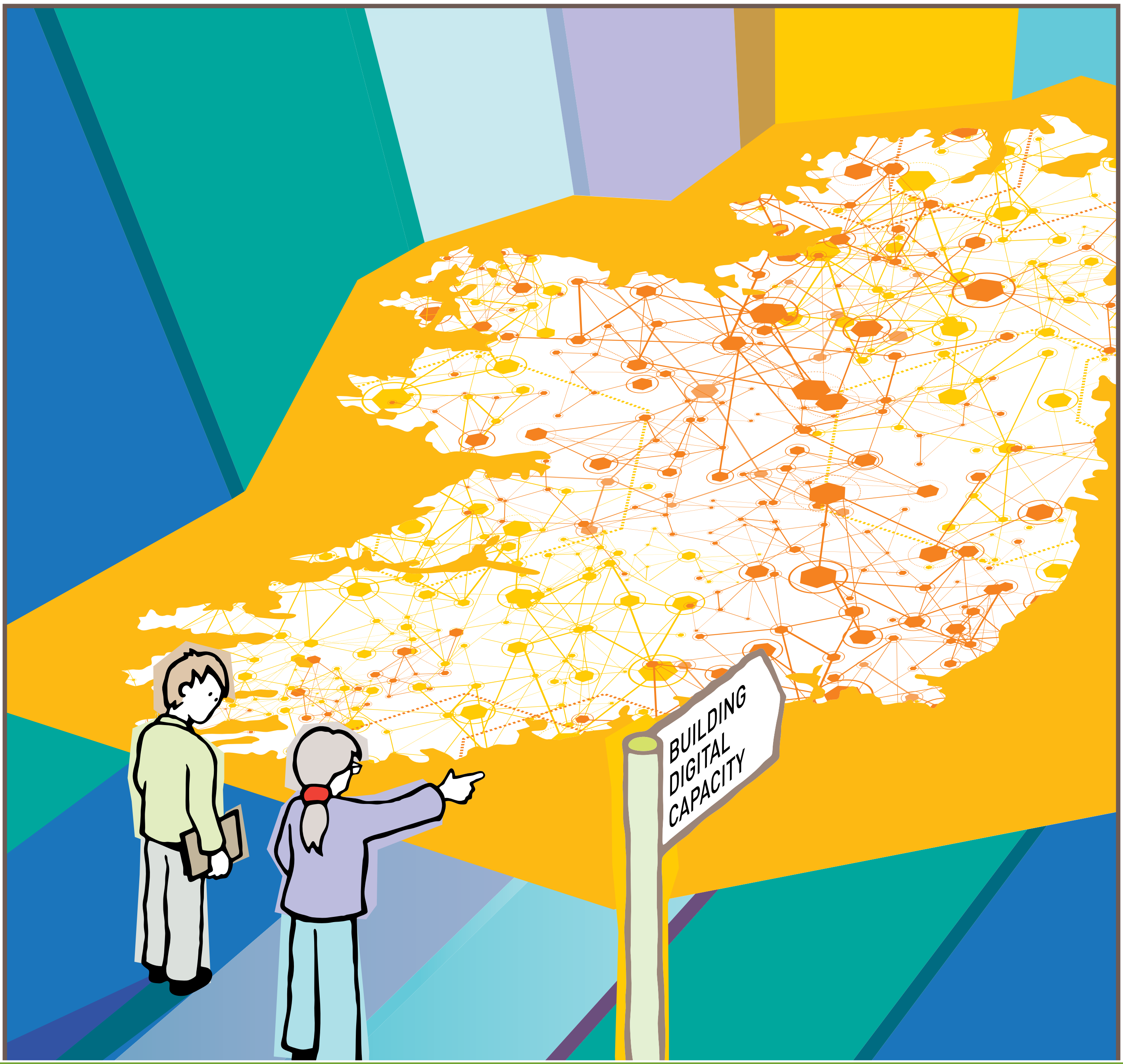

PRE-SPECIFIED NATIONALLY CO-ORDINATED PROJECT

USING LEARNING ANALYTICS TO SUPPORT THE ENHANCEMENT OF TEACHING AND LEARNING IN HIGHER EDUCATION

T&L NATIONAL FORUM
FOR THE ENHANCEMENT OF TEACHING
AND LEARNING IN HIGHER EDUCATION

Using Learning Analytics to Support the Enhancement of Teaching and Learning in Higher Education

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Preface and Key Messages

Lecturers in higher education have effected considerable advances in pedagogy in the years since the establishment of the National Forum for the Enhancement of Teaching and Learning in Higher Education. This progress has been realised by a growing community of academics working cooperatively from across the Irish higher education sector. The advances are positively impacting both the student experience and Ireland's commendable reputation and place in the vanguard of educational advance.

This current study focuses on how academic management and lecturers can better employ and mine the considerable volume of data that resides in the system. In this it is a facilitating piece of work that also provides a context for the further consideration of learning analytics. It is a fruit of a recent National Forum project, Learning Analytics and Educational Data Mining for Learning Impact, which was strongly supported from across the higher education sector. The involvement from more than twenty higher education institutions in this project attests the breadth of interest and engagement in this subject. It foregrounds the potential of learning analytics and in so doing offers assistance to higher education institutions that are fostering capacity in this area. This work is complemented by three National Forum Insights that look at the benefits for academic mangers, staff, and students that can be gleaned from learning analytics.

Learning analytics can reveal much about the progress of learners and the suitability of the contexts in which learning takes place. Employed intelligently, it can supply predictive models that can inform pedagogical approaches; it can inform earlier and more focused student interventions; and it can act as an evidence base for quality assurance and enhancement. This study provides an insight into current developments both nationally and internationally. The report also faces up to the concerns and limitations associated with learning analytics. Existing experience within Ireland is recognised and the perceived barriers to greater usage of learning analytics are explored.

One practical consequence has been the establishment of the Online Resource for Learning Analytics (ORLA), an open-access online library which offers guides and resources for institutions who wish to be informed by good practice in designing and implementing a learning analytics strategy. A second outcome has been the collaborative initiative to create the Data-Enabled Student Success Initiative (DESSI). This affords a coordinated approach to future learning analytics development through the adoption of four key principles.

From its inception, this has been a collaborative and inclusive piece of work. From the scoping exercise chaired by Jim Devine to the project leadership provided by Lee O'Farrell, this national initiative has benefitted from wise guidance and wide engagement.

On behalf of the chair and colleagues on the board of the National Forum, I compliment the executive and the many committed and generous colleagues throughout the sector who have contributed to this paper and I commend their work to you.

Dr Joseph Ryan

On behalf of the Board of Directors of the National Forum for the Enhancement of Teaching and Learning in Higher Education

Glossary

Academic analytics	The use of organisational data from academic institutions to enable reporting and decision-making.
Big data	Very large, complex data sets, often interpreted through data analytics/data mining.
Dashboard	An interface that presents information from multiple sources in a visual and user-friendly way.
Data analytics	The use of data for decision-making.
Data mining	An approach to data analysis whereby raw data is trawled to identify previously unidentified relationships and/or patterns.
Learning analytics	The use of student data to understand and enhance teaching and learning with a view to optimising student success.
Metadata	A set of data that provides context or additional information about a related data set. Metadata related to user activity, for example, may include login times, durations or navigation paths.
Student information systems (SIS)	Systems that enable educational institutions to manage student data, such as module registrations and grades.
Virtual learning environment (VLE)	An online platform that enables educators to share learning resources (such as lecture notes and online quizzes) with students. It is also sometimes referred to as a learning management system (LMS).

