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The Use of Data Analytics to support the development of assessment practices in higher education

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Abstract: The ways institutions are using assessment and feedback are rapidly evolving. In this application chapter we will reflect on three innovative applications of learning analytics to support assessment and feedback practices at two distinct universities, namely Maastricht University in the Netherlands and The Open University UK. We have specifically chosen these two universities as they provide innovative education to their students in unique ways. In our first application we explore how computer based assessments in conjunction with dispositional learning analytics can help educators to provide appropriate feedback. In our second application we explore why it is important to include learning design metrics in learning analytics applications. Finally, in our third application we illustrate how using assessment data and learning analytics some unique and perhaps unexpected results can be identified in terms of assessment alignment across modules.

Keywords: learning analytics, assessment, formative assessment, computer-based assessment, automated feedback, learning gains

Introduction

The ways institutions are using assessment and feedback are rapidly evolving (Evans, 2013; Greiff et al., 2017; Jensen et al., 2021). In particular since the combination of educational technology and data science in higher education, such as in the form of learning analytics, substantial new innovations and evidence-based practices have emerged (Larrabee Sønderlund et al., 2019; Tempelaar et al., 2015; Zheng et al., 2021). Learning analytics is described as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Ferguson, 2012).

In this application chapter we will reflect on three innovative applications of learning analytics to support assessment and feedback practices at two distinct universities, namely Maastricht University (UM) in the Netherlands and The Open University UK (OU). We have specifically chosen these two universities as they provide innovative education to their students in unique ways. While these three applications do not necessarily represent "box-standard" provisions of assessment and feedback practices in these two universities, by critically describing what we have learned from these cases this might help you when you are considering to implement some innovative assessment and feedback practices and want to include some learning analytics data. Alternatively, these three applications might give you some handholds when investigating your educational data practices at your institution and how you might use these insights to potentially update your assessment and feedback practices.

Assessment and feedback innovation and two distinct universities

UM has implemented Problem-Based Learning (PBL) since its inception in 1976, whereby students work in small groups (i.e., 12-15 students) supported by a tutor using PBL-tasks. A particular focus of PBL is the application and critical evaluation of knowledge, skills, and competences to address a respective problem in a PBL task (Gijbels et al., 2005; Schmidt et al., 2009). At the UM students would normally meet face-to-face twice a week in their small groups to work on three to four PBL tasks, as well as meeting for one or two seminars/larger lectures. Using the so-called 'seven jump' (i.e., pre-discussion: clarifying terms, defining problem(s), brainstorming, structuring and hypothesis, learning objectives; independent study; post-discussion: synthesis) students first pre-discuss a PBL task and activate any prior knowledge and expertise in the group, and afterwards search for answers to this task by self-study, after which they post-discuss this PBL task for a second time (Gijbels et al., 2005; Schmidt et al., 2009). By providing both knowledge and broader perspectives of a specific topic as well as applications in smaller groups students are actively co-constructing knowledge and skills over time. For the UM we specifically focussed on our nearly 20 years of research on Computer-Based Assessment (CBA), and how by combining CBA with learning analytics and dispositional learning analytics in particular we have aimed to support a diverse group of international and local students studying at a business school.

The OU is the largest university in Europe and a distance learning provider for 51 years. As the OU works at scale and has an open access policy (i.e., anyone can study at the OU irrespective of their prior qualifications or experience) the educational provision needs to support a wide range of students (Nguyen et al., 2020; Richardson, 2013). This is where learning analytics can provide important opportunities to support each and every learner irrespective of the scale of provision. According to several studies (Wakelam et al., 2019; Wasson & Kirschner, 2020), the OU is trailblazing the use of learning analytics at scale and in the use of assessment in particular.

Application 1 Computer Based Assessments and dispositional learning analytics

While there are a range of studies showing the long-term effectiveness of PBL at Maastricht University and elsewhere (e.g., Dolmans, 2019; Gijbels et al., 2005; Schmidt et al., 2009), one of the concerns of students and teachers raised about PBL is that when there is a substantial diversity in knowledge and prior expertise within groups, and in particular when learners in those groups have not sufficiently prepared themselves for the post-discussion of a

PBL task, the quality of the post-discussion may be of insufficient quality. As students are expected to self-regulate their learning, some students decide not to fully engage with the respective learning tasks in a timely manner until a respective summative assessment (Rienties et al., 2019; Tempelaar et al., 2015; Tempelaar, Rienties, Mittelmeier, et al., 2018).

