Chapter 3
Preparing for Learning Analytics

3.1 Introduction

In the education sector, learning analytics has become a famous slogan. Learning Analytics will undoubtedly be a powerful tool for organizations to promote retention and demonstrate that institutions deserve federal funding in the future. Nonetheless, steps are necessary before it can be introduced (Weitzel, 2019). Just because organizations have software that gathers student data does not mean that they can turn a key and unexpectedly use learning analytics. It is an effort for which organizations have to plan and develop.

They have to determine what they want to know from their data before creating a learning analytics initiative. Institutions should collect data to understand the student's results and/or institutional policies and operations effectiveness. Before developing their learning analytic processes, organizations must determine what they want to know so that staff will analyze data that correspond to the organization's objectives.

The most significant step must be taken by institutions to ensure standardization on all campuses. Institutes must improve standardization at all levels, including departmental policies and teacher actions, to monitor student outcomes' reliable data. Many higher education institutions give teachers flexibility across their classes, making it almost impossible to equate learning data with different teaching styles. Institutions need to reduce discrepancies for data to tell a good story to use learning analytics. For standard practices, students ideally follow the same educational process irrespective of the curriculum. Add standard policies into the mix that decide how data are gathered and what information is gathered, and school staff can compare accurate student data and obtain relevant insights.

In the future, private institutions are well-positioned to incorporate learning analytics because, as an industry, they tend to write standard training practices from attendance tracking and content delivery to technology. Additionally, private institutions are not as diverse in teachers' teaching styles and can make changes quicker than non-profit institutions.

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In addition to university-wide standardization, universities will invest in analytical tools and software. Institutions cannot rely on manually entered data to use learning analytics since it will likely contain prejudices and allow room for human error. Technology is essential for the accurate and rich collection of data to produce more reliable forecasts. Nevertheless, technology data collection sheds much light on student behavior. Institutions will identify behavioral trends with more informative data.

In addition to investing in technology for effective learning analytics, organizations may recruit or reassign personnel to track the data, report relevant insights and assess where and how the data should be stored and handled before and after review.

As the education sector modernizes and new technologies become prevalent in the classroom, Learning Analytics is a valuable opportunity for higher education institutions soon. To prepare for learning analytics, organizations now need to lay the foundation for updating policies to include data collection. Students must also be mindful that staff and teachers regularly follow these procedures to ensure that the data collected accurately reflects their behavior and results. When standardizations are met, universities may start learning analytics to improve students' performance, increase retention, and reduce the average time it takes for students to graduate. They have to define; until then, the measures are needed to prepare for effective learning analytics!

3.2 Role of Psychology in Learning Analytics

The role influential peers play in setting a norm or pattern others would like to emit important for self-efficiency and self-regulated learning (Zimmerman, Bandura, & Martinez-Pons, 1992). While self-regulated learning theories vary from behavioral to socially cognitive to constructivist, lead proponent Barry Zimmerman demonstrated that the social context is central to building one's self-regulation capacity. In short, we gain initial knowledge and reflection when matched with a good mentor or model that usually takes four steps (Fritz & Whitmer, 2017):

- ***Observational***: Students learn to differentiate between the main elements of the skills or technique of a student.
- ***Emulative***: The performance of a learner approximates the overall type of skill or technique of a student.
- ***Self-control***: students may exercise skills or techniques based on a successful model's mental representation.
- ***Self-regulation***: Learners should regularly adapt their skills and strategies as circumstances change.

The faculty will look for an improvement in the design of courses focused on Learning Analytics, but only if they have a minimum number of people with a more successful method. That is why and how learning analytics will help recognize, encourage, assess and facilitate significant activities and practice by acting as a benchmark against which the faculty not only tests itself but also points to a path forward, against encouraging students to accept responsibility for learning. Sure, technology could help, but only if the teachers first believe it would, sufficiently try it or look for people who did. Thus, the students responsible for their learning are the only flexible way to learn, and the teachers must, therefore, take care of "teaching failures" by being open to particular pedagogical examples and working hard to understand and execute them.

Such pedagogical and psychological contexts that motivate and persuade people may start to have important implications for successful learning analytics, be they nudges, visualizations, or messages directed at students (or faculty), incorporated into academic technology. In short, it is not enough simply to present what we believe is straightforward and reliable quantitative data. Further research must clarify how we can identify and share stories in data that shift our hearts and minds. To increase student self-regulation or increase professional consciousness about their education, we need to define, express, and present quantitative findings. To illustrate, consider a few examples.

Normally, it was a more challenging task to find the right messages for students. It could be demotivating to submit a message like "You are in the bottom five percent of your class in LMS activity," but to create the right message was harder and something the data science team might poorly construct. Designers and text-on-page experts will do this. A language that uses a "concerned friend" tone motivates students to provide conference messages that catch students' attention and include information on activities that cause the notification.

These psychologically influenced messages can support radical educational innovation through learning analytics. On the other hand, people with experience in data analysis and quantitative techniques are as rarely (and almost as expensive) as scientists, though the value of effective communication has been recognized in other industries. Maybe it is time to introduce new data science initiatives for people with lower interest in numbers and algorithmic solutions through data visualization or design thinking tracks.

Truly functional approaches are designed to promote and harness students' or teachers' encouragement in an evidence-based intervention that increases their consciousness to try (or accept) institutional help. However, this will probably take more than a quantitative approach to the identification and dissemination of evidence.

For systemic transformation and improvement, we need data and research with specific forecasts, but, as suggested in (Macfadyen & Dawson, 2012), we need to go beyond the forecasts to enable us to find and say stories about successful practices and practitioners whose examples may be much better by example.

Ultimately, we cannot use theoretical approaches to punish others, but as enlightenments for education and educate people about what is possible. Showing people how they can function constructively without humiliating them will enable them to take the next steps forward. With the right stories that touch people's hearts about the importance of learning analytics and reliable results, everyone will consent to the possible uncomfortable pursuit of excellence.

3.3 Architecting the Learning Analytics Environment

Learning analytics is an area that has been taking shape since 2010, and over the years, has frequently been featured in studies on the future of learning technology. This focuses on the integration of learning (learning, educational studies, learning/assessment sciences), analytics (statistics, simulation, computer science, and artificial intelligence), and interaction of humans and computers (participatory design, behavioral science, social-technical system design, usability assessment). For some colleges and universities investing substantially in their analytical infrastructures, how does an institution develop itself to evolve pedagogically and analytically in this academic crossroads to meet significant, strategically relevant educational and learning challenges? Briefly, how does an organization evolve to have a sustainable impact?

Learning analytics focuses on using analytical methods to gain insights into educational data to improve teaching and learning. Whether this offers new "power tools" for academic researchers who have been researching teaching and learning data nondigitally for decades, Learning Analytics would, without a doubt, be a step forward. This work is the first step essential to validate the approaches. However, as we move from research to development, the real potential of learning analytics will be realized, and human-computer systems will be generated to automate this analysis process from data collection to visualization and recommendations, which provide more timely, reliable, and actionable input to students, educators, instructional designers and other stakeholders who are the participants (Lang, 2017).

The term automation evokes many significances. It is important to note that automation does not automatically mean the full automation of assessments, decisions, and behavior, putting educators "out of the loop." Automation may only turn the data collection, cleaning, review, and visualization phase into a commodity service that previously needed qualified, but limited, researchers or analysts. The responsibility for making sense of and acting on that input may be shared entirely with a human student, instructor, or analyst (e.g., The analytics system can suggest areas of concern that encourage users to prioritize attention or recommend courses). Feedback and guidance can also be entirely collected by professional teachers but customized through custom contact (Huberth, Chen, Tritz, & McKay, 2015).