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Introduction

Data analytics has become an integral part of many areas of society, such as healthcare, retail, crime prevention and public transport (Gandomi & Haider, 2015). Learning analytics (LA), the use of student data to enhance teaching and learning, is gradually allowing higher education to take similar advantage of the data it gathers to understand and enhance teaching and learning with a view to optimising student success. The National Forum project, Learning Analytics and Educational Data Mining for Learning Impact[1], of which this report is an output, ran from September 2016 to June 2017. The project aimed to raise awareness of the benefits of LA and enhance the ability of Irish higher education institutions (HEIs) to design, develop and implement effective LA strategies. The project stemmed from the National Forum's Roadmap for Enhancement in a Digital World 2015-2017 (National Forum, 2015b), which listed among its recommendations a need to ensure a strong evidence base for enhanced pedagogy through the use of analytics.

Various policy documents and reports support the design, development and implementation of effective learning analytics strategies across Irish higher education, as can be seen in Figure 1.

European Union

- LA has the potential to contribute to the quality of teaching and learning and the modernisation of educational systems in Europe. (European Commission, 2016)

Department of Education and Skills

- The National Strategy for Higher Education to 2030 emphasises the importance of an evidence-based approach to learning by both teachers and students, a quality student experience and institutional responsiveness to the iterative needs of students (DES, 2011).
- The Data Management Plan prioritises the sharing of data and information with a view to informing understandings of the effectiveness of the curriculum, progression and retention rates and related policy requirements (DES, 2017a).

Higher Education Authority

- Areas of focus within the System Performance Framework 2014-2016 include student retention and progression, enhancing sectoral efficiency and underpinning a high quality student experience through the promotion of excellence in teaching and learning (HEA, 2016).

National Forum for the Enhancement of Teaching and Learning in Higher Education

- The review of student data to identify 'at risk' students has been recommended in order to reduce non-completion on ICT courses (National Forum, 2015)
- LA is seen as one of the top five priorities among Irish HEIs over the next three years (National Forum, 2017).
- Senior managers across Irish HEIs view LA as an emerging theme but most currently lack the local expertise or resources to fully explore the potential of LA (National Forum, in press).

Expert Group on Future Skills Needs

- According to the Expert Group on Future Skills Needs, data analytics is 'a fundamental element for both private sector and public sector organisations who wish to compete' (p.31). Across the public sector, 'there is . . . substantial potential for enhanced efficiency, cost savings and improved outcomes through deployment of analytics on a more widespread scale'. (p.111)

Figure 1 Selected policy documents and reports supporting the use of LA in Irish higher education

1 A 2016 National Forum Insight provides an overview of this project and associated terms. See here: http://www.teachingandlearning.ie/wp-content/uploads/2016/12/Learning-Analytics-Insight.pdf

Aim of this report

The aim of this report is to provide an overview of LA, and insights into how it can be used to enhance teaching and learning in Irish higher education. To this end, the report includes the following:

- An outline of LA, its evolution and its practical applications
- Some considerations for HEIs as they aim to take an informed approach to LA
- A brief overview of the current landscape of LA internationally and in Ireland
- A description of future plans for the development of LA in Irish higher education

What is learning analytics?

LA refers to the use of student data to understand and enhance teaching and learning with a view to optimising student success[2]. Its aim is to provide accurate and actionable insights into the learning process through the exploration, modelling and aggregation of relevant data and to provide an evidence base for optimising the conditions in which learning can flourish.

Once compliance with data protection legislation has been ensured (see more details on page 11), data from a vast array of sources can be used in LA. Such sources include everything from Student Information Systems, library usage, attendance data, participation in online forums, and Wi-Fi logs to eye movement and facial recognition data. The most widely-used source of data is student interactions within the virtual learning environment (VLE). VLEs are online platforms, such as Blackboard, Moodle and Sakai, that house a range of learning resources which teachers can make available to their students, such as lecture notes, quizzes, online groups and previous exam papers.

LA can be used by higher education staff and students in the following ways:

- It can let teachers know which resources their students are using and how active they are.
- It can let students know how engaged they are with course material, relative to their peers.
- Real-time information can give both teachers and students the opportunity to take timely, informed action, as appropriate.
- It can inform the curriculum and programme design.
- It can identify patterns of activity that are most likely to engender deep learning and have a successful outcome for the student.
- It can identify at-risk students and empower them to change their academic trajectory before they suffer any negative consequences.
- It can identify and prescribe actions and resources that are most likely to yield a favourable outcome for students.
- It can be used to identify students with sudden changes in engagement that can be indicative of a wide range of non-academic issues. By identifying students that may be facing personal, emotional, medical, social or financial challenges, LA can help support staff to proactively intervene and provide relevant, targeted supports to students with the greatest need.

2 Three 2017 National Forum Insights have been published which explain the benefits of LA for students, staff and institutions. See here: http://www.teachingandlearning.ie/forum-resources/national-forum-insights/

It should be noted that, for all of the potential benefits of LA, it is just a tool for answering questions and providing insights. In order to enhance teaching and learning, LA must be grounded in a broader, effective, action-oriented strategy. For example, LA alone cannot improve student retention but, when used effectively, it can become an essential and invaluable asset for supporting and informing an effective retention strategy.

The Development of Learning Analytics

Over the past decade or so, the concepts of big data and data analytics have become core to many sectors. Those in the higher education sector, suddenly finding themselves in an environment laden with data from VLEs and other digital platforms, have begun to recognise the potential of this data for overcoming a wide range of challenges. These include the need, driven by the global economic environment, to deliver more efficient services with significantly reduced resources, the increasing demand on HEIs to quantifiably demonstrate their value, and the challenge of optimising resources to provide a meaningful education to an ever-increasing number of online students (Ferguson, 2012).

Within this context, the term 'learning analytics' began to emerge around 2011. The Society for Learning Analytics Research (SoLAR) was founded to foster research, promote the development of educational resources, raise awareness and create opportunities for communication and collaboration among LA researchers and practitioners (solaresearch.org/about/). With the establishment of SoLAR, and the annual Learning Analytics and Knowledge (LAK) conference, LA began to build momentum as a research field. In fact, much of the early related literature focused on building the foundations of LA and distinguishing it from fraternal areas such as academic analytics, data analytics and data mining (e.g., Siemens & Baker, 2012; Siemens & Long, 2011; Van Barneveld, Arnold, & Campbell, 2012). There was also an early focus on establishing frameworks for research and practice within the area (e.g., Chatti, Dyckhoff, Schroeder, & Thüs, 2012; Duval, 2011; Greller & Drachsler, 2012).

At LAK 12, Arnold and Pistilli gave a seminal presentation on Purdue University's Course Signals platform, which became an early flagship for the application of LA[3]. The success of this platform in identifying, assisting and supporting the progression of at-risk students began to draw attention to the burgeoning field of LA, particularly among senior managers of HEIs. As more examples of implementations at scale emerged, predominantly in US institutions, the literature began to focus on issues of implementation and practical application (e.g., Drachsler & Greller, 2012; Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Macfadyen & Dawson, 2012; Macfadyen, Dawson, Pardo, & Gasevic, 2014).