While most students typically would follow the structure of the PBL tasks and prepare their work accordingly, some discussions in the small groups are not reaching their full potential as substantial time is spent on explaining the key concepts, theories, and applications to those who have not fully mastered these. While explaining these concepts, theories and applications to their peers is a valuable learning experience for students, the quality of these discussions could be further extended if nearly all students came appropriately prepared to the next group discussion.

In 2002 we first introduced a weekly online quiz for first year students studying economics (Rienties & Woltjer, 2004), whereby students were expected to pass five out of seven weekly CBAs. These quizzes consisted of 20 multiple choice questions presented in a virtual learning environment (VLE) that were randomly extracted from a larger database of questions linked to a respective chapter that was discussed in that respective week. By engaging with a range of questions that were conceptual in nature as well as applications of economics, students were able to test and apply their knowledge and skills, and, if needed, further refine their understandings. By engaging with these questions students received automated feedback on their knowledge and skills. As a result both students and tutors reported that the quality of the post-discussions improved as more students came prepared to class (Rienties & Woltjer, 2004).

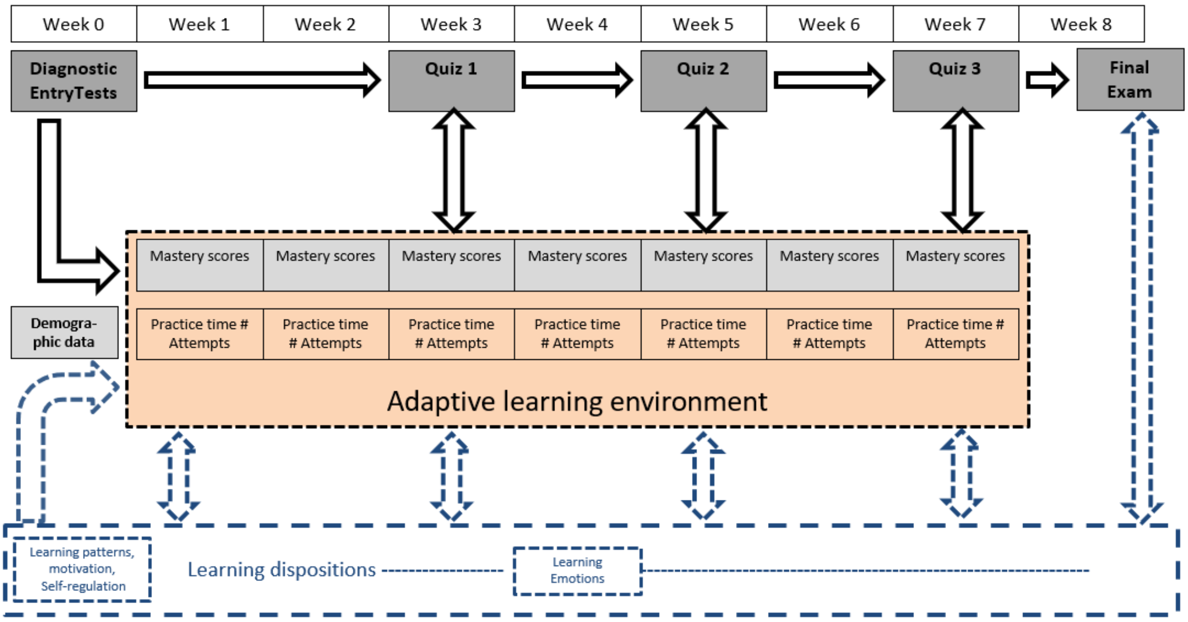
In subsequent years we gradually improved our understandings, affordances and limitations of CBA and how we could better support our students, in particular using (dispositional) learning analytics. For example, CBA tests could be used extensively to help (prospective/novice) students to gauge whether (or not) they were ready to start studying economics at the UM (Tempelaar, Kuperus, et al., 2012; Tempelaar et al., 2006). Furthermore, we learned over the years that adaptive learning environments like ALEKS (Tempelaar et al., 2011; Tempelaar, Rienties, et al., 2012; Tempelaar et al., 2006) or SOWISO (Rienties et al., 2019; Tempelaar, Nguyen, et al., 2020; Tempelaar et al., 2021b) can successfully identify which knowledge and skills a student had already mastered (or not) and provide stimulating and personalised pathways to help to support each of these students to develop sufficient mastery.