In conclusion, the data revolution's potential in teaching and learning consists of creating much more timely feedback loops to monitor a complex system's efficiency. In a field where feedback has already been identified as a critical tool for students and educators, the question is how effective human-computer systems can realize this potential.

3.3.1 The Problems

While some of the best scholars in data science, analytics, user interface design, and organizational creativity are located there, a school or university is unwilling to innovate in monitoring, reviewing, and feeding knowledge to enhance teaching and learning on those fronts. While paradoxical to an outsider, the inherent chaos is all too common for the insider: Academics do not have opportunities to focus on strategic planning and learning challenges in their organization. As a result, research-active analytical groups do not necessarily respond to the analytical needs of their institutions. Academics do not want to be identified with the hated logo of the service center that has not research-worthy connotations. There will be some issues (Shum & Mckay, 2018).

1. **Academics are under pressure to perform new research**. They need to make an empirical breakthrough worthy of publications and grants checked by peers as they make proof-based statements on data based on robust analysis and sometimes use state-of-the-art technology well beyond what is available in existing products. They respect their intellectual independence, and they prefer to perform work on learning analytics that interests them. Academics reserve the right not to solve the "boring" (though serious) data issues in the organization because they see the problems as repetitive and/or because they do not want their study story dictated. Scientists, distribution, and resources are spent on procurement. There is time to compose, train PhDs, and submit and review articles.
2. **There is no praise for academics for developing scalable applications**. Any competent academic group can develop fresh, well-founded, and small-scale analytics, but it reserves the right to take on future challenges. Researchers have no incentive for more widely validating or moving progress into mainstream implementation. You definitely do not think it is your job to repair the institution's dysfunctional data structures; it is an IT or business intelligence (BI) job. Crossing the gap between innovation and technology often includes several competencies that are not common in research communities, technical software development, user interfaces, interface design, behavioral science, and innovation advocacy. This also includes an ongoing emphasis on the user community's needs. The key deployment of analytical instruments often includes comprehensive cross-campus collaboration with other academics and units to develop their commitment. It is a long-standing challenge for research and development of learning technology.
3. **Universities and colleges want students to have an impact**. This effect takes several forms. It increases student engagement, offers more effective education, tackles inequality in student results, protects budgets, and enhances retention and graduation rates. Such realistic findings are often seen as counter-incentives by academics. Academics should be careful when alleging causal ties or being pressured to justify their research financially. Unless the mainstream application of analytics involves scalable infrastructure that academics cannot provide, commercial products are created. We can include simplistic dashboards which give analytics a lousy reputation and which academics, as end-users or researchers, are reluctant to associate with. Things tend to reach the broader traditional mass markets rather than the future-oriented cutting edge of teaching and learning.

3.3.2 Organizational Architectures for Learning Analytics

Shum and Mckay (2018) suggested three learning analysis organizational models that can be considered by the college or university leadership to facilitate advanced analytics to accomplish their own goals and context.

The three main organizational models used to provide learning analysis are:

- IT Service Center model
- Faculty Academics Model
- Hybrid Innovation Center Model

1. ***The IT Service Center Model***: Under this model (Fig. 3.1), an IT service center offers analytics from an enterprise platform. For example, the following are:

    - The LMS team leads to the provision of analytics by using/configuring the product dashboards for academics (and perhaps students).
    - The enterprise data warehouse, BI, or institutional research (IR) team offers analytical information by combining LMS data and other data sources.
    - A team in the Center for teaching and learning works with these units to help academics use analytical technology.

    Advantages:

    - The center is designed to provide a production-grade analytics service near 24/7 uptime and system support accessible to all students and employees as a central integrated network for other institutional systems. The research typically involves "academic analytics" (conventional demographics, enrollment, and grades of students) and different types of learning analytics (finer-graining, mid-course progression, and activity data).
    - Staff will innovate what products can do and how they can integrate with current infrastructure.

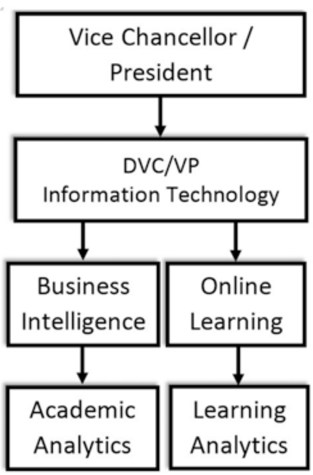

Fig. 3.1 Archetypal Organization Chart, IT Service Center Model. (Shum & Mckay, 2018)

- End-users are typically academics because, to date, most LMS and other items have dashboards to help educators monitor students' progress.
- However, generic LMS products continue to supply student dashboards (but poorly grounded in learning sciences), and when specialized products are used (such as an adaptive tutor on a specific topic), they can also deliver feedback to students since a model of the curriculum and the level of student masters is such a rich one.
- If products permit the customization of report/dashboards or facilitate the export of data, and if the center provides the capability for coding and analysis for subsequent analysis or visualization, user experiences can be provided.

Disadvantages:

- The staff typically only deal with data that products can supply by predefined user interfaces. It is highly doubtful that a participatory design model has helped end-users shape a product with the possibility of getting analytical services accessed on a limited basis and instead of obtaining them poorly.
- Staff seldom know the fields of data science, user interface, learning design, or advanced analytics techniques, thereby restricting the reach of the center's analytics innovation. Such expertise must come from other groups, and most IT services centers have little heritage of widespread collaboration.

2. **The Faculty Academics Model**. Faculty academics (possibly in collaboration with an IT service center) (Fig. 3.2) conduct applied research in the model. Examples are as follows:

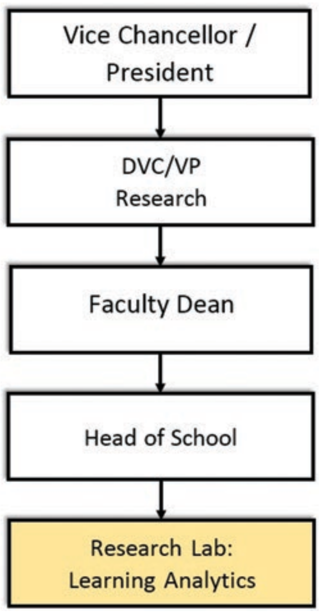

Fig. 3.2 Archetypal Organization Chart, Faculty Academics Model. (Shum & Mckay, 2018)

- Faculty academics develop creative (often externally funded) learning tools to facilitate unique LMS-supported modes of learning. This produces much richer data than generic (i.e., discipline-agnostic) LMS products usually provide. This can be used as research data on learning sciences and input to educators and students.
- Approval of research provided by their institutional LMS and/or BI teams examined by faculty academics. We recruit academics who want to test these analytics, research student reactions, and maybe include other groups such as student support teams.

Advantages

- This model offers sufficient room for revolutionary innovation for academics who can explore beyond existing products with unconventional sensors and advanced analytical techniques.
- Empirical evidence for adopting vendor products is gathered, which typically identifies obstacles to employee readiness, instructional activities that are incompatible with analytics or other organizational factors.
- Evidence-based statements are likely to be submitted with a high rigor, consistent with the Board of Human Research Ethics guidelines and peer-reviewed studies when published.

Disadvantages

- The work is advanced but requires sufficient research skills in design, implementation, and maintenance. This is also a limited knowledge, only briefly available.
- Because analytics become advanced, early adopters attract pilot students, but if these students move away from a subject's theory, the studies are over.
- The experiments are typically fairly limited and/or use different cohorts of students and/or short-term (e.g., only before external funding expires).
- Researchers are less likely to take user's design ("customer discovery") needs into account, and while prototyping analytics are conceptually involved, they may either be unusable or fail to answer widely understood requirements.
- After the lead researcher or key project staff leaves, nobody will drive the analytics service vision. Vision is required so that creativity can be continued through resource codes management, additional grants, strategic exposure, and essential partnerships.
- Developing a hybrid software/pedagogical concept to an enterprise-wide infrastructure is a process of growth that is frequently not compensated for re-searching and involves skills lacking in research groups.