More recently, there has been a noticeable growth in autonomous areas of focus within the field of LA. These include, but are not limited to the following:

- **Predictive analytics** focuses on analysing data from historic datasets to identify behaviours and circumstances that can be modelled to predict the outcomes of current and future events with similar characteristics. This area is largely associated with the identification of at-risk students (e.g., Dietz-Uhler & Hurn, 2013; Wolff, Zdrahal, Nikolov, & Pantucek, 2013).
- **Social learning analytics** uses social network analysis to look at the social interactions of students, often in online forums, and the learning impact of such interactions (e.g., Shum & Ferguson, 2012; Wise, Cui, & Jin, 2017).

3 See the Learning Analytics Applications section of this report for further details on Course Signals.

- **Multimodal learning analytics** seeks to extend the boundaries of traditional LA by moving away from a solitary focus on electronic data stored systems such as VLEs and library systems. In addition to sources such as these, multimodal learning analytics draws from the analysis of 'real-world' data sources such as classroom layouts, facial expressions and eye movements (e.g., D'Mello, 2017; Raca, Tormey, & Dillenbourg, 2014; Simsek, et al., 2015).
- **Discourse analytics** focuses on the highly complex analysis of unstructured data such as written texts and the contents of online discussion forums (e.g., Ferguson, Wei, He, & Buckingham Shum, 2013; Shum et al., 2016; Rosé & Tovares, 2015).

This wealth of literature related to LA has informed a wide variety of practical applications which have shown signs of positively impacting students, their learning and their success.

Learning Analytics Applications

LA can be broadly categorised as being either descriptive, predictive or prescriptive (See Figure 2). The potential applications of each of these types of LA will now be illustrated through high-profile international exemplars.

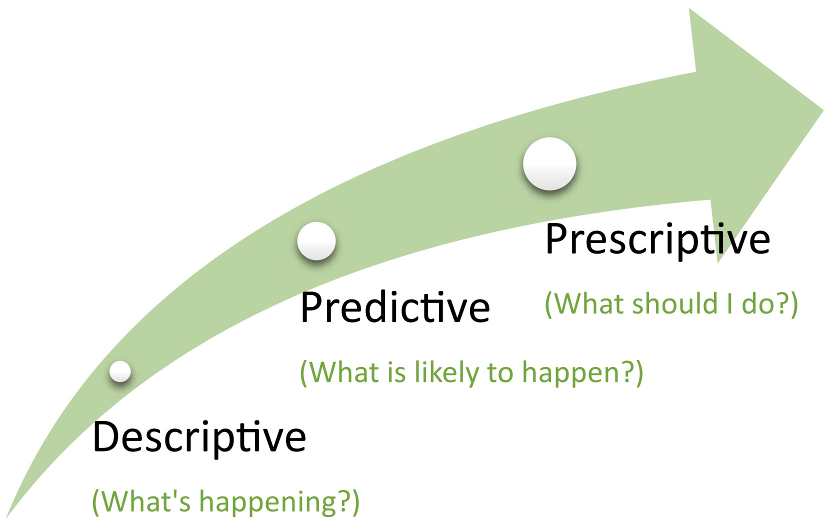

Figure 2 Three levels of application of learning analytics

Descriptive analytics

Outputs within the descriptive category use data to provide greater insight into current or past events. They use visual representations (such as pie charts) or comparative aggregations (such as averages) to give a clearer understanding of what is happening or has happened. They translate an abundance of coded, itemised data, akin to pieces of a jigsaw, into a coherent, informative picture. 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.

Exemplar: Nottingham Trent University

One of the major applications of descriptive analytics in LA is the creation of teacher- and student-facing 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. It was developed in 2013 with the aims of improving student retention, increasing students' sense of belonging and improving academic attainment (Sclater, Peasgood & Mullan, 2016). 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 clear 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. In the University's 2015/16 first year transition survey, 72% of students reported that using the Dashboard had inspired them to increase the time they spent studying (Nottingham Trent University, 2016). In addition to providing the same information to tutors, 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.

Predictive analytics

Systems that use a predictive approach are based on models drawn from historic data to identify relationships and correlations between a given set of data and a subsequent outcome. These models can then be applied to current data to predict likely outcomes based upon current circumstances. Arguably the foremost application of LA to date, and certainly that most widely associated with it, is the use of predictive analytics to proactively identify students that may be in need of targeted support. This ability of LA to provide accurate predictions has been the subject of much research (e.g., Barber & Sharkey, 2012; Gašević, Dawson, Rogers, & Gasevic, 2016; Gašević, Zouaq, & Janzen, 2013; Macfadyen & Dawson, 2010; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). This research 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. These profiles can then be assessed against modelled historic data to give accurate predictions of students' risk of non-completion or of underperforming in a given module. Currently, the earliest that most institutions can identify at-risk students in first year is with the ratification of semester one results in January/February. For some students, this is too late as they may have already failed several modules. Predictive LA enables the identification of such students up to four months earlier, allowing for targeted, pro-active interventions which direct students to essential learning resources while there is still time for them to change their potential academic trajectory.

Exemplar: Purdue University

Course Signals (CS), developed at Purdue University, is arguably LA's most famous early alert system and has garnered much attention for LA since being unveiled in 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 (Arnold & Pistilli, 2012).

Prescriptive analytics

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. This functionality is called prescriptive analytics. Recommender systems and adaptive learning environments (ALEs) are good examples of how this approach can be used to support student success.

Recommender systems

Recommendation has become an increasingly core objective of LA (Chatti et al., 2012). This approach goes beyond describing the current state of affairs or predicting outcomes to suggesting how a user can increase the chance of improving learning outcomes. Recommender systems are automated programmes that construct a profile of the user and use the historic actions/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.

Exemplar: Austin Peay State University

One area in which the recommender approach has been successfully employed is in course recommender systems such as Degree Compass. 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 (Denley, 2013).

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 as 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 (Denley, 2013).

Adaptive learning environments

In order to empower students to thrive in the digital age, it is important to give them the power to manage their own learning and to find new, personalised ways of retrieving and engaging with information (Jaros & Deakin-Crick, 2007). Some have argued that current VLE functionality does not cater adequately for the individual learning needs of 21st century students (Sahabudin & Ali, 2013; Savio-Ramos, 2015). Adaptive learning environments (ALEs) have been proposed as a means of allowing students to engage in more self-directed, 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. Brusilovsky and Peylo (2003) outline the beneficial features of ALEs 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: effective 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.

Exemplar: Carnegie Mellon University

The Open Learning Initiative (OLI), an ALE developed at Carnegie Mellon University, is one 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 practice 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 traditional, 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 (Lovett, Meyer, & Thille, 2008).

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. This is the essence of evidence-based teaching and clearly demonstrates the potential of ALEs.

Taking an Informed Approach to Learning Analytics

The principles presented in Figure 3 provide a useful guide for Irish HEIs as they begin to embed LA within their efforts to enhance teaching and learning and facilitate student success. These principles are designed to enable institutions to take an informed, ethical approach to their LA planning and implementation.

Learning analytics as a way to enhance understanding

- This principle highlights that the relationship between teachers, students and the subject matter is far more complex than a simple series of stimulus/response activities; conveying lists of facts is not the same as developing understanding. LA must understand and function within this deeper dynamic.

Students as agents

- It is essential that institutional analytics strategies are developed with the understanding that students are active partners in the learning process, rather than passive subjects. As active partners, students should be encouraged to collaborate, engaged to reflect, and inspired to act.

Student identity and performance are subject to change over time

- This principle recognises that our personalities and behaviours are fluid, rather than rigid. The picture of a student's behaviour LA presents is a snapshot, reflective of their behaviour at a given time only and should not be treated as an ongoing definition of who they are and what they do.