While these adaptive learning environments could be powerful, in subsequent studies we learned that students' dispositions to learning (e.g., motivation, learning strategies) had a substantial influence on how they used CBA and self-regulated their learning. Learners' orientations to learning, or learning dispositions as referred to by Buckingham Shum and Deakin Crick (2012), have been shown to be a helpful approach for us to develop, build, and empirically evaluate explanatory learner models. As argued by Tempelaar et al. (2021b) in Dispositional Learning Analytics (DLA) "researchers aim to complement trace data with other subjective (e.g., survey data) and/or objective (e.g., continuous engagement proxies) measures of learners' orientation to learning". There have been several attempts to identify behavioural proxies of learning dispositions using trace-based data (Jivet et al., 2021; Salehian Kia et al., 2021). However, our work on the first quantitative methods (QM) course that business and economics students encounter in week 1 of year 1 has mainly focussed on self-survey instruments and critical reflection. In this QM course, around a thousand students participate every year, whereby the majority of students are from outside the Netherlands with a diverse background in quantitative methods and learning patterns (Tempelaar et al., 2015; Tempelaar, Rienties, Mittelmeier, et al., 2018).

As illustrated in Figure 1 at the start of the QM course students complete a diagnostic entry test that was initially developed as part of a national initiative of mathematics by Dutch universities (Tempelaar, Kuperus, et al., 2012). As illustrated in Figure 1, some of the data boxes are coloured in grey, indicating that these are relatively objective data points. Others like the learning dispositions are coloured in blue with dashed lines, indicating that these are relatively more subjective data points. Indeed in week 0 students receive a range of learning disposition questionnaires that measures amongst others their self-regulation, motivation, and learning patterns (Rienties et al., 2019; Tempelaar et al., 2015; Tempelaar, Rienties, Mittelmeier, et al., 2018; Tempelaar et al., 2021b).

A first unique design feature of this QM course is that students get access to their own generated data (Tempelaar et al., 2021b), so they can reflect on their own learning dispositions. Furthermore, they will receive an anonymised dataset of other students' dispositions as well and they will work with these authentic data in the first couple of weeks to learn basic quantitative methods techniques (e.g., descriptive statistics). By seeing and analysing other students' data this might trigger students to reflect on their own learning patterns.

Figure 1 Learning dispositions, assessment and feedback



Updated from Tempelaar et al. (2015)

A second unique feature of this course is that in parallel to the regular PBL classes students are given access to an adaptive learning environment (ALE). In this ALE, students can work on authentic mathematics and statistics tasks and they receive feedback on their progression in a variety of ways (Tempelaar et al., 2015; Tempelaar et al., 2017a, 2017b; Tempelaar, Rienties, & Nguyen, 2018; Tempelaar et al., 2021a). As found in some of our previous studies, some students spent a lot of time in ALE and obtain high weekly mastery, while others spent less time on it, or mostly engaged with the environment before a respective quiz or summative assessment (i.e., exam). By providing personalised adaptive feedback students receive a lot of opportunities to engage with mathematics and statistics, and as described in various of our studies participants have different support options to choose from (Tempelaar et al., 2017a; Tempelaar, Rienties, et al., 2020).

A third unique feature to encourage students not to wait to start to engage with the learning materials until week 8 of the course when the exam is provided is by the introduction of three quizzes. These quizzes are based on learning materials discussed in previous weeks and student can receive bonus points if they manage to complete these assignments.

From this design a lot of useful (and less useful) learning analytics data and dispositional learning analytics data are extracted, which is also shared with students. By providing students with a mirror of their current learning dispositions and illustrating what other students might do a range of options are provided to students to explore which combinations of learning dispositions might work well for them.

Main lessons learned: Learning analytics can help to identify which groups of students are doing well, and which groups of students might need more support. The use of CBAs helps seems to be a productive way to encourage richer follow-up group discussions, and provides personalised feedback to learners. At the same time, without a deep understanding of students' learning dispositions providing automated feedback that might work for one group of learners (e.g., work harder on assignment 4) might completely backfire on other groups of learners.

Application 2 Use of online assessments and learning design

Since 2005 the OU has been investing in learning design to understand how teachers make decisions in designing their learning activities for their students (McAndrew et al., 2005; Rienties, Nguyen, et al., 2017). In the conceptual development of the Open University Learning Design Initiative (OULDI) seven learning activities were defined by Conole (2012), including assessment (i.e., All forms of assessment (e.g., summative, formative and self-assessment): e.g., write, present, report, demonstrate, critique). In a range of studies we have shown that assessment plays an important part in how, what, and when students study at the OU (Nguyen et al., 2017; Rienties & Toetenel, 2016; Rienties et al., 2015).

