Scholarly insight Autumn 2017: a Data wrangler perspective

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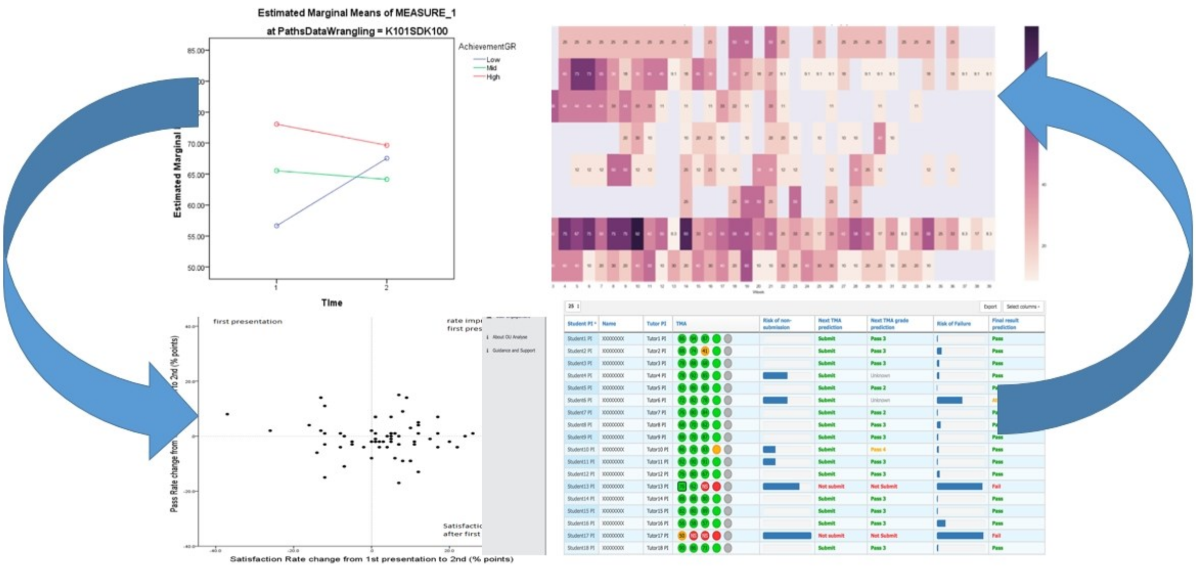

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FOREWORD

As the OU is going through several fundamental changes, it is important that strategic decisions made by Faculties and senior management are informed by evidence-based research and insights. One way how Data Wranglers provide insights of longitudinal development and performance of OU modules is the Key Metric Report 2017. A particular new element is that data can now also be unpacked and visualised on a Nation-level. As evidenced by the Nation-level reporting, there are substantial variations of success across the four Nations, and we hope that our interactive dashboards allow OU staff to unpack the underlying data.

The second way Data Wranglers provide insight to Faculties and Units is through the *Scholarly insight* report series. Building on the previous two reports whereby we reported on substantial variation and inconsistencies in learning designs and assessment practices within qualifications across the OU, in this *Scholarly insight Autumn 2017 report* we address four big pedagogical questions that were framed and co-constructed together with the Faculties and LTI units. Many Faculties and colleagues have reacted positively on our Scholarly insight Spring 2017 report, whereby for the first time we were able to show empirically that students experienced substantial variations in success within 12 large OU qualifications. As evidenced in our previous report, 55% of variation in students' success over time was explained by OU institutional factors (i.e., how students were assessed within their respective module; how students were able to effectively transition from one learning design of one module to the next one), rather than students' characteristics, engagement and behaviour.

We have received several queries and questions from Faculties and Units about how to better understand these students' journeys, and how qualifications and module designs could be better aligned within their respective qualification(s). As these are complex conceptual and Big Pedagogy questions, in Chapter 1 we continued these complex analyses by looking at the transitional processes of the first two modules that OU students take, and how well aligned these modules and qualification paths are. In Chapter 2, we explored the more fine-grained, qualitative, and lived experiences of 19 students across a range of qualifications to understand how OU grading practices and (in)consistencies of assessment and feedback influenced their affect, behaviour, and cognition. In addition to building on previous topics, we introduced two new Scholarly insights in Chapter 3 and Chapter 4. As the OU is increasingly using learning analytics to support our staff and students, in Chapter 3 we analysed the impact of giving Predictive Learning Analytics to over 500 Associate Lecturers across 31 modules on student retention. Finally, in Chapter 4 we explored the impact of first presentations of new modules on pass rates and satisfaction, whereby we were able to bust another myth that may have profound implications for Student First Transformation.

Working organically in various Faculty sub-group meetings and LTI Units and in a google doc with various key stakeholders in the Faculties[i], we hope that our Scholarly insights can help to inform our staff, but also spark some ideas how to further improve our module designs and qualification pathways. Of course we are keen to hear what other topics require Scholarly insight.

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EXECUTIVE SUMMARY

1. How do the paths students take through their qualification impact their achievement?
Chapter 1 explores the issue of potential inconsistencies in assessment practices between modules by investigating how the paths students take through their qualification impacts their achievement in terms of final marks. This works builds on our the Data Wrangler *Scholarly insights Spring 2017 report* (Chapter 1, Rienties et al., 2017), whereby using multi-level modelling we found that eleven out of twelve qualifications showed a longitudinal decline in marks over time as students progressed through their qualification. As highlighted by a wealth of research and practice, the transition in the first two modules is of essential importance for successful progression and continuation of study. Therefore, in Chapter 1 we are particularly interested to unpack the transitional experiences and academic performance of students in their first two modules. If qualifications and introductory modules in particular are appropriately structured and respective assessment are "well aligned", we would expect students who are high achievers on their first module will also be high achievers on their second module, and low achievers on that module to be low achievers on the next module.

In contrast to our initial expectations, analysis across 6794 students in six OU qualifications indicate strong assessment and grading misalignments of students completing their first and second module. Significant time-achievement interactions between first and second module were found in each of the six qualifications, whereby high/mid/low achieving performed substantially different in their second module. In many cases, this was a convergence in average marks: high-achieving students tended to do less well in their second module, and low-achieving students did better in their second module. Perhaps more worrying, in all but one qualification, there was a significant time-path interaction: that is, students' marks fluctuated for their second module depending on which study path they chose in a qualification. In plain English, some paths in a qualification are better aligned for students than others, but at this point in time the OU does not give concrete suggestions to students and staff which paths might be most appropriate, and which paths might be particularly suited for particular groups of students.