Student success is a complex and multidimensional phenomenon

- This is the recognition that human learning and behaviour are far too varying and complicated to ever be fully understandable through an assessment of data. While LA can undoubtedly give detailed insight into what is happening, it will never be able to give a full picture of the complexities of learning.

Transparency

- This is the principle that institutions must fully disclose every aspect of their analytics use. This is not only good practice, it is also a legal requirement under data protection legislation.

Higher education cannot afford to not use data

- This principle recognises the fact that analytics, if undertaken accurately, ethically and in compliance with the other principles of the framework, is an invaluable tool for enabling institutions to enhance both their impact as educators and their effectiveness as organisations.

Figure 3 Key principles of ethical LA approaches (Adapted from Slade & Prinsloo, 2013)

Concerns regarding use of data

The use of data to model and predict human behaviour can be a contentious subject. Some perceive LA as invasive or focused on surveillance. Such concerns emphasise the importance of any LA strategy being well-planned, ethical, collaborative and legally-compliant. Much has been written on the subject of ethics with regard to LA (see, for example, Greller & Drachsler, 2012; Ferguson, 2012; Siemens, 2013; Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Concerns include those related to privacy, consent and transparency.

It is essential that any institutional implementation of LA in Ireland is compliant with the Data Protection Acts 1988 and 2003. Institutions should also be aware of the upcoming General Data Protection Regulation (GDPR) that comes into effect across the EU from May 2018. HEIs must ensure that any use of personal data meets the requirements of these acts and are strongly advised to reference the Data Protection Checklist that is available on the Data Protection Commissioner's website[4]. A key concept of the legislation that applies to LA is that of informed consent. The Acts require that data subjects (e.g., students) are informed at the point of data collection as to how the data collected will be used. In addition, secondary uses which may not be obvious to data subjects (such as the processing of metadata from the VLE) should be drawn to the subject's attention and fully explained to them.

Transparency is not limited to the use of data, but covers every aspect of an institution's LA approach. Students must be fully informed of what data is gathered, how it is used, who has access to it and the purposes for which it will be used. This transparency is not only a legal requirement, it is also essential to retaining a sense of trust between institutions and their students. A proactive, transparent stance which recognises that some students or lecturers may feel unease regarding LA is recommended (Siemens, 2012).

Limits of learning analytics

A prevalent concern regarding the potential to oversimplify teaching and learning recognises that only certain types of data are encompassed within LA systems. While LA can accurately identify students' behaviour in, for example, the VLE, other teaching and learning situations and opportunities are beyond the reach of LA. These may include face-to-face teaching, conversations with lecturers or peers, and the use of learning resources found online. If care is not taken, there can be a risk of LA practitioners developing what Kahneman (2011) describes as 'what you see is all there is' thinking, the false inference that the partial picture to which they have access gives a full understanding of student behaviour. This position overlooks the complexity of human behaviour at the heart of teaching and learning. Without a more nuanced, considered understanding, the risk of commodifying students becomes a genuine threat to how students are perceived and treated by the institution. Another potential impact of this thinking is the development of generic, one-size-fits-all interventions that may be insensitive to the entire range of extra-academic issues that individual students may be facing or a false understanding that all students, regardless of personal circumstances, must adhere to a given model of learning and 'success'.

4 See: https://www.dataprotection.ie/docs/Self-Assessment-Data-Protection-Checklist/y/22.htm Also, a number of resources available on the National Forum's Online Resource for Learning Analytics provide considerable detail and guidance on developing an LA strategy that is consistent with data protection legislation (www.teachingandlearning.ie/NFOrla).

A National Forum Insight detailing some of the implications of the GDPR for the use of learning analytics to support student success will be published in January 2017 at https://www.teachingandlearning.ie/national-forum-insights/

While LA has gathered considerable momentum and the potential it has for enhancing teaching and learning has been correctly lauded, LA cannot overcome all challenges faced in higher education, nor can it alone ensure student success. LA's ability to provide accurate predictions is, for example, only a single aspect in successfully promoting student success, ensuring progression and maximising retention (Dawson, Jovanovic, Gašević, & Pardo, 2017). Similarly, models only influence course completion and retention rates when combined with effective intervention strategies (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). As noted previously, LA is just a tool for answering questions and providing insights. In order to enhance teaching and learning, it must be grounded in a broader, effective, proactive strategy.

Taking a holistic view of student success

Student success is not reflected solely in module grades and course completion rates. It also encompasses student welfare and student learning experiences. As the principles outlined in Figure 3 emphasise, institutions will have a better chance of achieving broad student success if their LA strategies consider the whole student, the dynamic nature of learning, and the conditions within which learning occurs. Such overarching, contextual factors are important to bear in mind when using the results of LA to inform module content, programme design and the arrangement of support services.

The International Picture

Taking a global perspective, the development of LA was formalised with the establishment of SoLAR (the Society for Learning Analytics Research) in 2011. This international LA community, through its annual LAK conference and related activities, served to build upon and consolidate many years of informal LA practice around the world. The US, Australia and various European countries have been particularly active in embracing the potential of LA within their higher education contexts.

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 (US Department of Education, 2012; Ferguson et al., 2016). Federal LA structures aiming to enhance the use of LA in elementary and high schools have filtered through to state and district levels (Alliance for Educational Excellence, 2014). 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 (Sclater & Mullan, 2017). 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 (Educause, 2017; Ferguson et al., 2016; New Media Consortium, 2016; Sclater & Mullan, 2017). 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).

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 (Siemens, Dawson & Lynch, 2013). 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 (Colvin et al., 2016). 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.

Learning analytics in Europe

A recent study by the EU Joint Research Commission (JRC) identified the Netherlands, Denmark and Norway as being among the more advanced European countries with regard to the development of national approaches and the establishment of an LA infrastructure (Ferguson et al., 2016). In Spain, the Spanish Network of Learning Analytics (SINOLA) is a collaborative community that is also building practice for LA researchers. SINOLA hosted one of SoLAR's Learning Analytics Summer Institutes in 2015. In the UK, a recent report provided an overview of the national LA landscape (Higher Education Commission, 2016). An included survey of HEIs found that over half of the 53 respondent institutions have implemented LA to some degree, but cross-institution coordination of LA activities is rare and just one institution reported full institutional implementation and support (Newland, Martin, & Ringland, 2015). JISC, in conjunction with a number of private software vendors, recently launched a beta-stage national LA service which is expected to significantly accelerate the proliferation of LA across UK HEIs.

An EU-funded project entitled Learning Analytics Community Exchange, which ran from 2014 to 2016, brought together LA representatives from seven European countries with a view to building evidence, sharing good practice and working towards a common future (www.laceproject.eu). A significant output of this project was the Evidence Hub website (http://evidence.laceproject.eu/), which recorded and organised evidence relating to the theory, research and practice of LA and associated educational data mining. Following from this project, a special interest group, entitled Learning Analytics Community Europe (LACE SIG), was established as the European arm of SoLAR.

Another EU-funded LA project, Supporting Higher Education to Introduce Learning Analytics (SHEILA, http://sheilaproject.eu/), recently joined the LACE SIG. The SHIELA project aims to design a policy development framework to assist European universities to become more mature users and custodians of digital data about their students. It conducted a study exploring the LA landscape across Europe (Tsai & Gašević, 2017). Initial results from the study can be seen in Figure 4.