3. **The Innovation Center Model**. A hybrid, autonomous innovation center is built in the third model to serve the entire organization. However, such innovation centers work outside the organization in close partnerships with faculty academics, IT/BI/LMS college/University teams, etc. This model appears to be dealing with fewer organizations, which we now turn into two examples:

- Research-active academics and data scientists sponsored by practitioners have a Core of innovation beyond the faculties and independent from institutional IT/Analytics. (For example, Connected Intelligence Centre, University of Technology Sydney)
- A center for innovation outside Universities, separate from the IT/analytics agency, is committed to the maturation and mainstreaming of the popular analytics technologies that academics create and the invention of their analytical services. (For example, Digital Innovation Greenhouse, University of Michigan)

(i) *Connected Intelligence Centre, University of Technology, Sydney*. The University of Technology Sydney (UTS) Connected Intelligence Centre (CIC) (Fig. 3.3) is an Innovation Center built to develop the capacity of the University to gain insights into analytical instruments and techniques — the teaching and learning cycle, testing, and operating units (Ferguson et al., 2014, 2016).

Staffing CIC is a small center with about 20 staff (not all full time). It looks in several respects like a University community of researchers at all levels, PhDs, faculty, and professionals.

While CIC can appear as an academic research group — because it has the mission to create research-driven, sustainable innovation within the UTS — academics are recruited for their research skills and their teamwork, transdisciplinary perspective, and communication skills. CIC has developed and launched the Master of Data Science and Innovation (MDSI) program coordinated and taught mainly by CIC's

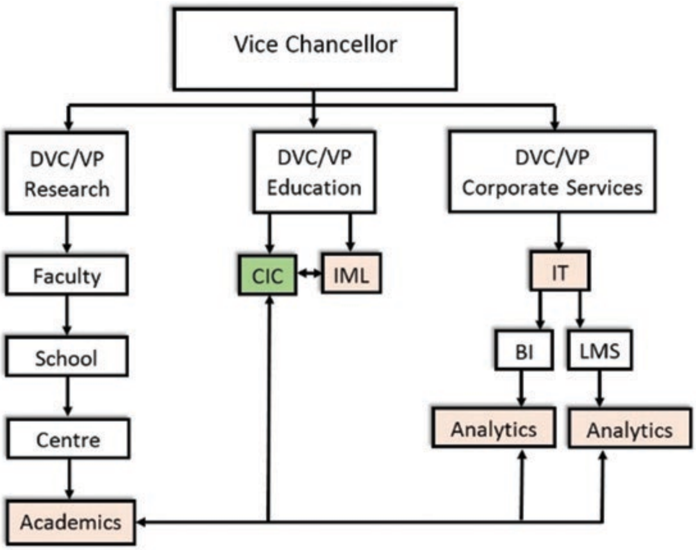

Fig. 3.3 Connected Intelligence Centre, University of Technology Sydney. (Shum & Mckay, 2018)

academics in 2015. It was the only degree program at UTS to take place outside a department until 2017 when UTS launched its Faculty of Transdisciplinary Innovation. The staff will oversee the MDSI program in 2018, but the same personnel will continue to teach it.

CIC has thus operated as a mini-faculty, running MDSI and an optional subject in quantitative literacy and critical thinking ("Arguments, Evidence & Intuition"). CIC's Academic Board of Studies reflects its transdisciplinary nature across UTS. These teaching programs created revenue that allowed CIC to expand beyond the University's baseline funding.

CIC reports to the Deputy Vice-Chancellor of Education. The Director of CIC has the opportunity to address the obstacles to accessing data, operating servers, coordinating meetings, and more with IT administrators, Teaching & Learning Innovation, Student Support, and libraries. This opens up strategic possibilities that would usually not be available to a faculty team.

Critical transitions for CIC will occur from the prototype to small-scale pilots, pilots with several hundred students, and the mainstream implementation to thousands of students. Also, students start expecting certain services and complain about downtime. In general, CIC is pushing a digital technology frontier (e.g., Amazon Web Services), facilitated by and in collaboration with the IT Division (ITD). However, this form of research needs to be secure and involves a positive and respectful relationship with ITD staff, who feel that fulfilling CIC specifications prepare them for what faculty members are likely to request in the future. For example, CIC and ITD co-funded a cloud specialist to assist MDSI students, hoping that other degree programs will call on this cloud services specialist in a limited period.

Cultivating Research-Grade Innovation in a Non-Faculty Center In this work, it is essential to attract and retain high-quality researchers who build an academically stimulating culture that provides the incentive and direction that researchers need in various stages their careers. It involves building national and international exposure through research conferences, providing affordable funding, and time for thought and writing.

Nonetheless, operating a hybrid academic/service process calls for managing conflicts between creativity and effect. For example, when is there "enough" evidence for scaling a prototype with compelling interest by academic research standards? CIC researchers recognize that their work needs to be tailored to bring UTS value as critical customers while collaborating closely with faculties and other client groups. Therefore, all PhDs work together with one or more experts, offering credible test beds while integrating risk factors into a Ph.D. program. Technology breaks new ground but is built in collaboration with ITD employees, who are not used by any other 24/7 student-facing network. Compared to R & D centers in industries, CIC's goal is to improve existing and future programs' productivity but does not necessarily pursue "blue sky" innovations out of curiosity. The CIC was built to create a sustainable capacity for data science and data analytics resources in UTS staff and students.

(ii) *Digital Innovation Greenhouse, University of Michigan*. Learning Analytics at the University of Michigan (UM) began in 2011 (Fig. 3.4) with SLAM Student Learning and Analytics in Michigan as a coherent work topic. This series of seminars combined a forum to share ideas and knowledge between faculty and staff on the campus with an opportunity to connect with external speakers. The UM project was inspired by the interest in SLAM in 2012 to launch a three-year, faculty-led Learning Analytics Task Force (LATF) that would encourage increased use of campus data and finance various Learning Analytics projects. Such programs took two forms: data collection to inform policy and practice; development of methods to use data to facilitate teaching and learning. Many of these methods were used as pilot projects in the classroom and received funding from external research (Lonn et al. 2017).

In 2014, the Digital Innovation Greenhouse (DIG) was introduced to address a common issue faced by LATF ventures. Innovators from the Faculty and their research teams have planned, built, and tested analytical methods to enhance education and campus learning. These technologies have usually been studied in academics' home environments, mostly in classes to be taught. When news of their existence and impact on the campus became known, interest in expansion to other areas came to light. While often involved in this development, the founding research groups lacked the requisite tools, expertise, and/or incentive mechanisms to develop a seedling invention into an aspect of the campus infrastructure.