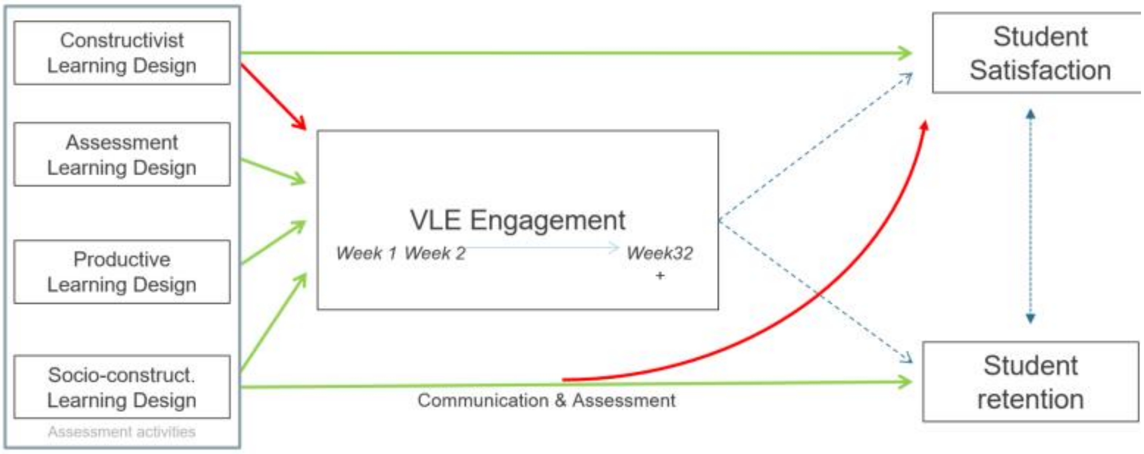
In our first studies exploring learning design decisions made by OU teachers, Rienties et al. (2015) used K-means cluster analysis on 87 modules to identify four common patterns of learning activities of how OU teachers developed distance learning modules. The findings indicated four relatively distinct learning design clusters: assessment-driven (i.e., relatively high and frequent focus on assessment activities), balanced-variety (a mixture of seven learning activities), constructivist (relatively strong focus on assimilative activities), and social constructivist (relatively strong focus on communication and interactive).

Of particular relevance for this handbook, in the assessment driven cluster, teachers allocated a fair amount of time for assessment (both formative and summative) while having limited focus on assimilative, communication, and interactive activities (Rienties et al., 2015). Indeed with a larger sample of 157 learning designs Toetenel and Rienties (2016) found that students were expected to spend on average22% of their study time on assessment, although with substantial variation (SD = 15%, range 0-78%). In follow-up studies (e.g., Holmes et al., 2019; Nguyen et al., 2022) assessment activities were found to be important regardless of design, but again a unique cluster was identified whereby teachers specifically focussed relatively a lower of emphasis on assessment.

After initially highlighting substantial differences in assessment practices in terms of time allocated to assessment, in follow-up research linking learning design decisions with learning analytics approaches to determine whether these decisions influenced student engagement and performance, we again found strong support of the notion that "assessment drives learning". In the first study (Rienties & Toetenel, 2016) to link 151 learning designs with student engagement comprising 111,256 students, their academic performance and student satisfaction, we found that learning design substantially predicted how students were learning. We found that in particular learning activities labelled as communication (i.e., student to student, student to teacher, teacher to student) were highly predictive for both student engagement and academic performance. In contrast, and perhaps surprisingly, assessment did not predict student engagement or academic performance, but did negatively predict student satisfaction (Rienties & Toetenel, 2016).

One of the potential reasons for this finding was that the data analysis (multiple regression modelling) did not necessarily take time into consideration. In follow-up work by Nguyen et al. (2017) we explored on 74 undergraduate modules and 72,377 students how learning design decisions influenced student engagement, academic performance and satisfaction using fixed-effect models using weekly data. We found that an increase in assessment activities in a week was significantly linked to a fall in the time allocated for all other learning design activities, except for interactive (Nguyen et al., 2017). In other words, when educators introduced assessment activities they reduced other activities in order to avoid an overwhelming workload for students. In follow-up modelling we found that assessment activities were positively predicting student engagement when looking at week-to-week data, although again communicative activities had an even stronger impact on engagement. Finally, assessment activities were positively predicting academic outcome (i.e., pass-rates), whereby again substantial divergence was found in the qualitative descriptions of six case-studies on how teachers actually designed and implemented assessment practices in their courses (Nguyen et al., 2017).