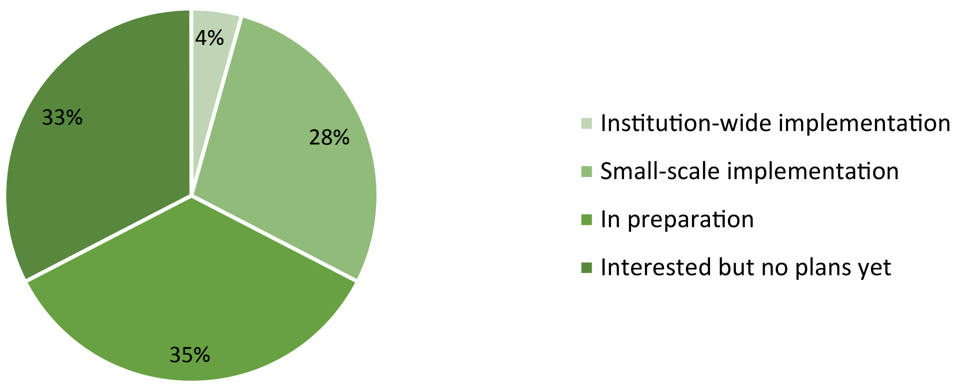

Figure 4 Percent of surveyed European HEIs at various stages of LA implementation (n = 46) (Adapted from Tsai & Gašević, 2017)

Identified drivers for LA activity in European HEIs included student drivers, such as learning performance, student satisfaction and retention, teacher drivers, such as teaching excellence, and institutional drivers, such as informing strategic plans and effective management of resources (Tsai & Gašević, 2017). The EU JRC report characterised the European LA landscape as promising but fragmented. The use of LA for the enhancement of teaching and learning is still in its infancy in Europe and the focus remains largely on the gathering and interpretation of data, without a significant shift towards the use of such data to positively impact teaching and learning (Ferguson et al., 2016).

Across the US, Australia and Europe, the evidence points to the importance of clear understandings, proactive strategies and institutional collaboration for the development of sustainable national LA infrastructures that have the capacity to develop towards the realisation of student success.

Learning Analytics in Ireland

Insofar as LA refers to the use of learner data to understand and respond to students' learning needs, there is no doubt that it is currently being practiced in every HEI in Ireland. In every institution, lecturers are using assessment results to identify students that require additional supports, schools and departments are using grade curves to identify and address modules that deviate from the normal distribution and services are being initiated or improved based upon qualitative data generated through feedback surveys. This use of data is being undertaken by proactive individuals or in isolated pockets around campuses. And, although the term learning analytics is widely known, most of these practitioners would not consider their actions or approaches to come under the heading of LA.

The National Forum's Learning Analytics and Educational Data Mining for Learning Impact project aimed to formalise the building of LA context, community and capacity in Ireland. As can be seen in Figure 5, HEIs across the country actively engaged with the project and demonstrated interest in the potential of LA for enhancing teaching and learning.

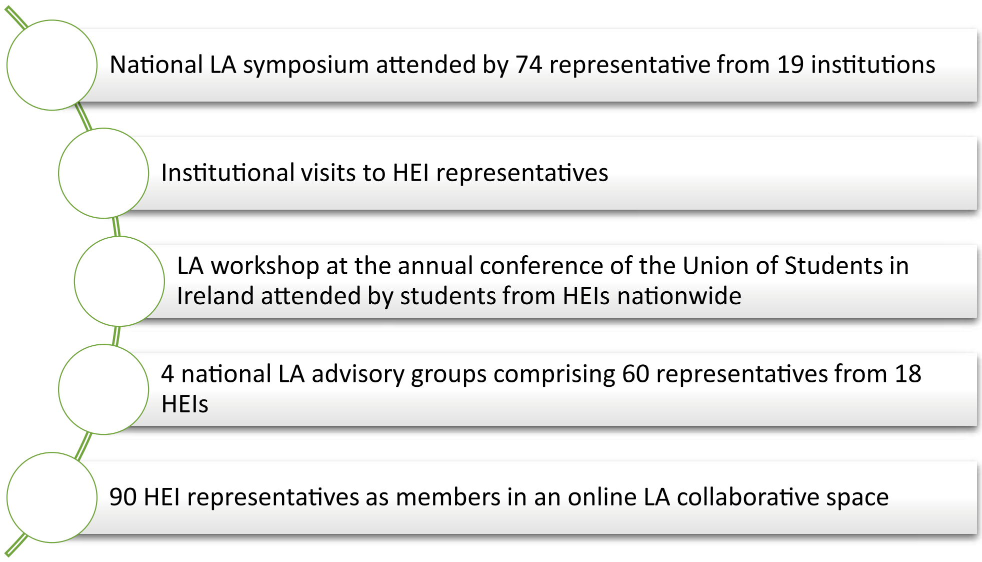

Figure 5 Sector-wide engagement in the National Forum's Learning Analytics and Educational Data Mining for Learning Impact project

Figure 6 depicts the picture of LA in Ireland that emerged from the National Forum LA project. Among the representatives from over twenty HEIs across the country who took part in the National Forum LA project, just one staff member held a role which formally included intervening with students whose digital footprint suggests of a lack of engagement. In general, private HEIs demonstrated strategic institutional LA approaches more commonly than public HEIs.

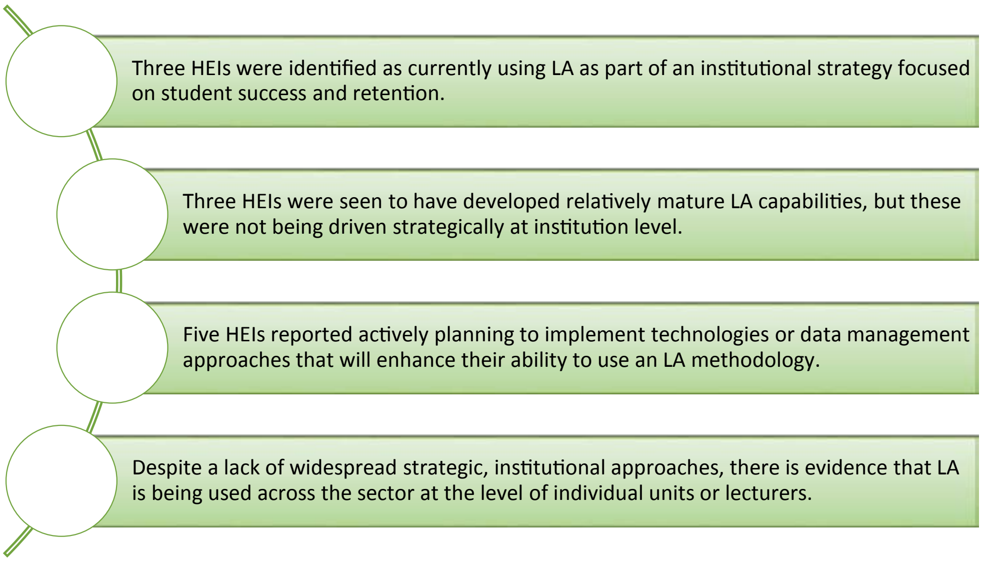

Figure 6 Reported level of LA development across Irish higher education

Those institutions that indicated having established LA platforms and/or capabilities were asked to submit brief descriptions of their activities. A selection of these are listed in Figure 8. More detail on these platforms is available in the Online Resource for Learning Analytics, recently developed by the National Forum and accessible here: www.teachingandlearning.ie/NFOrla.