Many of these initiatives have sought to scale up by distributing their resources to the campus's ITS unit. In setting up and maintaining mature software

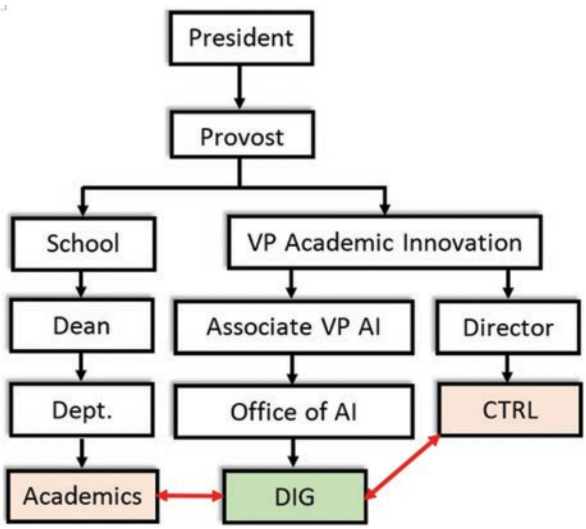

Fig. 3.4 Digital Innovation Greenhouse, University of Michigan. (Shum & Mckay, 2018)

systems, ITS as an enterprise is very successful. Unfortunately, the unit's skills and organizational strategies are not compatible with the researchers' loose, rapid "duct tape and chewing gum" methods. Eventually, DIG was founded as a pilot in 2015 to take advantage of the dynamic innovation culture on campus. They aimed was to adopt a series of existing digitally engaged innovations from research laboratories they had grown out of, take them through the "Valley of Death" innovation, and provide them to ITS as a campus-wide infrastructural tool. By doing so, DIG has accomplished the immediate aim of increasing current research resources' availability and the long-term objective of demonstrating the importance of this greenhouse strategy to create digital communication tools of the twenty-first century.

The University turned to the Office of Digital Education and Innovation to build a home for DIG. In 2013, this unit was initially set up to support UM's newly growing involvement in MOOCs and is reporting on the Vice Provost for Academic Innovation. It has become the focus of campus educational research and development activities and was renamed the Office of Academic Innovation (OAI) in 2016. OAI is currently home to teams working on three main subjects: designing, developing, delivering, and experimenting with online and hybrid education; growing analytics-driven educational innovations to scale; and promoting the gameful design of educational experiences. Both teams also work together with the long-standing Center for Research on Learning and Teaching (CRLT), particularly on residential learners' initiatives.

Staffing In a highly collaborative environment, DIG projects proceed, including at least four elements:

1. *Faculty champions and their research teams*. DIG carried out each project with a principal advocate from the faculty, usually assisted by research team members. DIG is now also investigating how technologies funded by students and staff can be funded. Innovators help drive each project's vision. Also, they regularly contribute to the design and impact of innovation research, often with external support.
2. *The DIG team of software developers, user experience and interface designers, behavioral scientists, and innovation advocates*. The group provides the professional credentials and award program required for technologically mature inventions in close contact with the increasing user community. A wide variety of graduate and undergraduate student fellows assist full-time DIG staff who provide additional effort, a fresh perspective, and close interaction with DIG resources.
3. *An expanding campus community of users, from early adopters to those who intend to use DIG tools as infrastructure*. Continuous, intense contact with this faculty, staff, and students' group is key to the DIG tools' success. The DIG team connects between faculty innovators and this group by ensuring that deep and mutually beneficial ties can be established and maintained.

4. *The UM ITS organization*. The DIG team works with ITS to achieve the technical support needed (servers, single sign-in authentication, data access) and ensure that the DIG tool implementation process stays within ITS systems on campuses.

Also, the main DIG team of these four classes is officially working in the OAI. The DIG team was initially formed as a team of three leading software developers and included a constantly expanding, full-time personnel. Support for the employee comes from three sources: UM Third Century Initiative grants for DIG launch, additional university contributions through the OAI budget, and project funds from various sources (NSF and other grants). OAI provides excellent administrative support and has proved essential to build and maintain a smooth, responsive organization within a sometimes peaceful and conservative campus community.

Engaging Faculty in Academic Innovation DIG was formed as an employee unit within the OAI, without official appointments for any faculty members. The model is focused on strong cooperation between faculty champions, their research groups, DIG staff, and the broader education community across the campus. Although this model has worked well, there have been significant tensions for some faculty members, particularly those who do not concentrate on education. They carry out this work in addition to their current research, teaching, and service responsibilities. To advocate an empirical breakthrough as it spreads on campus is not a simple challenge, mainly though the DIG team provides comprehensive professional support. In reality, the rapid growth and expansion that the DIG team can offer make the professorship champion more demanding. For this purpose, the DIG compares educational R&D – applied research aimed at reinventing higher education at an information age – to the activities taking place in the OAI. With this lens, DIG and OAI can be considered a research institution, similar to UM's former Institute for Social Research or its Life Sciences Institute. All units include faculty members with different positions, from 100% working to 0% affiliated faculty status. In 2018, OAI explored such appointments to ensure professional champions have the support they need to expedite innovation.

Reflections on the Innovation Center Model CIC and DIG have begun at various points and respond to various drivers. Since the launch of CIC, research-active scholars have been running their own Master's and Ph.D. programs, but now they have to build developers' capacity as demand for their analytics tools increases. DIG has also introduced projects from established academics with technology staff but is now looking at new models that include academics. Today the DIG and the CIC appear to shift towards a similar position: they are independent centers reporting to a VP/DVC with advanced data and analytical resources to address strategic teaching and learning issues while collaborating with facilities, professional development, and IT services in collaboration.

At this point, we can summarize the hallmarks of CIC and DIG:

- Reporting the center directly to a VP / DVC senior leader provides the strategic leadership required to improve data access and campus-wide analytical or innovation services.
- The center either integrates or operates very closely with their faculties (DIG) academics and research students (CIC). This helps the center innovate based on the study, which focuses on teachers' and students' needs, contributes to proof-based arguments, and meets ethical standards.
- The center has a central function and can translate these creative concepts into reliable analytical services incorporated with the institution's infrastructure and are subject to IT-approved requirements (e. g. security, architecture). When the prototypes of CIC begin the transition to more wide-ranging internal "products," the value of the DIG software design, development, assessment, and communication team is recognized.
- The center may add additional revenues to its institutional support, including internationally funded faculty collaborative ventures, domestic strategic grants, student fees from formal educational programs, and faculty purchases from academics.
- The Center will generate substantial design efficiencies and organizational synergies by providing a campus-wide focal point for creating analytical resources. For example, the DIG team has built a common, expandable framework for access to campus data that can be used by all tools to eliminate the need to replicate this framework with each tool. It has also coordinated a toolkit of products commonly useful for education in comprehensive introductory courses to improve the use of the entire array of resources. Similarly, CIC has re-archived the written feedback method to improve the range of services it can provide a better understanding of academics' various needs.
- If the center (like CIC) is home to its scholars and Ph.D. students, it looks like faculty study groups. The center must also be particular in stating that it is doing "business-as-usual" research and focuses on data issues facing the institution and generic/customized analytical services for academicians, students, and professional business units around the campus value. The developments of the center must be carried out with the support of institutional "clients."
- In cases where (as DIG) the center only has the personnel and cooperates with faculty who are not given a formal position in the organization, a significant burden may be imposed upon both the faculty's innovators and early adopters from its practice group. The incentive programs for research university faculty members are carefully designed such that new modes of practice are little known. If faculty members' home departments approve these creative activities as either study or service, the faculty can contribute easily.
- The center complements but does not duplicate a campus division's work, which leads to academic and educational professional development. These well-established centers provide pedagogy and student development expertise, but they cannot enhance learning analytics at the college or the university. For example,

CIC has collaborated very successfully with the UTS Institute of Interactive Media in Learning, whose academic learning and literacy specialists have advised and co-authored research papers on the CIC automatic writing-feedback. DIG and its representatives are working closely on the launch of the Fundamental Course initiative (FCIP) with the UM's Center for Research on Learning and Teaching and the Sweetland Center for Writingin the M-Write project.