This analysis is strong, further evidence that students' marks are not well aligned within six large OU qualifications. In other words, there is an urgent need to ensure consistent grading practices within and across modules within qualifications. In our *Scholarly insight Spring 2017 report* we already highlighted a need to improve the grading practices and alignments of assessment practices within and across qualifications (Chapter 1, Rienties et al., 2017). Our current Annual Quality Review practice and focus on module performance rather than analysing students' journeys on a qualification level might distract our efforts to ensure a consistent learning design, learning experience, and assessment and feedback practice over time. This analyses further provides evidence for urgent strategic intervention by Faculties:

> Recommendation 1: We recommend that clear OU guidelines and grade descriptors across a qualification are developed, as well as for each level and module, which are clearly communicated to staff and students.

> Recommendation 2: It is essential that grades are aligned not only within a module but also across a qualification. For exam boards we recommend including cross-checks of previous performance of students (e.g., correlation analyses) and longitudinal analyses of historical data to determine whether previously successful students were successful again, and whether they maintained a successful learning journey after a respective module.

One particular concern that needs urgent action is how the OU is providing advice to students which modules are appropriate to follow. Our analyses indicated that even when students were successful in completing their first module, depending on the respective follow-up module students selected they might again become successful, or experience substantial difficulties. In part this is due to the inconsistencies in learning design practices in OU qualifications (See Chapter 2, Rienties et al., 2017), and in part this is due to misalignments of assessment and grading practices. At present there is a lack of systematic provision of advice that is evidence-based upon actual successful and unsuccessful trajectories of OU students, which might significantly disadvantage some groups of students. Outside the OU there are already several study-recommender systems developed, tested and successfully implemented on a large scale (Denley, 2014; McKay, 2017; Phillips, 2013) that provide students with consistent advice and recommendations which modules and qualification pathways are best to follow, and which modules or qualification pathways might be more challenging. These large-scale implementations of study-recommenders have found 2-5% increases in qualification completion over time. As highlighted by the forthcoming Innovative Pedagogy Report (Ferguson et al., 2017), it is important that the OU provides smart learning analytics to students and staff to help them to make the best decision of which qualification pathways might be the best way forward.

> Recommendation 3: The OU needs to invest in smart learning analytics recommender systems that can help staff and students to support which paths within qualifications lead to highest success.

2. How do students experience marking and learning gains across qualifications?

Chapter 2 focuses on the student perspectives of assessment and feedback practices in qualifications, and is based on nineteen in-depth interviews with undergraduate students from FacultyC, FacultyC and FACULTYA. Building on Chapter 1, the analysis presents a range of insights into what and how OU students feel they are 'gaining' from learning at university study and, in so doing, it problematises the assumed link between grades and learning gain by probing the work-study-life complex within which distance learners study. This helps to address questions about the role and significance of the assessment marks in students' affective, behavioural, and cognitive (ABC) development.

Evidence from these interviews suggests that in many cases achieving slightly lower scores helped students to adopt a deeper, more self-directed approach to learning. In such cases, students appeared to be gaining in respect to affective or behaviour aspects of their learning, whilst performing less well in assessment scores (i.e., a measure of cognitive gain). This underlies the importance of considering affective, behavioural and cognitive gains together and recognising that whilst there may be an apparent fall in one there may be unobserved gains in the others. Furthermore, there are indications that from a student perspective, the value and purpose of instructional activities may change as the student becomes a more self-confident and self-directed learner. This may reveal a potential gap between how the institution and the student interprets and takes meaning from particular measures of learning gain.

As highlighted in Chapter 1 as well, the inconsistent grading practices within and across modules in qualifications might negatively impact students. Several students used lower-than-expected grades as a positive stimulus to work harder for the next assessment, while others got discouraged and changed their ABC. Therefore, there is an urgent need to better understand the lived experiences of our students throughout the qualifications.

> Recommendation 4: The OU needs to better measure, understand and unpack the transitional processes of OU students through their qualification/student journey to improve the provision of our Students First approach.

3. What is the impact of predictive analytics on student retention?

Predictive Learning Analytics (PLA) are used at the OU to identify which students are going to pass a course, and which of them are at-risk (Calvert, 2014; Herodotou et al., 2017; Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Wolff, Zdrahal, Nikolov, & Pantucek, 2013). PLA data can provide useful, complementary information to module teams and Associate Lecturers (ALs) to help them identify students at-risk of failing while also allow them to support other groups of students (e.g., well performing) and maximise their potential. In Chapter 3, using two large-scale studies we will explore whether providing weekly PLA data to 500+ ALs across 31 modules had a positive impact on student progression and retention.

In our first large-scale study with 240 ALs across 10 modules we found a significant positive impact of PLA usage on students' progression and retention. ALs who actively used PLA on weekly basis had a significant impact on student progression and retention, in comparison to ALs who did not use PLA. However, a strong variation in actual PLA use was found, whereby some ALs actively used the predictive data on a weekly basis, while others only logged in sporadically (Herodotou et al., 2017). This highlights complex and myriad relations between PLA and retention, which in part as explained by the voluntary nature of using OUA, in part related to a lack of consistent policy what ALs are expected to do in terms of PLA, and in part related to a lack of consistent tracking of what ALs actually do based upon PLA. In modules where ALs are actively using PLA in general there seems to be a relatively positive effect on progression and retention, while the effects amongst modules with low PLA usage indicate limited to no effects. At present ALs are not "forced" to use PLA in their AL contract, and therefore uptake and usage of PLA is solely dependent on the goodwill of ALs and module teams. Given that most students drop out in Level 1 and Level 2, it is essential that the OU develops a clear and consistent approach to support staff and students with PLA.

> Recommendation 5: The OU needs a consistent policy and implementation of Predictive Learning Analytics across Level 1-2, as providing PLA data to Associate Lecturers who act upon this data significantly improves retention and progression.

In the second large-scale replication study with 251 ALs across 21 modules, we were able to confirm the initial findings of the first study, whereby active use of ALs significantly increased student performance. What this data suggests is that: (a) PLA should be used by module teams, ALs and Student Support teams to support students at risk of failing their studies. (b) ALs need to be systematically engaged with predictive data to make a difference to student performance and retention. (c) Engagement of ALs with PLA can predict student performance. (d) Predictive data can inform ALs about their students' online behaviour, complement and strengthen existing teaching practices. An alternative approach that will need to be tested in the near future is whether providing PLA data in a sensitive, inclusive, and positive manner to students could have a more direct, positive effect on progression and retention. Of course given the sensitive nature of PLA and the context of our OU students, this will need to be tested extensively and carefully.