Figure 2 Learning design, assessment activities, and student performance



Adapted from Rienties and Toetenel (2016) and Nguyen et al. (2017)

As indicated in Figure 2, the way teachers design their courses and assessment practices in particular substantially influence VLE engagement, as well as student satisfaction and student retention. For example, in courses where teachers designed a relatively high focus on assessment (i.e., assessment learning design) there was significantly more engagement by students in the VLE on a week by week basis, although this high engagement did not necessarily lead to higher student satisfaction or student retention. Both studies find that while communication and assessment activities have a negative impact on student satisfaction, this has a positive impact on student retention. Overall, 69% of weekly engagement by students was predicted by how teachers designed their weekly learning activities, indicating the substantial importance of learning design and what teachers do (Nguyen et al., 2017).

Main lessons learned: The way teachers design and implement learning activities has a substantial influence on how, what, and when learners learn. Without an appropriate understanding and appreciation of learning design any learning analytics application is bound to be limited in its application to behavioural trace data. For a deep understanding of why learners in say week 2 engage with some learning materials and not others while their behaviour might change in week 3 it is important for learning analytics applications to understand the blueprint of learning design.

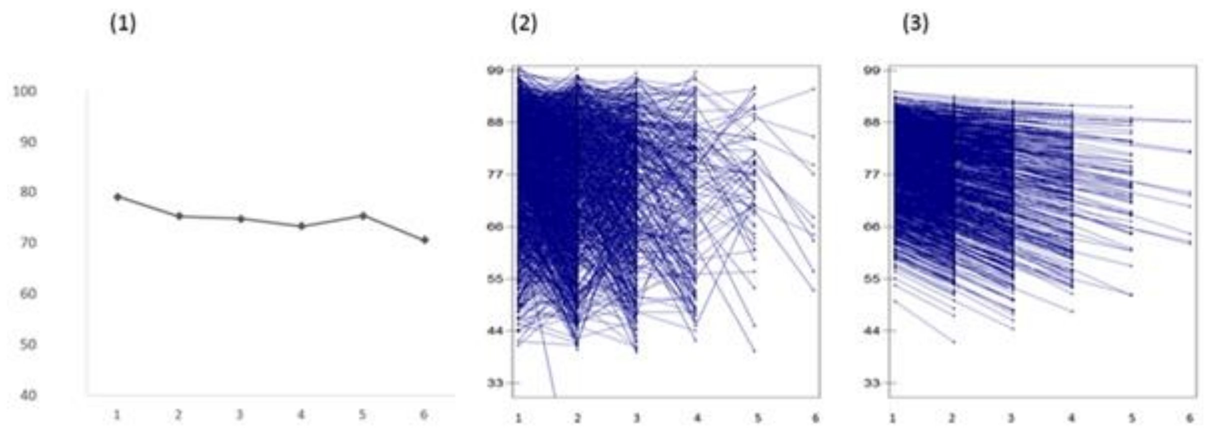
Application 3 Measuring learning gains within and across modules in a qualification

Enhanced emphasis on accountability processes in higher education is one of the key trends over the last ten years. One way of assessing the 'value' of HE is to look at learning gains. Learning gain is a commonly used term that refers to change in students' knowledge and skills in relation to desired learning outcomes (Evans et al., 2018; McGrath et al., 2015). For example, a recent systematic literature review by Rogaten et al. (2019) of 51 studies with 41, 000 students indicated a rich but diverse variety of adopted methodologies and approaches were used by researchers attempting to "measure" learning gains. Our third and final application will briefly summarise how we used learning gain concepts to learn from our assessment practices at the OU.

In our initial work we explored whether students progressed well through their respective qualification (Rienties, Rogaten, et al., 2017; Rogaten et al., 2020). Within the UK government higher education Teaching Excellence Framework (TEF) framework, there is an assumption that as students develop knowledge and skills in a qualification, students will strengthen their abilities to interlink concepts, to master key skills, and to be able to solve increasingly complex problems (Evans et al., 2021; Higher Education Commission, 2016; Rogaten et al., 2020). As argued by Rogaten et al. (2020) if a qualification is well designed and assignments are aligned according to well-defined grade descriptors and/or rubrics, it would be reasonable to assume that as the level of difficulty increases the grading over time will be adjusted. If there is a lack of alignment in terms of grade descriptors between modules within a qualification, students might perform really well on one module, and underperform in a module that has relatively harsh grading policies. If we find large variations across modules or even "negative" learning gains across a qualification, this may imply that we may need to look at the potential alignments or misalignments between assessments within and across modules within a qualification.