- The center supports the function of the IT section but does not replace it. While colleges and universities already have an existing LMS and BI network, the center's focus is not on learning modes, data forms, and analytical user groups. The center will work closely with other departments and divisions involved in data management and create new test system services. Similarly, the center may be the first non-IT organization that supplies software applications for students or staff 24/7, which needs solid IT collaborations to provide security, network infrastructure, sensitive maintenance, etc. The partnership in IT will be mutually beneficial. For example, CIC and DIG have provided IT workers with secondment opportunities to work in a more start-up-like environment, learning new skills in various projects.
- The center continues to build resources to facilitate the work of skilled researchers in fields beyond education. The DIG ECoach method, for example, was used as an experimental framework for social psychology, online interaction, and the visual representation of quantitative knowledge. Similarly, CIC's framework for text analytics, social networks, and multimodal communication research can be widespread in non-educational contexts to support other UTS students.

Finally, it might not be a coincidence that both CIC and DIG have converged separately on the common strategically relevant problems of education and learning; it is about working together on the role that analytics can play:

- *Personalized messaging enabling feedback at scale*. Although all education evidence points to the value of timely, realistic, and personalized feedback for successful learning, it is incredibly challenging to provide this feedback in large classes. Both universities have built systems that allow students to generate coaching messages (e.g., over a week): UM has built the noted ECoach platform, while UTS has been running its own customized message platform for a decade and a collaborator of the Australian National OnTask project to create an open-source tool. The research task is to evaluate students' behavior profiles from multiple sources and compile feedback into a personalized e-mail, with the evidence that students interpret this feedback well and enhance the results (Huberth et al., 2015; Wright, McKay, Hershock, Miller, & Tritz, 2014).
- *Text analytics to send reviews to students*. Critical, compelling, reflective, scholarly writing is challenging to read, challenging to teach, and challenging to receive quick feedback. Both universities design natural language processing software to provide immediate formative input on student drafting (not summative grades) to promote revision and reflection. Scalable text analytics platforms are needed to adapt to the different writing features that allow usable feedback. According to curriculums, assignment tasks, and grading rubrics, the acknowledgment that

these instruments are most successful if they are matched with the right "learning style," is common to both efforts (the UTS Academic Writing Analytics tool and the research program and UM M-Write initiative).

- *Human-centered analytics*. Software design has slowly changed from technology-driven to human-centric, and it is no accident that both universities have academic professionals from the relationship of human computers on their teams and user interface designers. The Learning Analytics' human aspects range from assessing users' general needs to designing the user interface and analyzing users' participation by studying data ethics, algorithms, and visualizations. In order to achieve, these goals it is essential to find ways to engage stakeholders early on through participatory design approaches (Brown, Demonbrun, & Teasley, 2017; Knight, Buckingham Shum, Ryan, Sándor, & Wang, 2018; Lonn, Aguilar, & Teasley, 2015).

3.4 Major Barriers to Adopting Learning Analytics

3.4.1 Barriers

Learning Analytics Community Exchange (LACE, 2020) reports that the key challenges in using learning analytics are as follows.

1. ***Data availability***: The data generated by students in institutional systems are frequently pointed out that it is not 'big' data and that 'small' data techniques may be better suited to education. However, for some instances, the obstacle is not so much that educational data are low, but they are not accessible.
2. ***Data accessibility***: When data are available (as is increasingly the case), analytical applications are not automatically usable. Institutions and/or their employees may have ethical concerns that prevent their involvement. The laws governing the collection and storage of data generated by users (and children in particular) are also different in countries, so that effective solutions in one context may not be replicable elsewhere.
3. ***Interoperability***: The diversity of IT systems presents the challenges of analyzing data stored at multiple locations in different formats. This problem can be solved by restricting the scope to a single form of data collection (which can mean a single system), but this cannot be done in all situations.
4. ***User resistance***: The intended users of apps to learning analytics, especially teachers and parents, may have personal concerns regarding privacy and political concerns regarding surveillance. This can lead to boycotts or campaigns.
5. ***Incidence of professional roles***: Initiatives of learning analytics have long been explicitly linked to data-driven management technologies. The high-level leader (except institutional managers) should have access to institutional performance data to promote assistance, incentives, and consequences decisions. Professionals who fear expanding managerial power and responsibility and a symmetrical

restriction of their professional autonomy could be limited, and support their concerns should be supported. Such issues contribute to obstacles ranging from widespread distrust of advances in learning research to well-developed criticism and active resistance.

6. ***Hype***: It is evident that empirical approaches have tremendous potential to transform science, pedagogy, and management of education and create significant business opportunities. Most learning analytics applications aim to provide evidence-based, actionable insights, which would lead users to plan their use of learning analytics with plenty of evidence. However, as with other emerging innovations, implementation studies have also been driven by highlighting the enticing prospects while skirting the possible obstacles. Although the chances can be real, inflated expectations will lead to excessive cynicism if the benefits offered do not materialize, putting up further deployment barriers.

3.4.2 Steps to Successfully Adopt Learning Analytics

You will need to incorporate learning analytics within your organization to get the most out of your learning management system. However, it is easier to say than to do. Organizations would undoubtedly resist change, and obstacles to the implementation of learning analytics can be predicted (Ifenthaler, 2020).

However, you can significantly improve the chances of effectively applying learning analytics by taking a systematic approach. The Rapid Outcome Mapping Approach (ROMA) offers a valuable seven-stage approach to LA implementation that can be applied to an organization, regardless of its aspect, culture, or industry (Leah, Clow, Tynan, & Dawson, 2015). ROMA is a policy management model focused on evidence to help you understand your organization, assess its resistance to changes, and recognize the tools and stakeholders which can contribute to your success.

Make sure your Learning analytics is successful; follow the seven steps (Leah et al., 2015) to implement your organization's learning analytics.

1. ***Defining your policy objectives precisely***: The most critical prerequisite to successfully making a policy change is that the justification for it should be communicated. Your goals will reflect the organization's overarching purpose and match it with its core values, mission, and culture. Specify your goals very clearly, and the improvements you want to make to incorporate learning analytics. Remember also the sort of improvements that you intend to introduce.
   Several instances are:
   - Patterns of communication
   - Procedures
   - Recording
   - Perceptions and attitudes
   - Behaviors and habits

While procedures, records, and communication require careful preparation, investment in considerable time, attitudes, and behaviors present the most significant challenges as these changes allow the employees to change themselves. Expect resistance to some extent.

2. ***Map the Context***: Mapping your project context is essential because it allows you to recognize economic, political, cultural, and other factors that will influence the outcomes of your implementation efforts. Knowing the organization's history will help you predict obstacles you will have to resolve and encourage partners to succeed.
   Mapping the context involves analyzing the following:

   - *Context*: Individuals, organizations, and structures that may lead to or discourage change.
   - *The evidence*: How can you convince skeptics that reform is essential, and how do you present your case?
   - *Links*: People and processes that provide you with access to meaningful connections. This is the set of networks that you can use to support the implementation of Learning analytics.

3. ***Identify key stakeholders***: The primary stakeholders are more than the individuals in the organization who apply Learning analytics. They are the ones that are better served by Learning analytics. Several stakeholders should be identified. When you know who is most advantageous by using learning analytics, consider which stakeholders exert the most influence. This may be individuals or stakeholders, such as the heads of your organization. Once you recognize the top players, you will also begin to gain insight into your strategic plans and the approach to involving, advising, supporting, and preparing key staff.
4. ***Identify the goals of Learning analytics***: It depends on your clear understanding of your organization's purposes for Learning Analytics to implement Learning Analytics in your organization successfully. Learning Analytics can serve a wide variety of purposes, and many do not apply to your organization. You may, however, have several valid purposes for your organization to use Learning analytics.
   Types of purposes for Learning analytics may include the following:

   - Awareness of learners
   - Tracking and monitoring
   - Research
   - Assessment and planning.
   - Communication and reporting

   Think about the goals and interests the organization is concerned with – not all interests have the same needs or priorities. Remember which goals and stakeholders are your top priorities to direct your plan.
5. ***Develop a plan***: A strategic plan ensures that the execution is consistent and regulated. Your implementation is much more likely to go off track without a plan. Your strategic plan should identify everything you need to do to achieve your

objectives. The previous steps you have taken should be informed until now and involve the stakeholders. Create plans, review, and update the plan as appropriate.