- **Mark Lande, University College Dublin**
  - An in-house reporting platform focused on cross-institution integration of data, provision of a consistent user experience, provision of real-time information, partnership between data owners and consumers, and strong security and access control.

Infohub

- **Jonathan Lynch, National College of Ireland**
  - This platform is used to integrate data such as student attendance, exam results, VLE interactions, and module pre-requisites, with a view to providing assistance to students identified as at risk.

NCI Engagement Platform

- **Owen Corrigan, Mark Glynn, Alan Smeaton & Sinead Smyth, Dublin City University**
  - A platform that uses academic data to predict how a student is doing in a particular module, that is, whether they are on the path towards passing or failing.

PredictEd

- **Jonathan McCarthy, Cork Institute of Technology**
  - A faculty dashboard reporting on key metrics at department, school and faculty level across the Institute. Designed to be interactive and intuitive, eliminating the need for technical skills for users.

CIT Enterprise Reporting Portal

- **David Molloy, Dublin City University**
  - A student information system developed in-house to facilitate the presentation of student information in an efficient, user-friendly manner and provide a platform for the development of a number of sub-systems.

GURU

- **Tim O'Donovan, University College Cork**
  - A reporting platform for the University's student IT helpdesk that gathers a snapshot of a student's digital footprint on a single dashboard, pulling data from multiple systems.

UCC Student IT Helpdesk Dashboard

Figure 8 Overview of selected Irish analytics platforms

The level and nature of participation from across Irish higher education in the National Forum LA project suggests that there is a keen interest and considerable expertise in this area among higher education staff. A number of HEI staff have been conducting research related to LA in Ireland. Figure 7 lists a range of recent and ongoing LA research projects across the country. Studies include those which investigate student behaviour, institutional LA cultures, and those which explore early warning systems, adaptive learning environments, recommender systems, and/or curriculum development. More detail on each study can be found in the appendix.

Educational Analytics in Computer Science

David Azcona, Insight Centre for Data Analytics, DCU

- Utilising classifiers to identify programming students that may not be on track and provide them with personalised feedback and exemplar models from higher-performing students

Learning Factor Models of At-Risk Students

Geraldine Gray, Institute of Technology, Blanchardstown

- Developing an early alert method for identifying incoming students that may be at risk using student enrolment data and an online, self-reporting, learner-profiling tool

Learning Analytics in UCD

Emma Howard, University College Dublin

- Using VLE data from two large first-year modules to predict student grades and provide tailored supports

A Journey Towards a Data Driven Culture in CIT

Jonathan McCarthy, Cork Institute of Technology

- Reviewing the impact of business intelligence on decision-making behaviour among senior institutional staff

LA Approaches and Methodologies

Phelim Murnion, Galway Mayo Institute of Technology

- Exploring measures for assessing the impact of LA initiatives

LA and a Student WiFi Footprint

Philip Scanlon, Insight Centre for Data Analytics, DCU

- Using Social Network Analysis and WiFi-generated digital footprints to investigate student sociability behaviour

Elective Recommender System

Barry Smyth & Michael O'Mahony, Insight Centre for Data Analytics, UCD

- Developing a system for recommending relevant elective modules to registering students

Data Analytic Features of Blackboard

Patrick Walsh, Dublin Institute of Technology

- An evaluation of the inbuilt analytic features of Blackboard and an exploration of lecturers' perceptions of LA and the opportunities and challenges faced by this emerging technology

Figure 7 Sample of ongoing and recent Irish LA research

There were a number of identified barriers to the proliferation of LA across Irish higher education. These, and the responses that emerged through the project are listed in Table 1.

Table 1 Perceived barriers to LA proliferation, and associated responses

Perceived barrier	Responses provided during LA project
The perception that, although LA would be 'nice to have', in an environment of limited resources, other business-critical priorities, such as improving Wi-Fi networks, are seen as being of a greater immediate need.	While it is true that a single 'big bang' approach to implementation could require an investment of institutional resources, LA can easily be implemented in a phased basis that is far less resource-intensive.
The perception that developing an effective analytics capacity requires a considerable and specialised expertise that many institutions may feel they do not currently possess.	This position overlooks the potential value of less complex uses of data that may have a significant impact on the effective provision of targeted services.
The perception that the potential of analytics can only be achieved through significant financial investment.	Smaller scale pilots that take advantage of software that already exists within HEIs have been proven to be effective.
A widespread lack of awareness of the analytics features that are readily available, without further development or expense, within the VLE platforms already in use in Irish institutions.	Blackboard, Moodle and Sakai all have reporting features that can give teachers a better understanding of their students' learning activity and behaviour as well as means of identifying students that may be less engaged than their peers.

LA was recently ranked within the top five institutional priorities for Irish HEIs over the next three years (National Forum, 2017). The emerging picture of the LA landscape in Ireland is one characterised by developing interest, growing understanding and expertise, and a gradual leaning towards strategic embeddedness. As HEIs develop their LA capacity, it is important that they have the resources and the support they need to contribute towards a strategic, efficient, sustainable, student-centred national LA infrastructure.

The Future of Learning Analytics in Ireland

Looking to the future, there is great potential for Irish higher education to build upon the growing interest, expertise and collaborative engagement in LA that has been evident in recent years. Equally, there is a need for future development to be informed and supported if LA is to yield sustainable benefits for students and staff across the sector. To this end, two national LA initiatives have been established: The Online Resource for Learning Analytics (ORLA) and the Data-Enabled Student Success Initiative (DESSI).

The Online Resource for Learning Analytics (ORLA)

As part of the National Forum's LA project, the need was identified for shared resources to assist institutions to build their LA capacity. In response, the Online Resource for Learning Analytics (ORLA) was established. ORLA is an open access online library that houses a broad suite of guides and other documents aimed at providing institutions with key information needed to design and implement an LA strategy founded upon good practice. The compiled resources are designed to be of benefit both to institutions new to LA and to institutions that have already built some LA capacity. An overview of ORLA can be seen in Figure 9.

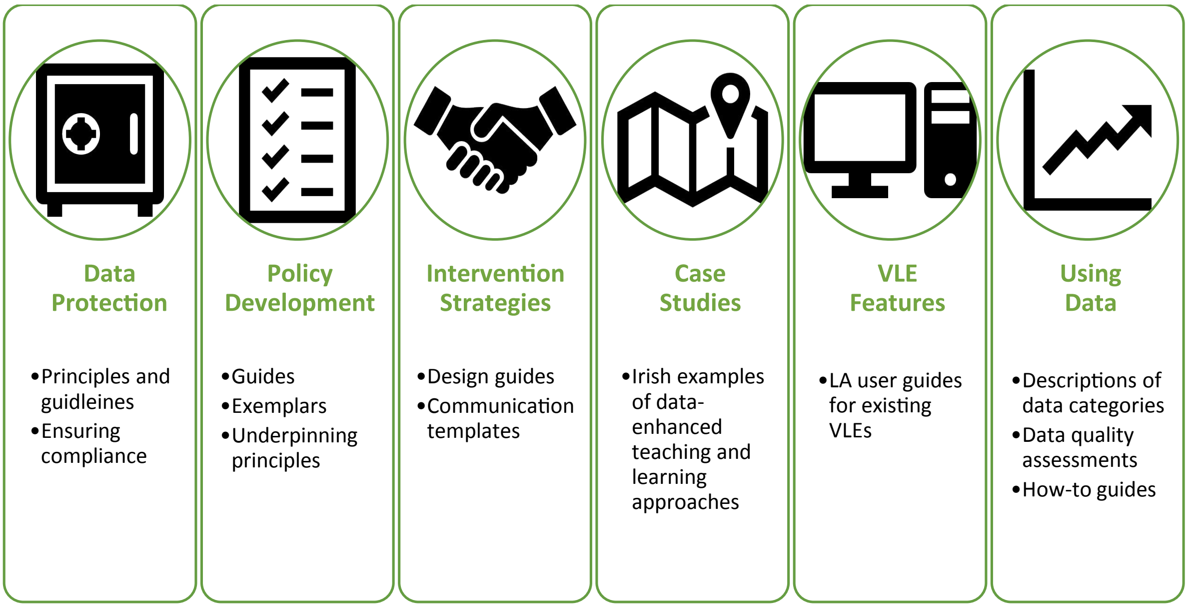

Figure 9 Online Research for Learning Analytics (ORLA) (available at www.teachingandlearning.ie/NFOrla)