By using a 3-level growth curve model (Rogaten et al., 2020; Rogaten et al., 2017) of 13,966 unique student learning journeys we were able to distinguish *module characteristics* (Level 1: for example module structure, workload, complexity of assessments, alignment of assessments with previous and follow-up modules) from *individual student characteristics* (Level 2: for example effort, socio-demographics, gender, prior ability) from respective qualification characteristics (Level 3: for example qualification pathways, constructive alignment of learning outcomes across the qualification , employability focus). In contrast to our initial expectations, we found that most qualifications had a negative progression over time (Rogaten et al., 2020). For example, in one computing degree we included six modules and found that students' grades (corrected in our multi-level model) dropped from 79.2 (SD = 11.3) for this first module to 70.6 (SD = 13.2) as illustrated in Figure 3.

Figure 3 Average module scores (0-100) across six modules of a computer degree



Source: (Rogaten et al., 2020)

Based upon our multi-level modelling described previously (i.e., modules, individual students, qualifications), the variance partition indicated that there was 12% of variance between the different qualifications (i.e., Level 3), while 45% of variance was explained by student characteristics, and 43% was explained by module characteristics. In other words, the largest portion of variance in this model was explained by individual student characteristics (e.g., effort, ability, socio-demographics). Given the widening access agenda of the OU (Higher Education Commission, 2016; Richardson, 2013) one would hope that students from a widening access background, who might initially struggle on the first module, will become more successful over time. However, our multi-level analyses (Rogaten et al., 2020) indicated that students with below average achievements on their first module tended to have a steeper drop in their consequent module attainments. In contrast, students who obtained above average grades in their initial module had a smaller drop in their subsequent module attainments. In other words, while most students over time got lower grades, our multi-level models showed that this decline was particularly stronger amongst students who initially already had relatively lower performance. Similar multi-level modelling on a "Traditional" UK University amongst 2,702 students indicated that variation on a qualification level was substantially lower (8%), while student characteristics were substantially higher (67%), and module characteristics again were lower (25%) in comparison to the OU. In other words, this seems to suggest that the way assessments were developed over time at the OU were perhaps less well aligned relative to the comparison university.

In follow-up work (Rogaten et al., 2020) we specifically looked at the first two modules that "new" students took at the OU in order to determine whether we are providing a consistent practice at the start of their journey. We found a significant time-path interaction in five out of six qualifications ($p < .001$). In other words, students' grades changed over time depending on which study path they chose: some paths led to grades going up, and some to grades going down. Perhaps the most striking effect in this analysis is that there was a highly significant time-achievement interaction in every single case ($p < .001$). That means that students in different achievement groups (high, mid, low) had different changes to their grades over time. If assessments were well aligned, one would expect achievement groups to be, on average, stable over time. This was recently highlighted by Boud (2018), who noted that researchers need to tread carefully when comparing grades across time and discipline when the underlying frameworks of assessments and grading practices are not well aligned on an institutional level.

Main Lessons learned: Our big data learning gains explorations highlight a potential need to better align expectations and modules within a qualification across the OU, as students get substantially different experiences depending on the respective qualification they are enrolled into. There could many potential explanations for these findings. There are substantial challenges in aligning modules which have roles in multiple qualifications. This adds extra weight to the recommendation to developing university-wide, cross-faculty processes for better aligning assessment and grading (Bearman et al., 2016; Rienties, Clow, et al., 2017).

Discussion

In this application chapter we reflected on three innovative applications of learning analytics to support assessment and feedback practices at two distinct universities, namely Maastricht University in the Netherlands and The Open University UK. In our first application we explored how CBA in conjunction with dispositional learning analytics could help educators to provide appropriate feedback. In our second application we explored how learning design decisions made by teachers had a substantial impact on how and when students learn. Finally, in our third application we illustrated how using assessment data and learning analytics helped to identify some potential misalignments in grading practices across modules and qualifications.

There were some similarities and differences across these applications that are useful to reflect upon. First of all, in all three applications the insights that were developed over time evolved after substantial investment and dedication by authors and the surrounding stakeholders (e.g., educational experts, learning designers, managers, students, teachers, technicians). For example, in both the CBA and learning design application years of preliminary explorative and conceptual research was done before substantial steps were made in advancing our state-of-the-art research insights. For example, at Maastricht we have used CBAs for over a decade before we started to explore how learning analytics applications could potentially enrich our feedback provision. Similarly, the learning design conceptualisations led to a range of practical workshops and methods to help teachers to reflect on their practice, but it was not until 2015 that these data were used in conjunction with learning analytics data to explore whether decisions made by teachers substantially impacted students, and if so how and why.