6. ***Analyze the potential of your resource***: You are facing a long uphill battle if you do not have the money, expertise, or staff to incorporate learning analytics in your organization.
   Most organizations will require expertise in areas like:
   - Data Science and qualitative analysis
   - Project implementation and assessment
   - Development of the database
   - Management of learning technologies
   - IT support and interface development.
   - Design and development of analytics
   - Reporting on learning analytics
   - Business intelligence and strategic analysis
7. ***Creation of a Monitoring Control and Learning System***. By implementing learning analytics in your organization, you continuously monitor your progress and make the necessary adjustments. The continuous assessment helps you understand your current initiative and provides valuable insight into the future.
   Review your first principles, the initial policy priorities, and vision — in this phase, to ensure they are still valid, and you keep going in the right direction. At the end of implementation, review the overall process and report on future efforts.
   Implementing change in your organization can be a risky move, especially if you do not take the time to consider the challenges you are likely to face. However, even in the most resistant organizations, you can effectively execute Learning Analytics if you prepare correctly and use the people and tools at your disposal. Follow these seven steps to ensure your project is successful.

3.4.3 Recommendations and Opportunities for Policymakers and Education Leaders

Wolf, Jones, Hall, and Wise (2014) and the Alliance for Excellent Education formulated several recommendations aiming mainly at capacity building and ensuring that policies enable innovation in learning analytics instead of hindering it. Policymakers and educational leaders should do the following.

1. ***Develop a good understanding of learning analytics ability and rationale***: Learning analytics can help ensure equity for all students through the provision of useful information and information to educators, parents, and students to satisfy the requirements of each student. Although data usage also poses issues about privacy and security or the notion of a vast amount of information, Learning Analytics can be applied carefully and systematically that addresses security, safety, and feasibility.

Education leaders need to unlock the value of learning analytics by

- Encourage support for the importance of individual and equitable learning.
- Ensure that community leaders, board members, staff, parents, instructors, and students recognize teaching and learning advancement through learning analytics.

2. ***Build ability for learning analytics implementation***: While more comprehensive data systems have been developed in recent years, especially for longitudinal data systems and learning management systems, most students cannot still regularly, even daily, use data to inform educational and learning decision making. Capacity includes establishing infrastructures and data and evaluation systems and developing the human resources needed for an environment where evidence-based decision making is the standard. Education leaders need to develop the capacity needed for learning analytics for impact training:

   - To create an informed decision-making culture in which data is seen as a tool to make teaching and learning decisions and critical aspects.
   - Define new positions and school environments required to optimize learning analytics, including data scientist and instructional coaches who can help bridge pedagogy and data discussion
   - Develop human capital through professional learning possibilities at different embedded, permanent, and sustainable employment levels.
   - Build infrastructure and technologies to ensure bandwidth is readily available for data processing, evaluation, and access to synthesized data for educators and administrators, as well as meeting privacy and security needs

3. ***Identify and develop policies to support and facilitate Learning analytics***: Policies and guidelines at the level of policymakers/government have a significant effect on the future implementation and use of learning analytics.

   (a) To ensure that policies make it possible to personalize learning instead of hindering the use of data, education leaders must

   - continue to clarify what is and is not acceptable and to provide technical assistance;
   - increase funding to expand broadband access to allow efficient and effective use of data systems, online evaluations, and other digital content;
   - Add opportunities that promote learning analytics to ensure a holistic approach to the acquisition of technology and data in line with curriculum and instruction, data, and assessment decisions.

   (b) Education leaders must ensure that policies allow and not hinder the use of data to personalize learning.

- recognizing and directing the use of student data to enhance education;
- Create policies to ensure compatibility between longitudinal data systems (interoperability) with data systems;
- ensure enforcement with policies and processes with elements with data quality and action steps;
- find policies to support, facilitate and promote the adoption and successful use of learning analytics by incorporating standards and modern online assessments;
- make the use of data and Learning Analytics as to the required component of education, teacher preparation, and teacher evaluation programs;
- recommend policies that address the connection between learning analytics and competency-based learning.

(c) For policies to make the use of knowledge to personalize learning to be hindered, educational leaders must

- to explain how privacy is important to the use of student data and to provide administrators, teachers, and parents with a concise overview of how the privacy and protection of a student is per the laws;
- consider introducing responsibilities policies to increase access to, and accept responsibility of schools, students and parents with data, content, and curricula;
- Elevate data use and research analytics as a key component for technical learning opportunities.

4. ***Create models of funding to promote Learning Analytics***: There are several different funding sources and services related to the analytical field. It is also important to understand how the variety of sources of funding will contribute to the overall effort to personalize learning, including:

   - use current data and evaluation tools, broad-based networks, and cloud computing to incorporate learning analytics;
   - investigate and leverage alternative sources of financing not traditionally used in data and digital content systems;
   - Build plan opportunities and guidance

5. ***Conduct research supporting capacity building and policies critical to the Learning analytics:*** The identification and development of case studies that illustrate how capacities and strategies can be built will provide concrete examples for others to adopt. In this way, the scope of learning analytics can be expanded in more schools by knowledge obtained from early adopters and implementers.

The research will cover the following:

- a series of in-depth case studies that make significant progress with customized learning analytics;
- a review to better identify such capability-building approaches and resources, including an educated decision-making culture, appropriate infrastructure, human capital, and technical learning opportunities;
- analyzes to identify specific policies that allow analytical learning;
- Design a range of methods, techniques, resources, and sample policies to distribute Learning Analytics broadly.

3.5 Case Studies: Adopting/Implementing Learning Analytics at Institutions

3.5.1 The Open University, UK: Data Wranglers

The Open University (OU) is a distance education institution with more than 200,000 students and 10,000 academic and non-academic personnel engaged in educational assessment and learning analytics over 40 years ago. It has carried out two important activity programs, both explicitly rooted in learning analytics. This case study concerns Data Wranglers development.

Data Wranglers are academic staff who analyze various student learning information and make valuable suggestions to their University faculties'. Their position as interpreters of human data who help closure the feedback loop is described elsewhere in-depth (Clow, 2014).

The University has acknowledged that increased amounts of educational data are available but not effectively utilized (student input, activities in Moodle VLE / LMS, mode of delivery data, and quantitative demographics and findings). No integrated, systemic view to informing and improve teaching and learning practice was developed. Pilot testing was undertaken in 2010 and 2011, and the Data Wrangling project was released in 2012. The operation was not initially established with an apparent reference to the ROMA context but should be evaluated in those terms.

Step 1: Defining your policy objectives clearly: The project's goals were strongly incorporated into the current University policy and planning system. Initially, (1) a group of staff with expertise in the various faculty contexts should also be developed, (2) a system to collect, synthesize and report the available data should be created, (3) reports should be generated at regular intervals, and (4) good relations should be developed with the faculties. The primary types of improvement as per Young et al. (Young and Mendizabal 2009) were discursive changes to how data is exchanged and transmitted and structural changes to decision-making in curriculum development and support for students.

Step 2: Map the Context: The project leaders understood the dynamic organizational climate. In an established entity, the Institute for Educational Technology (IET), data confrontation was conducted to examine and impact teaching and learning. IET was already responsible for curating and sending some of the data involved. Many Data Wranglers already had connections to different faculties, and the unit had clear access to the management. There was already a considerable interest and commitment in learning analytics and data at the senior level, and a crucial relationship was identified in the early stage between the Data Wrangling project and the development of a broader analytical strategy.