> Recommendation 6: In an evidence-based design the OU needs to test whether providing Predictive Learning Analytics data to students in a sensitive, inclusive and positive manner can further improve retention and progression.

4. Does a first presentation of a new module impact pass-rates and satisfaction?
Anecdotal evidence suggests that some students avoid first presentations of new modules and that some staff advise students - particularly those with disabilities - to avoid taking new modules. There is, however, a lack of understanding of the impact of a module being in its first presentation on performance and satisfaction, which is particularly important given the focus within OU Redesign and Student First Transformation for more agile production of new and different types of modules. In Chapter 4, we will analyse 68 modules first presented in 2013 and 2014, for which there is now data to compare the first and subsequent two presentations.

In contrast to some beliefs, the analysis indicate no significant changes in pass rates between first presentations and subsequent presentations. A small improvement in satisfaction rates between first and subsequent presentations was found, but with very high variability between modules. However, prior research has found no relationship between satisfaction and performance in OU modules (Rienties & Toetenel, 2016), and again no relations between satisfaction and pass rates were found in the 68 modules in any of the three implementations. As the effect identified for satisfaction is not substantial in size and the satisfaction rates are extremely variable, the pass rate finding should arguably be prioritised. This suggests that there is no overall effect of first presentation modules on performance. In the second part of Chapter, we used qualitative data to investigate the student experience in modules where satisfaction or pass rate saw a substantial and persistent improvement after the first presentation.

Given that sensitive and confidential data about individual modules and qualifications are provided, we are have anonymised modules, qualifications, and Faculties in order to share the results in ORO. Please contact bart.rienties@open.ac.uk if you want to receive a full copy of the detailed report, and indicate specifically whether or not you are a member of the Open University UK.

1 HOW DO THE PATHS STUDENTS TAKE THROUGH THEIR QUALIFICATION IMPACT THEIR ACHIEVEMENT?

Highlights

1. Analysis across 6794 students in six OU qualifications indicate strong assessment and grading misalignment from first to second module
2. Significant time-achievement interaction between first and second module: students in different achievement groups had different changes to their marks over time. In many cases, this seemed to be a convergence in average marks: high-achieving students tended to do less well in their second module, and low-achieving students did better in their second module.
3. In all but one instance, there was a significant time-path interaction: that is, students' marks fluctuated for their second module depending on which study path they chose.
4. **Urgent need to ensure consistent grading practices within and across modules within qualifications**

1.1 Introduction

It is well known from the several studies carried out in to the reliability of assessment (e.g., Meadows & Billington, 2005; Moxley & Eubanks, 2015; Schuwirth & van der Vleuten, 2006), that there can be substantial disparities and inconsistencies between (and even within) human markers, and there is evidence to suggest this is a particular problem at the OU. For example, the Data Wrangler Scholarly insights Spring 2017 report (Rienties et al., 2017) explored students' academic performance as a proxy for estimating learning gains at the Open University. A multilevel growth curve model was fitted to student overall module marks. Of the top ten most popular qualifications, all but one showed a decline in marks over time as students progressed through their qualification. Alarmingly, the analysis suggested there may be considerable inconsistency in marking practices and standards within and between qualifications, and the report recommended work to align grades not only within modules but within qualifications and across the university. This aligns with the findings of the 2015 Student Experience of Feedback, Assessment and Revision Survey where the most frequently mentioned issue in the open comments was inconsistency in AL advice, marking and feedback – both between AL groups and between modules (Cross, Whitelock, & Mittelmeier, 2015).

One particularly troubling finding from the Data Wrangler Scholarly insight Spring 2017 report (Chapter 1, Rienties et al., 2017) was that students' journey from one module to another caused substantial transitional problems and imbalances in students' progression over time across modules (43% of variance). This was in line with other work suggesting students are not always successful in terms of completing consecutive modules (Calvert, 2014; Li, Marsh, & Rienties, 2016; Li, Marsh, Rienties, & Whitelock, 2017).

Therefore, Chapter 1 explores the issue of inconsistency in assessment by exploring how the path students take through their qualification affects their achievement in terms of final marks. As highlighted by a wealth of research in higher education and first-year experience in particular (Harvey, Drew, & Smith, 2006; Hillstock & Havice, 2014; Rytkönen, Parpala, Lindblom-Ylänne, Virtanen, & Postareff, 2012; Yorke & Longden, 2008), the transition in the first two modules is of essential importance for successful progression and continuation of study. Therefore, in Chapter 1 we are particularly interested to unpack the transitional experiences and academic performance of students in their first two modules. If qualifications and introductory modules are well structured and assessment "well aligned", we would expect students who are high achievers on their first module to tend to be high achievers on their second module, and low achievers on that module to be low achievers on the next (Conijn, Snijders, Kleingeld, & Matzat, 2017; Koester, Grom, & McKay, 2016; Popov & Bernhardt, 2013). We used a mixed ANOVA to explore the relationships between the path students took, their achievement group (high, mid, low), and their marks on subsequent modules. We selected students who had passed two modules in the periods 2013J-2016B, and examined the highest population qualification(s) in each Faculty. Our main research question is: **Does the path students take through the first two modules of their qualification impact their achievement in terms of marks?**

We will first describe the method we used to address this question in section 1.2. Afterwards, we will describe the results of the overall development of grades from students' first module to their second module in section 1.3. Given the large amounts of data and complex analyses, we will provide aggregate results in section 1.3 and will use one exemplar of qualification QualA to illustrate the main developments. Fine-grained and specific results of the other five qualifications are provided in the Appendix.

1.2 Methods

The sample of students analysed are those who passed at least two modules in the period from 2013J to the end of the 2016 calendar year (i.e. including 2016B but not 2016J). For each of the Four Faculties, the top two qualifications in terms of student numbers were selected, apart from FacultyB, where only the top qualification was chosen, because the second most-popular qualification was fairly similar to the first. Within each qualification, the most popular paths taken by students were selected. As a result, 6794 students across these six qualifications were included in the analyses, using the same multi-level analyses as previously described by Rogaten, Rienties, and Whitelock (2017). Afterwards, students were split into three distinct achievement groups – high, medium, or low – based on their marks in their first module. (Low = 40 – 59, Mid = 60 – 69, High = 70 +). For each qualification, a mixed ANOVA was carried out with time as a within-subject factor (first module to second module), and path (the top study paths, all others grouped) and achievement group (low, mid, high) as between-subject factors, and marks on the second module as the dependent variable.

If assessments are perfectly aligned within and across qualifications, and was assessing consistent subject matter, we would expect no significant main effect of time on marks and no significant main effect of study path, but we would expect a significant main effect of achievement group. In other words, marks would not trend up or down over time, marks would not depend on which modules students chose, and students who are high achievers in their first module would tend to stay high achievers and so on. We would not expect significant interactions between the factors.