The Data-Enabled Student Success Initiative (DESSI)

In line with the national imperative to pool resources and share services (Department of Education and Skills, 2017b), DESSI is an initiative led by the National Forum, in partnership with the Higher Education Authority (HEA), Quality and Qualifications Ireland (QQI), the Irish Universities Association (IUA), the Technological Higher Education Association (THEA), the Higher Education Colleges Association (HECA), HEAnet, EduCampus and the Irish Survey of Student Engagement (ISSE), which will run until the end of 2018. It was established to consolidate the sector's investment in LA to date and to work with institutions to ensure the future of LA in Irish higher education is guided by four core principles:

- Developments in LA should support a holistic view of student success.
- Taking a strategic institutional approach to LA is both valuable and necessary.
- Resources, tools and services should only be employed by HEIs to support LA following a review of their suitability, scalability and adaptability to the specific context.
- Every effort should be made to share LA services across the sector to avoid inefficiencies, or duplication of effort.

DESSI, supported by ORLA, will allow Irish higher education to take a strategic, proactive approach to LA, building upon national and international developments. It is intended that the spirit of collaboration already in evidence across the sector will be harnessed to allow institutions to efficiently foster innovative, evidence-based teaching and learning environments with student success at their core.

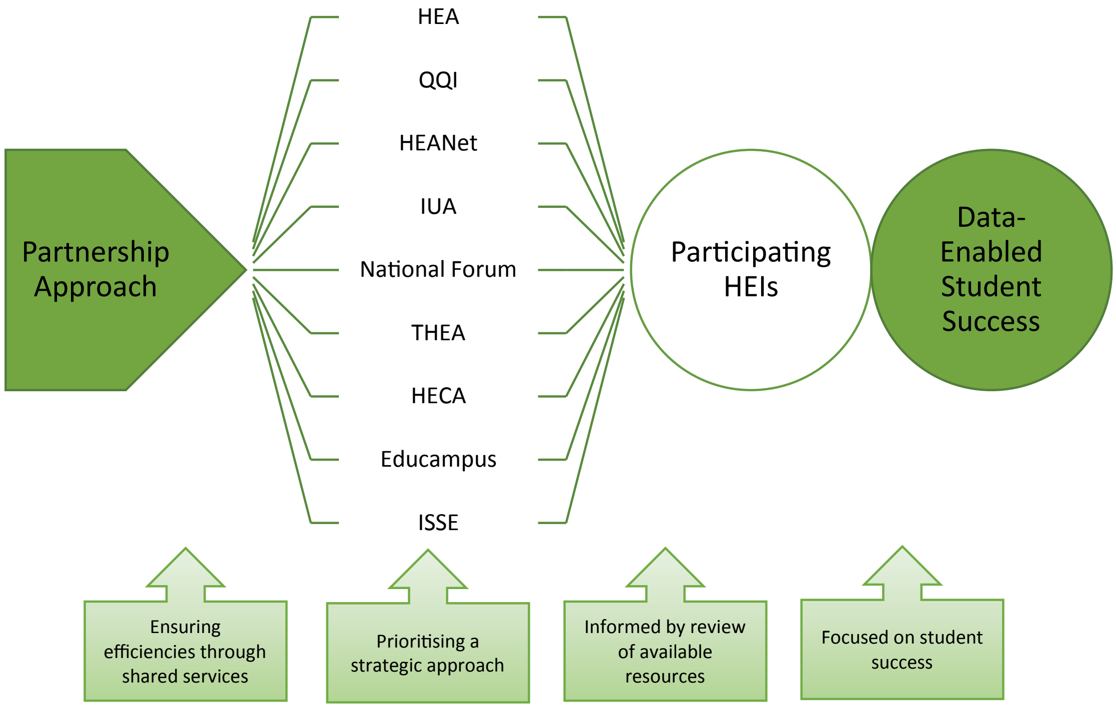

Figure 10 Data-Enabled Student Success Initiative

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The Forum would like to express its sincere gratitude to the staff and students across the sector who shared their thoughts and experiences to contribute to our better understanding of learning analytics within Irish higher education.

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Appendix: Detail of Current and Recent Irish LA Research

LA crosses disciplinary boundaries and is the subject of research across many Irish HEIs. Below, in the researchers' own words, is a sample of current and recent LA research conducted at Irish institutions.

Educational Analytics in Computer Science

David Azcona, Insight Centre for Data Analytics, Dublin City University

Big data and analytics have the potential to revolutionise higher education globally. At DCU we are transforming how students acquire computer science skills, particularly programming, by leveraging educational analytics and optimizing their learning. VLE data and program submissions are gathered via DCU's Einstein platform for teaching programming. Analytics in dashboards can show lecturers who needs support and who is on track by identifying patterns using student engagement, prior academic history, mouse movements and keystrokes; and enables them to dynamically adapt the course content after gaining visibility into the student's learning process. Students receive personalised feedback based on their programming learning progress and become more self-aware of what they need to do to reach their goals.

Predictive models are developed per course. A set of binary classifiers are built, one for each of the weeks of semester, which predict the student's likely pass or fail in the computer-based exam grades. Instructors can visualize and identify struggling students on a weekly basis plus how confident our classifier is for each prediction. Students are ranked based on the classifier predictions. Programs developed by the higher-performing students are offered automatically as recommendations to at-risk students based on a knowledge graph and the concepts lecturers want to reinforce each week.

Learning Factor Models of Students at Risk of Failing in the Early Stage of Tertiary Education

Geraldine Gray, Institute of Technology Blanchardstown

The purpose of this study was to predict students at risk of failing based on data available prior to commencement of first year. The study was conducted over three years, 2010 to 2012, on a student population (n=1,207) from a range of academic disciplines. Data was gathered from both student enrolment data and an online, self-reporting, learner-profiling tool administered during first-year student induction. Factors considered included prior academic performance, personality, motivation, self-regulation, learning approaches, age, and gender. Models were trained on data from the 2010 and 2011 student cohort, and tested on data from the 2012 student cohort. Factors found to be most predictive of academic performance in first year of study at tertiary education included age, prior academic performance, and self-efficacy. Early modelling of first-year students yielded informative, generalizable models that identified students at risk of failing.

Learning Analytics in UCD

Emma Howard, University College Dublin

Early warning systems are systems which identify students at-risk of failing or dropping out and provide feedback/intervention to students. In UCD we are developing an early warning system, and investigating the optimal time in a module to apply such a system. Two large first year modules were chosen which both have a large proportion of resources on the VLE, Blackboard. Through detailed variables (Blackboard data, demographic data and continuous assessment), mixed mode clustering and a prediction method of BART (Bayesian Additive Regressive Trees), we were able to predict students' final mark by week 6 based on mean absolute error (MAE) to within 2.5 percentage points of their actual mark (https://arxiv.org/pdf/1612.05735.pdf). We use students' marks as a numerical response variable rather than a binary response of pass/fail.