Step 3: Identify Key Stakeholders: Because of the results' nature, all university members were regarded as stakeholders. The project focused in particular on providing insight into the development of curricula and quality improvement processes. The unit responsible for this work was also involved in implementing learning design across the faculties so that design work could be based on evidence from Learning analytics. In both cases, several key contacts were the same. The unit also conducted programs that concentrated on other facets of the learning cycle. Thus, each faculty responsible for learning and teaching and/or curriculum development was the key stakeholder. The curriculum at the OU is built by module teams that have also been designated as stakeholders. Certain primary players included senior management and data collection and curation managers.

Step 4: Identify the goals of Learning analytics: The project focused on designing curricula and improving quality. In addition to the above drivers, this focus was influenced by data-related considerations. Twice a year, student feedback and final results data (completion and exit rates) are published. The development of the curriculum and improved quality processes at the OU follow a similar cycle. It offers two points per year, where the project Data Wrangling will incorporate data from the university's interactive learning environment Moodle. Moodle systems do not yet embrace real-time monitoring, and therefore adjustments in real-time are outside the project's reach.

Step 5: Develop a Plan. Extensive consultation and feedback culminated in an implementation plan being developed. Early pilot work led to informing the shape of the Data Wrangling project. The Host Unit had a comprehensive project management program, and documentation was created that included both an implementation plan and review dates.

Step 6: Analyze your resource's potential: A vital aspect of the project preparation was capacity review. The Data Wranglers themselves were among the original targets to establish a thorough understanding of the teaching and teaching background. Education was planned for the Wranglers in the advanced use of Microsoft Excel. There has been a significant amount of time researching and learning the knowledge, including liaison with those who collect and cure it. New technical tools (including Tableau workbooks and SAS stored procedures containing data from the Data Warehouse that Intranet) have been deployed and developed, requiring further personnel development. On the "client" side, one goal of the project was to gain an understanding and understanding of what the data could show and to be aware of how you would access it without a Data Wrangler intermediary. It was a method that was iterative. It was not easy for Data Wranglers to understand and interpret some of the data. Some of the challenges they faced have been solved, some have been established as challenging to address data quality issues, and some remain puzzled.

Step 7: Creation of a Monitoring Control and Learning System: Feedback from stakeholders was integrated into the reporting process. In July 2013, an explicit evaluation exercise gathered input from key stakeholders and informed further growth.

The project was highly time-intensive in terms of both employee time and the delay between completing the course and the Data Wrangler study. Reports were also very different from each other in terms of coverage and quality. To a certain degree, this was a positive aspect as each Wrangler negotiated and established a mutual understanding with client stakeholders. Many faculties were optimistic that they could read various data visualizations; others were interested in qualitative research, which would allow them to understand what was happening and why. Some broad faculties wanted their data to be broken down in various ways, while smaller faculties wanted to see the whole picture.

Much was learned, and a further analysis was carried out in the summer of 2014 to simplify the operation. The initiative has made it possible for the data used by training and quality assurance processes to be better understood. Tools were built that can rapidly and accurately produce data reports to high standards with minimal manual intervention. This reduces the time requirements for Data Wranglers, enabling them to explore data further to answer faculty clients' urgent questions.

This section discussed several ways of ensuring a degree of success in promoting adoption on a scale for the Data Wrangler project. The secret to this success is that it has been incorporated from the outset with existing systems, processes, and networks. The involvement of stakeholders at all levels was critical. The project required a substantial allocation of staff resources, including resources from stakeholders of the faculty "client." This account of the Data Wrangler project has been coordinated with the ROMA system to provide an excellent example of the process.

3.5.2 The University of Technology, Sydney, Australia

The University of Technology of Sydney (UTS) is an inner-city university with a dream of being a world-class technology university. It began in 2011 as a "data-intensive university" (DIU) in line with this dream. This case study focuses on the technique used and the progress achieved so far. As mentioned above in the OU case study, the UTS strategy was not initially designed directly for the ROMA process, but reviewing recent trends and achievements indicates that the UTS approach is well incorporated into this strategic planning structure.

The UTS project was launched to believe that access to data can improve all aspects of the University and provide a springboard to create and innovate. UTS first created an organizational concept that defines the value of data analytics for contemporary university practice: "A university where staff and students understand data and, regardless of its volume and diversity, can use and reuse it, store and curate it, apply and develop the analytical tools to interpret it."

Based on this concept, DIU was created to make better use of the data to enable students, staff, alumni, and partners in the industry to explore and flourish, to understand their climate, to solve problems and challenges, to lead their fields, and to provide opportunities for the creation of knowledge.

***Step 1-Defining your policy objectives specifically*:** The UTS project is driven by a broad methodological approach, which aims to cover all aspects of the university's work: teaching and education, research, and management.

UTS seeks to use learning analytics to enhance student performance and develop student experience in universities. The aim is to ensure that all stakeholders can understand and interpret today's data-rich environments.

The study's goals are to provide researchers with an atmosphere that makes it easier and more effective to access and manipulate data, allowing them to think and behave differently as they develop their investigative methodologies and practices.

The administration's main objective is to identify opportunities for data and analysis to be obtained, generated, visualized, and communicated to improve decision-making capabilities and improve core business outcomes.

At the University level, the approach focuses on the value of mining existing institutional data to find areas that can provide staff and students clear evidence or help. For example, data and analysis may be provided for employees to promote a collection of intervention approaches for students at risk of withdrawal before completing a course of study.

Step 2: Map the Context: The project was initiated and directed by a member of the University's Senior Executive, Deputy Chancellor, and Vice President (teaching and learning). Initially, it obtained pilot funding and secured ongoing funding after completing several pilot projects. The ongoing project funding has made it possible to create a Connected Intelligence Centre. As its first director, an internationally renowned professor of research analytics has been recruited. The presence of an Established Analytical Institute was crucial to the initial pilot projects' success with globally known experts in Big Data, Data Science, and Analytics.

Step 3: Identify Key Stakeholders: To obtain the level of continuous funding necessary to ensure the initiative's longevity, a broad level of support throughout the University, particularly by the senior management, deans, and directors of the appropriate units, was vital. The idea of becoming a "Data-Intensive university" was first proposed during a retreat in early 2011, and a scoping project was sponsored.

Around 190 UTS (150 present and 40 online) staff attended a one-day "Data-Intensive University Conference" during the latter part of 2011, thus opening a university-wide discussion. Although the project's premise was almost universal, the naming of the program was significant controversy. Although the phrase "data-intensive" is well established in several science areas, it was thought to create obstacles for many people to alienate academics in other fields of study. Therefore, the name "data-intensive university project" was replaced by the word "connected intelligence project."

The Deputy Vice-Chancellor (Teaching and Learning), Deputy Vice-Chancellors (Research, Corporate Services), and Deputy Chairs set up a working group. A senior library employee was appointed as the senior manager of the project. Each faculty was included in the working group, as was each of the administrative fields with relevant expertise. The success of the project was crucial to the achievement of stakeholder buy-in and continuing involvement.

Step 4: Identify the goals of learning analytics: Learning analytics are used or used for:

- Include information to decrease the attrition of students;
- Offering a more detailed explanation of the factors that influence low passes in subjects with very high failure rates over time, known as 'monster subjects';
- Offering a customized guide to students with more knowledge about their study and interaction patterns.
- Allowing a more comprehensive understanding of the effects of several potential interventions on pass rates and completion, for example, the impact on pass levels and retention overtime of the peer-assisted study scheme;
- Provide valuable input to future learning projects that include adapting and intervening to personalize learning.

Step 5: Develop a Plan: Elements of strategy have been planned from the beginning of the project to:

- Give attention to institutional culture — ensuring the engagement and dedication through effective communication and governance of key stakeholders;
- Participation in university-significant pilot projects and recording of results;
- Technology investment: — tools, software, services;
- Investment in expertise: — vital staff recruitment;
- Leadership and strategic leadership engagement.