Table 1.1: Qualifications in this analysis with top study paths selected

Qualification	**Top study paths selected**
QUALA	QUALAM1-QUALAM2, QUALAM1-QUALAM3, QUALAM1-QUALAM4
QUALB	QUALAM1-QUALAM5, QUALAM1-QUALAM6
QUALC	QUALCM1-QUALCM2, QUALCM3-QUALCM2, QUALAM3, QUALCM2
QUALD	QUALDM1-QUALDM2
QUALE	QUALEM1-QUALEM2, QUALEM1-QUALEM3
QUALF	QUALFM1-QUALFM2, QUALFM1-QUALFM3, QUALFM1-QUALEM3
QUALG	QUALGM1-QUALGM2, QUALGM1-QUALGM3, QUALGM30-DQUALGM3, QUALGM4-QUALGM2, QUALGM4-QUALGM3, QUALGM4-DQUALGM3

Note that this sample includes only those students who were successful on at least two modules: students who studied both modules in a path but failed on the second module are excluded. Note also that it is possible that a small number of students may have taken another module in between the two modules listed as a study path here. Students were assigned to a qualification based on their declared intention when they took the second module.

Many qualifications and modules have changed, sometimes substantially, since the start of this sample in 2013J, which in some cases means important issues are not captured fully by this analysis. Several of the qualifications explored here have been replaced and are now in teach-out; there was not enough data from students on the new, replacement qualifications to explore those. This is likely to remain a difficulty in any future analysis: qualifications are regularly refreshed, so by the time sufficient data for longitudinal analysis is available, significant revisions or replacements to modules and qualifications are likely to have been made. However, analysis can still yield actionable insights, particularly where the findings are so consistent across multiple qualifications, as here.

On many qualifications, students take a wide variety of study pathways, as was previously highlighted in our Spring Scholarly insight Report (Chapter 1, Rienties et al., 2017). This means that despite the relatively large sample, the only pathways with sufficient numbers for analysis were all at level 1. We had originally intended to explore longer study paths (i.e. more than two modules), but the low numbers on any given path in this dataset made this infeasible. This does, however, mean that this analysis focuses on the first transition within a qualification, which is a key step in the student journey.

1.3 Results

As shown in Table 1.2, there was a highly significant main effect of achievement group in all qualifications analysed ($p < .001$), with large effect sizes (not illustrated). This is as expected: whether a student was a high, mid or low achiever in their first module should be a good predictor of their results in the second module. On two of the seven qualifications, this main effect was qualified by an interaction between path and achievement group ($p < .05$).The main effect of time was significant in all but two of the qualifications, at various levels of significance ($p < .02$ to $p < .001$). This is consistent with the findings in the

Table 1.2 Results of mixed ANOVAs for six large-scale qualifications

Effect	QUALA	QUALB	QUALC	QUALD	QUALE	QUALF	QUALG
Path	$F(3, 579) = 8.16$, $p < 0.001$	n.s.	n.s.	n.s.	n.s.	$F(3, 922) = 14.0$, $p < 0.001$	$F(6, 611) = 3.44$, $p < 0.005$
Achievement group	$F(2, 579) = 190$, $p < 0.001$	$F(1, 213) = 117$, $p < 0.001$	$F(2, 2647) = 1456$, $p < 0.001$	$F(2, 971) = 593$, $p < 0.001$	$F(2, 851) = 110$, $p < 0.001$	$F(2, 922) = 643$, $p < 0.001$	$F(2, 611) = 270$, $p < 0.001$
Path * achievement group	$F(6, 579) = 2.71$, $p < 0.05$	n.s.	n.s.	n.s.	n.s.	$F(6, 922) = 2.58$, $p < 0.05$	n.s.
Time	n.s.	$F(1, 213) = 45.4$, $p < 0.001$	$F(1, 2647) = 5.32$, $p < 0.05$	$F(1, 971) = 20.9$, $p < 0.001$	n.s.	$F(1, 922) = 21.0$, $p < 0.001$	$F(1, 611) = 5.85$, $p < 0.02$
Time * path	$F(3, 579) = 11.3$, $p < 0.001$	$F(2, 213) = 3.51$, $p < 0.05$	$F(3, 2647) = 6.13$, $p < 0.001$	$F(1, 971) = 20.3$, $p < 0.001$	n.s.	$F(3, 922) = 24.1$, $p < 0.001$	$F(6, 611) = 5.07$, $p < 0.001$
Time * achievement group	$F(2, 579) = 25.0$, $p < 0.001$	$F(1, 213) = 36.3$, $p < 0.001$	$F(2, 2647) = 145$, $p < 0.001$	$F(1, 971) = 75.9$, $p < 0.001$	$F(2, 851) = 20.0$, $p < 0.001$	$F(2, 922) = 65.1$, $p < 0.001$	$F(2, 611) = 16.1$, $p < 0.001$
Time * achievement * path	n.s.	n.s.	$F(6, 2647) = 2.52$, $p < 0.05$	$F(2, 971) = 5.42$, $p < 0.01$	$F(4, 851) = 3.75$, $p < 0.01$	$F(6, 922) = 6.69$, $p < 0.001$	n.s.

NB On Q32, there were insufficient numbers in the 'low achievement' group, so this group was dropped from the analysis so there were only two levels (high, mid) for achievement group.

Spring 2017 Report that students' marks tend to decline over time. In other words, most students obtained a lower grade in their second module in comparison to their first module. In all but one instance, there was a significant time-path interaction ($p < .05$), and this was highly significant in five qualifications ($p < .001$). That is to say, with the exception of QUALE, students' marks changed over time depending on which study path they chose: some paths led to marks going up, and some to marks going down. This is not what one would expect if assessments (and the respective learning designs of introductory modules) were well calibrated and well aligned across all paths within the first part of a qualification.

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 marks over time. If assessments were perfectly well structured, we would expect achievement groups to be on average stable over time: high achievers would tend to get marks in the same high range, low achievers would tend to get marks in the same low range. That is not the pattern shown by these data. In many cases, there is a convergence in marks: high-achieving students tend to get lower marks in their second module, and low-achieving students tend to get better marks. In Chapter 2 we specifically will unpack some of the lived experiences of 19 students in terms of their grade developments.

These two-way interactions (time-path and time-achievement) were in four qualifications further qualified by a significant three-way interaction (time-achievement-path): that is, students on different study paths in different achievement groups tended to get different outcomes in their second module. Again, this is not what would be expected were assessments and learning designs perfectly aligned.