In semester one of 2017, we implemented two different feedback/intervention systems into the modules. The first method involved emailing students half way through the semester with suggestions for studying, helpful advice for online studying, distribution of the class continuous assessment marks to date, and email and opening hours for the maths support centre. Three emails were prepared. Each email presented the same information, however the emails were phrased differently depending on student needs. In the second module, students have a weekly quiz marked out of five. We gave students who did not acquire 5/5 on a quiz a second opportunity to obtain marks through the form of a remediation mark. Students were able to gain an extra mark if they reviewed their quiz and explained where, why and how they went wrong on their quiz initially. We are currently investigating whether the feedback/corrective measures impacted student study patterns or/and academic marks.

In UCD, we are also using LA to investigate student withdrawal rates, in particular identifying signals or variables which would indicate which students are likely to withdraw. Currently, UCD has a model (called the Integrated Assistance Network or IAN) based on five flags (Blackboard engagement, GPA performance, extenuating circumstances, fee compliance and credit workload) to signal whether a student is at risk of withdrawing (http://www.ucd.ie/registry/adminservices/records/). We are investigating whether this model could be improved upon using logistic regression methods and survival methods of random survival forests and cox regression. Initial research is promising with level of Blackboard engagement and semester credits proving to be valuable variables.

Changing Leadership Behaviours: A Journey Towards a Data Driven Culture in CIT

Jonathan McCarthy, Cork Institute of Technology

Student retention is important to all HEIs. This has driven considerable research and focus, much of which concluded that each HEI must define those factors by which it can identify student retention risk. These factors include student attendance, engagement, participation, academic performance and socio-economic background. Once these factors are identified, the HEI then works to put some sort of proactive intervention programme in place before the student moves from a retention risk to a retention statistic. Much of the research supports the move towards data-driven decision making for each HEI. Have some form of analytics that identifies the risk early, make a decision and mitigate that risk. Unsurprisingly, the research has predominantly focused on the behaviour of the student and/or institution and using data driven decision making to alter that behaviour. However, very little research has considered the impact on the leaders (decision-makers) themselves. This move towards a data driven culture has a significant dependency on the leaders making the decisions and thus their behaviour is also an important factor. This study looks at the impact a move towards a data-driven culture can have on leadership behaviour.

The data management capability was provided through a faculty dashboard (see www.teachingandlearning.ie/NFOrla for further detail). Initial expectations of the researchers were that the leaders would begin to exhibit more of the leadership behaviours from the leadership taxonomy. However, once the initial survey results arrived it showed that many behaviours were starting to show an alarming decrease in use (see table below). This was initially quite worrying until it was noticed that there seemed to be a trend in that the change oriented behaviour types were the ones showing an increase and most others showed the decrease. When this survey data was then compared to the interview and participant observation data a similar trend was observed. It became clear that the leaders began to exhibit a trend towards change-oriented behaviours after receiving significant data sets on student retention.

Behaviour Type	Leadership Behaviour	Survey Results	Participant Observation & Interview Results
Task-oriented	Short-term planning	↓	n/a
	Monitoring operations	↓	n/a
	Clarifying roles	↓	n/a
Relations-oriented	Supporting	↓	n/a
	Developing	↑	n/a
	Consulting	↓	n/a
	Recognizing	↓	n/a
	Empowering	↓	n/a
Change-oriented	External monitoring	↑	↑
	Encouraging innovative thinking	↓	↑
	Envisioning change	↑	↑
	Taking risks for change	↑	↑

Learning Analytics and a Student WiFi Footprint

Philip Scanlon, Insight Centre for Data Analytics, Dublin City University

There has been a large body of research within the domain of peer effects on students within third level education. Historically the data collection process for this involved either surveys, interviews and observation, or any combination of all three. Recent developments in the area of formative educational methods have enabled other data collection options. Data sources now available include VLEs, E-learning and Massive Open Online Courses (MOOCs) and many other knowledge management systems.

The growth in this form of educational environment not only provides additional resources to academics and learners, but also researchers who have access to the massive datasets generated through use of these technologies. Digitally collected data for research into educational methods has many advantages over that compiled manually through more traditional collection methods. Datasets of this type are less susceptible to the inherent biases introduced through the intervention of human interpretations, it is often structured, complete and traceable.

Our research aims to utilise the unique digital footprints created by student activities within a university environment and through Social Network Analysis to identify their influences within peer groups. The specific digital footprint we are interested in is generated through the use of the Eduroam Wi-Fi platform ubiquitously available within the DCU campus. We believe that it is possible through the analysis of colocation data to identify 'friendships' among the student cohort and the effect on the academic performance of these friendships.

Elective Recommender System

Barry Smyth & Michael O'Mahony, Insight Centre for Data Analytics, University College Dublin

Taught degree programmes in University College Dublin are delivered on the basis of a fully modular, semesterised and credit-based curriculum. Typically, students take 12 modules in each academic year. Of these, 10 modules are in the core area of study. In addition, students choose two elective modules which can either be taken from within the main subject area to deepen learning, or from outside it to broaden learning.

A number of factors can be identified which are likely to influence elective module choice - for example, career goals, ability to progress in an area of study, difficulty and format of modules, module pre-requisites and availability of places. Awareness of options is also likely to influence choice - students are simply unaware of the full range of options available, resulting in poorly-informed choices being made. The goal of this project is to develop a recommender system to help students to identify module choices that better reflect their evolving interests for a more personalised programme of study. Future plans include a live-user trial of the system, following which an analysis of elective module choices pre- and post-deployment of the system will be carried out.

The Data Analytic Features of Blackboard

Patrick Walsh, Dublin Institute of Technology

This study was a LA project that analysed data generated through student engagement with Blackboard, the VLE used in DIT. The primary aims of the research were to evaluate the inbuilt analytic features of Blackboard, capture lecturers' perceptions of LA and discuss the opportunities and challenges faced by this emerging technology.

The study determined that activity within VLEs, measured by logins, hit activity, and results in multiple choice questions provide indicators of student academic performance. Lecturers involved in the study felt the analytic features provided them with a sense of student engagement with course modules and a better understanding of their student cohorts. They felt the analytic tools aided them in identifying potential at-risk students, claiming, 'good data will highlight issues before they reflect themselves in dropout or poor performance'.

Integration of data from disparate Institutional sources remains a huge challenge faced by HEIs and highlighted in this study. Staff would like to see data collated into one system in order to build a richer student profile and identify potential at-risk students. The study highlights the lack of awareness of the existence of these analytic tools in VLEs. Therefore, further promotion of these analytics tools among academic staff across Irish HEIs may be needed, as these embedded analytic tools offer us a lens into the student learning experience.

LA is still in its infancy stage. It is an emerging tool, which needs to evolve in terms of adoption, popularity and effectiveness, particularly with Irish HEIs. In order to identify potential at-risk students, improve retention and the overall student experience, analysis of student data needs to become more commonplace in Irish HEIs.

For further research, the author is aiming to include data from other sources namely Banner and the Library Management System - Millennium. It is envisaged the next phase of this project will commence at the start of the 2017/2018 academic year and will extend to a larger student cohort.

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