Step 6: Analyze the potential of your resource: As UTS becomes a more data-intensive organization, one of the most critical elements in its success is to ensure that analytical actors can interpret data, judge their value, and then engage in decision making based on facts. There is no point in investing so much if students and staff are not adequately numbered and trained to use the analysis generated by analytical projects.

For this reason, a subject has been developed and studied to develop the "ability to engage with complex, extended arguments underpinned by numerical data as a key to participate as informed citizens in issues of significance to our culture and society." The goal is to continue this activity to increase employees' numeracy.

Step 7: Creation of a Monitoring Control and Learning System: Some of the early pilot projects have already been studied. For example, the Outreach program includes as many students as possible by telephone contact. Early findings showed a large decrease in attrition in the communication group. Without funds to reach each student, empirical approaches have been used to identify these students deemed most at risk.

Also, the project "Killer subject" defined many areas to be tackled by the course coordinator. Such concerns have now been solved, and the failure rate has decreased substantially. To date, UTS has participated in a range of Learning analytics projects under the auspices of the larger DIU project to assess scale and effect. Although this project remains a multidimensional project, the degree of institutional buy-in and funding commitment shows that the structural, strategic plan strategy used leads to the project's success and the inclusion of analytics in the institutional culture.

3.5.3 The OU Strategic Analytics Investment Program

Through extensive data sets and a willingness to enhance learner performance, the OU has launched an eight-strand research plan to encourage Learning Analytics to benefit students. Pro-Vice-Chancellor Learning and Teaching is funded by the institution and considers the interests of various stakeholders' interests, including university administrators, students, and educators.

The Strategic Analytics Investment Program was launched in 2012 and put together various groups around the university under one vision: strategically (by indicators) use and apply knowledge to sustain students and encourage them to develop and reach their study objectives. The goal was to focus on this on two levels:

- Macro-level work adds information from institutional learning experiences to inform strategic priorities to improve the retention and progression of students;
- Micro-level work uses analytics to conduct short, medium, and long-term interventions.

To achieve the vision of the program, three key areas are mutually dependent and underpin the work. These include (1) analysis and insight development, (2) data availability, and (3) processes with an impact on the success of the students.

The vision and associated action are informed by understanding data in action, data on the action, and data for action. Multiple stakeholders use data in action via a live portal to understand their learner behavior and make changes and interventions with immediate positive effects. Data on the action is a more reflective process following adjustment or intervention. Data for action benefits from statistical modeling and creativity to identify different variables and alter them using a range of analytical methods.

This student performance strategy allows for versatility and a continuous assessment of all behavior. The four steps of recruitment, retention, advancement, and completion are identified as key performance outcomes and lead indicators. Many stakeholders have programs focused on "learning and teaching" and "student support activities." Stakeholders use advanced analytics to advise programs to boost performance.

Such approaches are analyzed and then the basis for factors affecting student progress. For example, a "module pass rate model" is used as part of university quality assurance processes to equate real module pass rates with those predicted based on the statistical analysis of the previous student's achievement over the last 5 years. The use of the model has strengthened the university's comprehension of students' nature and behavior, who are more likely to fight for their studies. The Model for pass rates ensures that key stakeholders can introduce effective short- and long-term support interventions.

Another strategic move was the launch in 2014, the latest OU Student Support Strategy, along with a new data platform that allows subject-specific student support teams to facilitate involvement in their progress assessments, using demographic data, task submissions, and online activities.

The job plan promoting the progress of students has seven branches. They offer professionals opportunities to enhance their performance by designing and implementing tailored and evidence-based approaches in critical market cycles.

This strategy has built a group of stakeholders that rely on each other to their full advantage, led by a senior executive. Data are handled from a single database holistically to ensure the best standard and reporting standards are accepted in the work program. It has ensured a cohesive approach to how the University uses analytics.

The seven program standards are:

1. Intervention and Assessment

    - A student success review is used to define priority focus areas in terms of curriculum improvement and learning design and strategies for the students most at risk of not going forward with studies.
    - A common methodology for assessing the relative value of interventions is to measure student behaviors and performance, informing potential improvements to the student experience.

2. Usability of data

    - Clear data visualizations around key performance metrics are being created. This will be available to key stakeholders in almost real-time to track student success.
    - A new self-service analytics platform triangulates various data sources, allowing academics and support staff to recognize trends and the variables that affect their performance.

3. Ethics Framework

    - A Learning Analytics ethics policy outlines the data gathered and its ethical use to enhance education and help individual students.

4. Predictive Modeling

    - Predictive machine-learning models are now present in many subject areas at university and include a weekly forecast of the probability of each student's next assignment based on the analysis of key variables, including online behavior.

5. Learning Experience Data

    • In the future, the University will gather input during modules instead of depending on surveys at the end of each study session. It helps educators and student support staff to respond to all student issues more rapidly.
    • The University should investigate how these designs affect its diverse student base's performance through the systematic correlation between learning design data of study modules and student activity data.

6. Career growth

    • A professional research group based on retention and success in the first year uses the evidence to exchange best practice across faculty borders.

7. Student Tools "Small Data"

    • Small data provides citizens with relevant, practical information (big data and/or "local" sources), arranged and packaged – mostly visually – to be usable and comprehensible, and feasible for day-to-day activities. Tools to provide actionable analytically validated knowledge, help students monitor their progress, and make the correct study decisions as they progress through their studies.

Strategic Analytics at the OU and the ROMA Framework This high-level account of the OU method is an example of how institution-wide analytics are applied. This also provides the ability to show how pre-existing research in ROMA steps can be interpreted.

In Step 1, the OU's overarching policy objectives include discursive changes in the communication of the institution's data and analytics, procedural changes in the way the students are supported, and behavioral changes in support for sustainable change. At Step 2, the context mapping was done in several ways. University leaders, students, and educators are identified as main stakeholders (Step 3). This also split down such stakeholder groups.

The goal of learning analytics (step 4) is clearly defined in terms of the strategic use and implementation of information to retain and support students in achieving their study goals. It is done by a carefully thought-out approach (Step 5), which is implemented at the macro and micro levels and is organized around data in action, data on the action, and data for action.

Step 6 of capacity analysis and human resources growth is structural and thus not included in the overview mentioned above but includes training, capacity building, and establishing an ethical structure for Learning Analytics. Finally, the monitoring (step 7) is carried out through a continuous evaluation process that focuses on specific results and leading indicators.

In this scenario, an overview of the ROMA implementation system reveals that each move was taken. For other situations, the system may recognize missing steps and then propose potential interventions to improve current research.

3.6 Conclusion

We have laid down the psychological dimensions, challenges, and dilemmas that higher education institutions face: How can they organize themselves to advance learning analytics and see the sustainable impacts of learning analytics across traditional services. Three case studies on how businesses incorporate learning research through challenges to involve students and teachers in exploring and uncovering new insights into student learning and transforming institutions' attitudes towards continuous enhancement in education and learning processes have been presented.

3.7 Review Questions

Reflect on the concepts of this chapter guided by the following questions.

1. What are the psychological aspects of students, administrators, and institutions face in implementing leering analytics? How to overcome them.
2. Does the personality of an individual influence the use of Learning Analytics? How?
3. Illustrate, with an example the, three organization architectures/models for learning analytics.
4. Explain the advantages and disadvantages of each organization's architecture/model for learning analytics.
5. What are the major barriers to making use of Learning Analytics?
6. List and explain the steps to successfully implement learning analytics in an organization.
7. What are the recommendations made for policymakers and education leaders for building capacity and ensuring learning analytics innovation?

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