Figure 1.1: Mean marks for students on QAULA by achievement group, for those studying QUALAM1 then QUALAM2 (left-hand chart) and those studying QUALAM1 then QUALAM4 (right-hand chart).

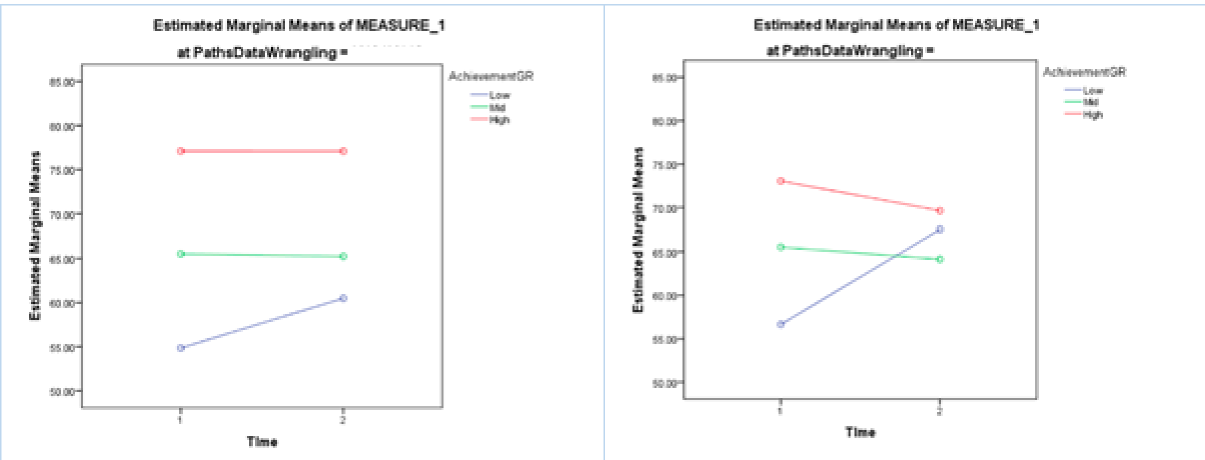


Figure 1.1 shows an example of divergent changes in marks over time depending on path and achievement group for QUALA. Low achieving students on QUALAM1 (blue lines) tend to get markedly higher results on QUALAM2, but those who study QUALAM4 get even higher marks – higher, in fact, than mid-achievers on QUALAM1 (green lines), who tend to decline in marks when they come to QUALAM4. High achieving students on QUALAM1 (red lines)

achieve consistently high results when they go on to QUALAM2 (left-hand chart), but their marks decline if they instead chose QUALAM4 (right-hand chart). In other words, while QUALAM1 seems to be a good preparation for some groups of students in the second module QUALAM2, for QUALAM4 with the notable exception of low performing students there seems to be a mismatch for mid- and high-achievers over time. This example was not selected to be the most egregious: it is merely illustrative. For the full results for the other five qualifications, please see the Appendix. Furthermore, a more fine-grained, qualitative perspective of the lived experiences of OU students of divergent grading practices is illustrated in Chapter 2.

There are many possible explanations for these interactions. A small degree of convergence between high-achievers and low-achievers over time might be expected or even desired: not all good students stay good, and the goal of the OU and our open, inclusive agenda, is always to try to support "weaker" students to improve. There is also evidence from qualitative interviews that some successful students decide to ‘ease off’ from study, which might explain a decline in their marks over time - see Chapter 2. Similarly, it may be that students who receive low marks are motivated to study harder to ensure they do not fail. Furthermore, as mentioned above, there are many individual factors between modules.

At the same time, there is of course an explicit limitation of our analyses, whereby we only included students who passed two consecutive modules. While high and mid-achieving students on the first module are likely to pass the follow-up module, amongst low-achieving students there might be a "hidden" selection effect appearing. Relatively "stronger" low-achieving students might survive the first relatively low assessment scores, or might even be encouraged to work harder in the follow-up module (see also Chapter 2), but weaker low-achieving students might become discouraged and drop out after the first module, or after the first part of the second module. These dropped-out students are of course not included in our analyses, which might also explain in Figure 1.1 why in some modules low-achieving students might actually outperform mid-achieving students. There may also be significant differences subject matter between modules, such that student aptitude on one topics is only weakly correlated with the other. In other words, the reader has to be careful to conclude that the OU is "successful" in helping low-achieving students to become successful students over time. However, the consistency of these findings, and the large size of the effects observed in many cases is so large that it suggests that at least some of the difference is due to inconsistent assessment practices between modules within the qualification. This is in line with the findings in the previous Scholarly insight report that found evidence for imperfectly-aligned assessment.

1.4 Conclusion

Building on our previous *Spring Scholarly insight report* (Chapter 1, Rienties et al., 2017), this analysis provides further evidence that students’ marks are not well aligned within OU qualifications. We would expect, if assessment and marking were well-aligned, that high-achieving students would tend to remain high-achieving in terms of grades, and low-achieving students to remain low-achieving, but in all cases we saw a highly significant effect of change over time depending on the achievement group. Similarly, we saw a highly significant effect of the study path chosen on marks in the subsequent module.

As discussed, there are many potential explanations for some of the particular instances observed: for instance, we would hope for some small improvement in marks for low-achieving students through our efforts to support them; different modules teach and assess different skills and knowledge, for which aptitude may not be so strongly correlated. However, the size and consistency of the findings here suggest strongly that there is a serious discrepancy in assessment between modules on the same qualification. There are substantial challenges in aligning modules which have roles in multiple qualifications - such as QUALAM3, which appears in this analysis both as a second module for QAULA and as a first module for QUALB, which are located in different faculties (FacultyC and FACULTYA). This adds extra weight to the recommendation to developing university-wide, cross-faculty processes for better aligning assessment and marking.

As discussed above, Chapter 1 has focused solely on the first and second modules taken, and level 1 modules, because the sample size for many combinations was too small. Many qualifications have changed or are changing substantially to become more prescriptive, with fewer module options, so the number of study paths is reducing. Therefore it may be that it will become feasible to use this method to look over longer pathways (e.g. to third module and beyond) as students' journeys are concentrated on to a smaller number of paths.