A second similarity in all three cases was the increased sophistication of methods and approaches used over time. While early initial studies were conducted using relatively simple and standard statistical analyses, over time the modelling and combinations of different data sets became increasingly complex, perhaps aligned with increasingly complex and advanced research questions. This should be seen by those who are just starting their journey of using learning analytics as an encouragement. Often it might be quite difficult to comprehend and implement the latest learning analytics applications or algorithms. Our experiences have shown that by starting simple, learning the complexities in our context and data, and appreciating that every small step might lead to more new insights, substantial innovation can be achieved over time that can influence both research and practice.

Practical implications

As highlighted from our practical hands-on experiences in three applications, we would encourage teachers, practitioners, researchers and policy makers to start small when considering to use learning analytics. Often times your organisation already collects a lot of interesting data, and you might have an idea about what might be useful research questions and data to explore. Starting small with some kind of theoretical framework is probably even more helpful. There is nothing more practical than a good theory so whatever data you might want to consider to investigate, having a good (assessment/pedagogical) theory that might help you to think about key concepts and links between these concepts will help you with a lens to get started.

For example, based upon our third application we found substantial variation in how students performed on assessments within modules, and across modules. We noted from informal observations that often a lot of time was spent during assessment boards to ensure that grades within a module followed some kind of "logical" pattern, whereby often times staff would eye-ball assessment data of students within a module, compare what they knew about respective students and their grades, perhaps look at average scores, standard deviations, outliers, and/or perhaps look at what the average scores were in previous implementations of the same assessments last year.

One practical and easy way to check whether the various assessments are aligned within one module is to run simple correlation analyses of the grades of the various assessments of students within a module. Even though we acknowledge that the skills, competences, and knowledge assessed on the various assessments in a module might be substantially different, one would assume that there would be some kind of positive (cor)relation between the assessment scores of say assessment 1, assessment 2, and assessment 3. These correlation analyses are simple and straightforward to calculate for teachers as they have all assessment data directly available in their module. Programs like Excel or SPSS can easily compute these correlations, and alternatively institutions could automate these correlations in their grading templates used for assessment boards.

If for example one would find a strong correlation (say rho = 0.81) between assessment 1 and assessment 3 but only a weak correlation between assessment 2 with assessment 1 (rho = 0.15) and assessment 3 (rho = -.05) respectively this should trigger a teacher to carefully look at assessment 2. Perhaps assessment 2 is a substantially different type of assessment that might require substantially different skills, and therefore one would not expect strong correlations with other assessments. Alternatively, there could be limited variation in the grades given in assessment 2 (e.g., just pass/fail). But if these two potential reasons are not present and a teacher would expect that the three assessments should be well aligned to each other these simple data metrics should be a warning flag, which might require additional screening, and perhaps reconsideration of the assessment design.

Obviously running these correlations of assessment scores within modules could also be done retrospectively in order to check whether there was indeed an alignment between assessment performance within/across modules. These historical assessment data could also be used to identify common benchmarks of the range of correlation coefficients that would be appropriate within a particular level of a programme, or discipline.

A next step, which perhaps would be more difficult for an individual teacher to achieve, is to longitudinally link assessment scores of students within say a year of a programme, or across a degree. Within VLEs and management information systems all these assessment data of students' performance on each and every assessment are available to the institution, and we are still surprised that these data are not routinely linked in our own institutions. By linking these data it would be feasible to identify which modules “under-assess” their students, while at the same time identify modules which perhaps “over-assess” their students. This under/over assessment could apply both in terms of the frequency of assessments, harshness versus leniency of grading, as well as consistency of graders within a particular assessment point. For an individual teacher it might be difficult to know how its students performed before and after their module, but nearly each institution has these data somewhere stored and ready to be analysed. On an institutional level using more advanced modelling processes it would also be feasible to explore whether particular sub-groups of students are doing more/less well over time, thereby potentially providing additional support (if needed). These quality enhancement data could also be shared with stakeholders.

For example, within the OU Analyse predictive learning analytics tool (Herodotou et al., 2019; Rienties, 2021) used at the OU assessment data (and other engagement and individual data) are used to predict whether a student is going to submit their next assignment. An obvious extension of this approach would be to include a predicted grade indicator for the next assessment as well as a historical/current/future ambition grade set by students that would help teachers to explore whether the student’s performance is in line with their historical, current and future ambitions.