2. HOW DO STUDENTS EXPERIENCE MARKING AND LEARNING GAINS ACROSS QUALIFICATIONS?

Highlights

1. 19 "successful" OU students who obtained low, medium or high learning gains were interviewed to gain their perspectives on OU grading practices.
2. Interviews highlight complex interaction of OU grading practice and feedback provision on students' motivation, affect, behaviour and cognition (ABCs).
3. Several students used lower-than-expected grades as positive stimulus to work harder for the next assessment, while others got discouraged and changed their ABC.
4. Urgent need to ensure consistent grading practices within and across modules within qualifications

2.1 Introduction

Chapter 2 focuses on the student perspective of learning gains and is based on nineteen in-depth interviews with undergraduate students from FacultyC, FacultyC and FACULTYA. This complements the analysis presented in the Spring 2017 Scholarly insight Report (Rienties et al., 2017) which found strong and inconsistent variations in marking across 12 major qualifications within the OU, often resulting in a decline or oscillation in average marks from early to late in a qualification. Furthermore, this chapter builds on Chapter 1 where we found strong variation and inconsistent grading practices from first to second modules, as well as grade developments for low-mid-high achieving students over time. However, this and previous work did specifically not address whether students were positively or negative affected by this 'practice'.

The analysis below presents a range of insights into what and how OU students feel they are 'gaining' from learning at university study and, in so doing, it problematises the assumed link between grades and learning gain by probing the work-study-life complex within which distance learners study. This helps to address questions about the role and significance of the assessment marks in students' affective, behavioural, and cognitive development (Jindal-Snape & Rienties, 2016; Ostrom, 1969; Rogaten, Rienties, & Whitelock, 2016; Zhou, Jindal-Snape, Topping, & Todman, 2008), and its utility as a measure of learning gain. Interviews with nineteen OU students totalling over twelve hours were undertaken in May 2017 as part of trio of qualitative methods, which also included a survey and study diary of two weeks of self-reported student engagement. The interview notes, recordings and transcriptions made to date have been given to the Data Wrangling team by the ABC Learning Gains project (https://abclearninggains.com/) for the purposes of this Chapter. The interviews asked students:

- How they felt they were progressing;
- Whether the way they thought, act and feel has changed;
- The relationship between marks gained and learning achieved;
- The relationship between learning, work and life.

Section 2.2 presents, by way of introduction, a detailed look at one student's experience. This student story touches upon several themes discussed later in Section 2.3 and helps to illustrate the contrasting and changing sense making taking place around student perceptions of learning gain. Section 2.3 highlights some of the emerging themes and issues from the interviews taking the assessment marks – more specifically the impact of a relative change in assessment marks between modules – as a starting point. In Chapter 2 we selected a range of students from three Faculties according to two measures: attainment on their current module/s (grouped into three bands 'low', 'medium' or 'high') and the relative trajectory of their module grades since starting their qualification (again grouped into three bands where 'lowest' indicates marks falling at a greater rate than the average and 'highest' indicates comparatively good grade progress). Six students are reported on in the analysis (see Table 2.1).

Table 2.1 Student characteristics of sampled interviewed students

	Gender	Attainment grouping as measured by assessment marks	Progress grouping as measured by assessment marks	Faculty
Student 8	Female	High	Lowest	FacultyC
Student 19	Female	Low	Medium	FACULTYA
Student 5	Female	Low	Highest	FacultyC
Student 10	Male	High	Medium	FACULTYA
Student 12	Female	Low	Lowest	FacultyC
Student 18	Female	High	Highest	FacultyC

Of course from the outset we need to acknowledge that this study is not a representative sample of students' OU experience. Although we have specifically sampled students with different learning gains and different starting positions, our approach only included students who were continuously "successful" in passing modules (Rienties et al., 2017; Rogaten et al., 2017). Furthermore, it is a common understanding that self-reported biases and perceptional differences might under- or over-represent students' affect, behaviour and cognition. Students who might have become a-motivated due to lower grades or inconsistent grading practices who eventually dropped out were not included in our analyses, and these interviews in particular. Therefore, by design all students described here as "successful".

2.2 Grounding experiences: the Case of Student 8

This section presents a short case study of Student 8 (female, FacultyC) who had been with the university for three years and whose grades have been falling - a trend that, by some measures of learning gain would be interpreted as a decline or decrease. This student was chosen because her interview was particularly detailed (lasting around one hour), she was a student whose grades seemed to follow many qualification trends of lower marks in Level 2, and her grades were neither in the highest or lowest decile. The research team felt this case provides a good introduction to several of the key issues discussed by those interviewed.

When Student 8 started studying at the OU she was in work but had little long-term goals, only a mind set that “I’m just going to do it, I have the time, I’ll do it.” Initially “it was very much like study for study purposes” but “about a year and a half into it, my mind-set [changed], it was like actually I enjoy what I’m doing and it’s giving me something tangible.” As a result, her long term aspiration begun to change: “ I would never have talked about having a career [three years ago but now it's] once I'm graduated this is where I want to be within that time frame… if I can get all this done I can't even imagine what the outcome is going to be."

For this student it was the newly found ability to apply her learning as a result of changing jobs that was transformational – an event the student also attributes to her study noting "I would not have the job I currently have if I hadn't been studying." She noted that in her former job she found it difficult to apply her learning which in turn made it difficult for her to appreciate how much she was learning. However, as she explained "this year was the first year when … it reflected back to my day job and that kind of early started to show me the areas of what I'm learning actually in practice." This realisation resulted in a change in the perceived purpose and value of her study to her work and future aspirations. As a result, the student decided to take more modules and intensify her study; perhaps due to desire to complete more quickly. At the point of interview, the student was taking three modules concurrently.

Taking several modules concurrently appeared to have impacted negatively on the marks she achieved, as she herself acknowledged "I [feel that I] have the knowledge, it's the time that I was missing and that's why the end grade has dipped quite significantly." Furthermore, she noted "I don't think for me the grade itself is … it's actually the knowledge." The pressure of concurrent study resulted in the practice of focusing on getting just enough done: "I was like okay this is now about 50% of it done can I send it away so that I can now focus on the next part."

However, in further conversation, several nuances became apparent indicating ambiguity and detail in how she conceived the relationship between learning, assessment mark, and applicable learning gain. Firstly, in the conversation it seemed that grades had how she thinks about grades such that getting a "good" grade is not important. It is important at the moment to get a sufficient mark so that I had an opportunity to do the exam and face the next step. Furthermore, she talked about the value of getting a good mark - "it's an incredible feeling when you have high scores" and wanting to use this positive feeling she associated with good marks as an incentive to force her to change the way she approached TMAs. She had recognised that she tends to leave writing TMAs until the last minute and wanted to cultivate a more organised and planned way of working. Good marks were *her* reward: "I have decided that I will care about my grades next year and try to get the highest scores I physically can for the last year just to see [how well I can do] if I don't have that additional 60 credits." The interviewee subsequently returns to this point: "I think that's what I need to get back to… instead of looking at it, a number that needs to be over something so that I can go and do my exam." In this example, the learner appears to be taking ownership of the grade, commonly seen as an extrinsic motivator and refiguring it as an intrinsic motivator.

2.3 Emerging themes from analysis of interviews

Cognitive Gains: The relationship between gains in learning and assessment marks

A common measure of Learning Gain has been the assessment mark (Adamson, Dyke, Jang, & Rosé, 2014; Boyas, Bryan, & Lee, 2012; Rogaten et al., 2017; Yalaki, 2010). It is important to understand the impact that an increase or fall in the marks may have on a student as they progress through their qualification but also the impact that other factors have on the marks they achieve. The case study of Student 8 indicates that lower assessment marks may not indicate that the student (at least from their perspective) has learnt less that in preceding modules. To give another example, Student 19 was a third-year student and felt that her marks had fallen because there was more of the module that she didn't already know. As she explains:

> "There were things in the first two modules that I already knew [but] when I come to the year that I've just done, [then] I would say probably 95% of what I've learned … I've never heard of. So, I think this has been a real turning point for me because it's all new… which has been great." (Student 19, Female, FACULTYA)

The implication here is that marks in the early modules may have been higher because there was less 'new' material to learn, although elsewhere the student felt the first two years "did reflect what I learned, like everybody you just gain knowledge as you go on." This student, like Student 8, found that receiving lower marks was a stimulus. This is evidenced in her explanation of how she engaged more assertively with their AL: "I sort of challenge[d the TMA score], not 'challenged' it really, but asked more questions. [I've learned] don't be afraid to … I thought I possibly would have done better, you know maybe 5 to 10 marks here and there so I have challenged it." Whether or not this was a result of stricter marking by a particular AL, the outcome was that "it helped me because I think the feedback that I've got has been constructive criticism." Elsewhere in the interview she expanded on this theme of greater awareness of value of feedback saying "I like to read [the feedback from tutors], dissect it [and] this year the feedback I've got has included things that possibly I might have missed." This experience was described as "my turning point" leading to the realisation that "your TMA is not everything. It's not, it's supposed to be what you actually physically know yourself inside that you've learned… I think that's really important."

Student 5 (Female, FacultyC) also spoke of the valuable role of AL feedback. Her marks had been averaging 80 but had recently fallen to around 60. Her AL had said that she was 'writing too much from the heart' and had given advise and pointers. She described how she had been reading around and learning about theories much more, improving her writing style and sharing more with peers and work colleagues. Getting a lower grade made her realise that grades are not as important; it's essential to get enough to pass, but the learning is more important. Student 10 (Male, FACULTYA) also had had lower marks at Level 2. For him, good marks were seen as a key priority, but he felt that "despite the drop in marks, I still think my understanding has deepened and now … I feel more engaged in [it] actually, not just ticking off what I need to do. In four out of six student accounts discussed above (Student 5, 8, 10 and 19) there is a clear conceptual demarcation between assessment scores and 'learning.'

Students gave a variety of other reasons for the fall in marks from those obtained in previous modules. For example, at least two students mentioned that: they 'expected' to be getting lower marks because the modules would be getting progressively 'harder'; that their most recent module was not a continuation of the last but was about a different topic or sub-field (for example, a student was taking a creative writing module after three humanities modules); that they were taking an interest in the broader area or focusing on specific areas relevant to their work (which may not necessarily be rewarded in the marking of assignments); and that a less effective (than the previous) module design had made it harder to understand the module material and, therefore, perform well in the assessment.

In other interviews, students spoke of how they had learned the skills of doing well at assessment and that marks were affected by the amount of effort or time invested in preparing the assignment. Returning to Student 8, for example, they explained "I may be spent four or five hours on [each TMA] maximum. I was like, I know how I can write an essay in four hours and can get really high marks because I've learned [how to do it]." In contrast, Student 18 (Female, FacultyC), a high achieving learner, explained that to receive consistently high marks over 85 in their mathematics modules required a lot of sustained effort:

> "I put a lot of work in. I work really hard … I basically sacrifice all of my weekends and I really push for good grades [well] I mean I don't push for good grades, I push for getting the knowledge and of course if you get the knowledge then if you are able to apply the knowledge in [an assessment] the you usually get good grades."

This does not, of course, deny that achieving good marks is important to students. As would be expected, student felt that receiving good marks was important for gaining a good qualification, judging progress, and for motivation. However, in such cases the gaining of high marks is in part an indicator of a specific student motivation as well as a measure of how well they know, or have learnt, the AL set learning outcomes.

Another factor contributing to lower performance and to lower satisfaction may have been poor module design and delivery, as also highlighted in Chapter 2 of our Scholarly insight Spring Report (Rienties et al., 2017). Student 12, for example, felt the design of the most recent module was less effective than the one they previously studied, making this one harder to In such cases the impact is on *both* student learning *and* on the assessment scores that students achieve. The impact of lower marks was also noticed at the distinction boundary. One student explained that they were mathematically no longer able to achieve a distinction and therefore may be adjusting the effort they put into the assessment. If inconsistent grading practices across a qualification might "randomly" impact some students on the boundary of distinction, first, second degree, or just passing, this could have both profound implications for students' motivation and engagement, as well as financial implications for the OU.

Affective Gains: Confidence and employment

The previous sections examined how progress and learning gain is understood and judged by students in respect to a range of factors, such as student motivations, goals, and ability to navigate a "less-well designed" module. Evidence from the interviews suggests that in many cases achieving slightly lower scores helped students to adopt a deeper, more self-directed approach to learning. In such cases, students appeared to be 'gaining' in respect to affective or behaviour aspects of their learning, whilst performing less well in a measure of cognitive gain (assessment scores). This underlies the importance of considering affective, behavioural and cognitive gains together and recognising that whilst there may be an apparent fall in one there may be unobserved gains in the others.

One key aspect of affective gain is self-confidence. This was the most frequently mentioned learning gain mentioned by students in the interviews, and is associated with students feeling they are making real progress in their understanding of the subject and adopting a more analytic approach. Students mentioned their awareness of this change in respect to their work or social lives. For example, Student 19 observed "the way I think, the way that I possibly act at times, my life feels different now" later adding "I can talk confidently to people." Student 8 linked the process of confidence-making to her subject understanding and critical skills being learnt:

> 'It's just when you learn something you automatically become aware of, for instance either news, work itself, everyday life, which again kind of changes your perspective and then it allows you to properly build your own confidence because you understand things … you start analysing everything around you… You always question and you can see straightway when things are wrong… your brain is analysing everything… I can see both sides."