Once you have started to explore your assessment data in your own context and shared your experiences with colleagues and perhaps students in your unit, do not stop there. Your stories and insights on assessment are important to be shared beyond the boundaries of your institution. For example, building on application three, when repeating the same approach at other institutions in the UK, we found some comparable but also very different patterns over time. By sharing assessment experiences beyond organisational boundaries, you not only help the community but also help to understand your own context a bit better.

Obviously one needs to be extremely mindful of institutional differences in assessment and feedback practices, as well as underlying educational goals and practices (Evans & Waring, 2020).

Suggested Readings

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior, 47*, 157-167.

In search for the most informative data for feedback generation: Learning Analytics in a data-rich context.has become one of the standards in applying learning analytics, assessment and feedback. In this article which provided more details about application 1 we explored which types of data might be useful for assessment and feedback purposes, and how one could practically identify data from diverse online and blended learning tools.

Rienties, B., Nguyen, Q., Holmes, W., & Reedy, K. (2017). A review of ten years of implementation and research in aligning learning design with learning analytics at the Open University UK. *Interaction Design and Architecture(s) Journal, N.33*, 134-154.

This overview provides a short but useful overview of how learning design has been practically implemented at the OU in the last ten years, and what lessons were learned from combining innovative practices around learning design with increasingly sophicaticated learning analytics applications. This article provides a useful introduction of what learning design is, and how it can be used as indicated in application 2 to help to position assessment activities in the wider design of blended and online education.

Nguyen, Q., Rienties, B., & Whitelock, D. (2022). Informing learning design in online education using learning analytics of student engagement. In B. Rienties, R. Hampel, E. Scanlon, & D. Whitelock (Eds.), *Open world learning: Research, innovation and the challenges of high-quality education* (pp. 189-207). Routledge.

This recent overview provides an up to date narrative of how further innovations have been made in learning design and learning analytics, as indicated in application 2. It builds on the previous paper and compares how assessment decisions and practices by educators in 37 modules at the OU influenced how students were engaging on a week by week basis. Furthermore, it explores how some groups of students are studying ahead of time for assessments, while others use procrestination strategies. This book chapter shows how learning analytics data combined with learning design data can provide important intertemporal data to educators (and students).

Rogaten, J., Rienties, B., Sharpe, R., Cross, S., Whitelock, D., Lygo-Baker, S., & Littlejohn, A. (2019). Reviewing affective, behavioural, and cognitive learning gains in higher education. *Assessment & Evaluation in Higher Education, 44*(3), 321-337.

This article reviews affective, behavioural, and cognitive learning gains in higher education. This systematic literature search included 52 studies (n = 41,009) which were coded into using affective, behavioural and/or cognitive learning gains and provides a useful extension of application 3. The review found a rich but diverse variety of adopted methodologies and approaches to “measure” affective, behavioural and cognitive (ABC) learning gains. Nonetheless, the review found that there was a lack of consistency in the ways in which learning gains were measured and reported, which might hamper effective comparisons of learning gains and teaching excellence.

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Boud, D. (2018). Assessment could demonstrate learning gains, but what is required for it to do so? *Higher Education Pedagogies, 3*(1), 54-56. https://doi.org/10.1080/23752696.2017.1413671

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Dr. Bart Rienties is Professor of Learning Analytics and programme lead of the learning analytics and learning design research programme at the Institute of Educational Technology at the Open University UK. He leads a group of academics who provide university-wide learning analytics and learning design solutions and conduct evidence-based research of how students and professionals learn. He has successfully led a range of institutional/national/European projects, and has received a range of awards for his educational innovation projects.

Dirk Tempelaar

Dr Dirk Tempelaar is senior lecturer at Quantitative Economics, School of Business (SBE) and Economics at Maastricht University (UM). He teaches introductory statistics in SBE and University College Maastricht programs, as well as foundational mathematics and statistics in preparatory summer courses for SBE and pre med students. His research interest is in modelling student learning processes, using the dispositional learning analytics approach.

Quan Nguyen

Dr Quan Nguyen is a Teaching Fellow at the University of British Columbia (UBC) Master of Data Science where he develops and teaches data science courses in statistical inference, time-series, and data science communication. Prior to UBC, he was a Postdoctoral Research Fellow in Learning Analytics at the School of Information, University of Michigan. His research applies statistical and machine learning techniques on large-scale clickstream data from learning management systems to predict student performance and interactions.

Jekaterina Rogaten

Dr Jekaterina Rogaten is course leader at London College of Fashion at University of the Arts London. Her main research interests are in the field of positive psychology and education. Most of her research is centered but not limited to evaluation of the effectiveness of Higher Education courses and programmes as well as the effect of individual differences of academic progression.