Student awareness of confidence gains is made visible in many ways, both within and 'outside' the demarcated learning environment of the university. Student 10 summarised this as follows: "I notice that my approach to things outside of the academic context is different … I judge it on the assignment side and the out-of-academic context side bit as well." This perhaps underlines the importance of students having 'non-module' based reference points for experiencing the impacts and changes to their learning and, consequently, for building the awareness of their learning gains that necessitates confidence-making. The impact of such gains is also evidenced in actions the students takes. This could range from greater engagement with their AL – as seen earlier – to a change in qualification or study pathway.

2.4 Looking ahead

This Chapter has introduced data from an ongoing investigation into student perceptions and understandings of learning gain. The cases presented hint at the breadth and interconnectedness of gains in learning across affective, cognitive and behavioural dimensions. Furthermore, there are indications that from a student perspective, the value and purpose of instructional activities may change as the student becomes a more self-confident and self-directed learner. This may reveal a potential gap between how the institution and the student interprets and takes meaning from particular measures of learning gain. Level 2 seems a particularly important period for students in respect to affective and behavioural dimensions and this needs to be investigated further in respect to factors such as student motivations, subject and demographics. Whilst the analysis presented above represents interim findings, ongoing analysis will further seek to understand more about the experience, measurement and interpretation of learning gains made across academic, work-place and social activities.

At the same time, as argued before we have to be mindful that the students interviewed were all "successful", as they all passed their respective and consecutive modules. As highlighted in Chapter 1 as well, the inconsistent grading practices within and across modules in qualifications might negatively impact students. Future research and practice should specifically focus on students who were initially successful in completing a module, but who dropped out afterwards when receiving a lower grade (e.g., on their next TMA). As documented widely in the drop-out literature (Christie, Munro, & Fisher, 2004; Franssen & Nijhuis, 2011; Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Wilcox, Winn, & Fyvie-Gauld, 2005) and out own OU research on drop-out (IET Student Statistics and Survey Team, 2014), these groups of students are particularly hard to reach. Both Chapter 1 and 2 highlight a sense of urgency to act, whereby the OU needs to get their assessment practices across a qualification right. The relative inconsistencies of grading practices has distinct impacts on students in affective, behavioural, and cognitive dimensions, as well as the OU's bottom line.

3 WHAT IS THE IMPACT OF PREDICTIVE ANALYTICS ON STUDENT RETENTION?

Highlights

1. 500+ Associate Lecturers (ALs) across 31 modules were given weekly Predictive Learning Analytics (PLA) data (OU Analyse) about progression of their students, and likelihood of passing the next assessment.
2. First large-scale study with 240 ALs across 10 modules indicated significant impact of PLA on retention.
3. ALs who actively used PLA on weekly basis had significant impact on student progression and retention, but strong variation in PLA use was found.
4. Second large-scale replication study with 251 ALs across 21 modules confirmed initial findings, whereby active use of ALs significantly increased student performance.
5. Given strong variation in actual PLA use amongst ALs, the OU needs to design and implement robust policies to encourage active use of PLA to support OU students.

3.1 Introduction

Predictive Learning Analytics (PLA) refer to the use of "a variety of statistical and analytical techniques to develop models that predict future events or behaviours" (Nyce & CPCU, 2007). Several institutions including the OU have started to adopt PLA to identify which students are going to pass a course, and which of them are at-risk (Calvert, 2014; Gasevic, Dawson, Rogers, & Gasevic, 2016; Joksimović, Gašević, Loughin, Kovanović, & Hatala, 2015; Tempelaar, Rienties, & Giesbers, 2015).

PLA data can provide useful, complementary information to module teams and associate lecturers to help them identify students at-risk of failing while also allow them to support other groups of students (e.g., well performing) and maximise their potential. The role of Associate Lecturers (ALs) is essential in acting upon PLA insights and intervene to help students. For example, van Leeuwen, Janssen, Erkens, and Brekelmans (2014, p. 28) indicated that “because the amount of data can be quite large, it may be impossible for the teacher to read or interpret all available information […] So called teacher supporting tools are specifically added to a digital learning environment to present summaries, visualisations, and analyses of student data to the teacher”. In this Chapter, we will look at the following research questions: To what extent does providing PLA data to ALs across 31 modules increase student progression and retention?

In section 3.1 we will briefly explain OU Analyse (OUA), the PLA system. Afterwards, in section 3.2 we will report on our first large-scale comparison of the impact of PLA across 10 modules on student retention. In particular, we will report on the actual AL user experiences. In section 3.3 we will report on a large-scale replication study amongst 21 modules using PLA, whereby we on the one hand aimed to confirm our initial findings, while at the same time aimed to test whether the initial findings could be replicated in different settings and modules. From the outset it is important to mention that ALs were not paid extra to use PLA, and those who participated using PLA did so on a voluntary basis. Furthermore, as ALs could volunteer to join or not (rather than a randomisation of use or none-use of PLA), this could obviously lead to self-selection issues. Therefore, taking into consideration what ALs actually did with PLAs during their respective module, why and how, is essential to determine and unpack the relative impact of PLA on retention and progression.

3.1 OU Analyse (OUA): A predictive learning analytics system

The Knowledge Media Institute (KMi), at The Open University, has developed a PLA system, the OU Analyse (OUA) (See https://analyse.kmi.open.ac.uk/), to support module teams' and ALs' practices and enhance student performance across the OU (Hlosta et al., 2015; Huptych, Bohuslavek, Hlosta, & Zdrahal, 2017; Kuzilek, Hlosta, Herrmannova, Zdrahal, & Wolff, 2015; Wolff, Zdrahal, Herrmannova, Kuzilek, & Hlosta, 2014; Wolff et al., 2013). OUA uses a range of advanced statistical and machine learning approaches to predict students at-risk so that cost-effective interventions can be made. The primary objective of OUA is the early identification of students who may fail to submit their next tutor-marked assessment (TMA). Four to six TMAs per module are typically requested from students. TMA submission along with an appropriate grade (pass) contribute to the successful completion of a module. Predictions of students at-risk of not submitting their next TMA are constructed by machine learning algorithms that make use of data from the previous year's presentation of the same module. Two types of data are utilised: (a) static data: demographics, such as age, gender, geographic region, previous education, number of previous attempts on the module, and (b) fluid data: the students' interactions within the VLE hosting a module. The resources a student may interact with have semantic labels called "activity types". Examples of activity types are: forum, content, resource, glossary, and wiki. All students' interactions with the VLE are recorded and saved in a database.

Figure 3.1. A section of OUA dashboard showing VLE engagement and average TMA score submission

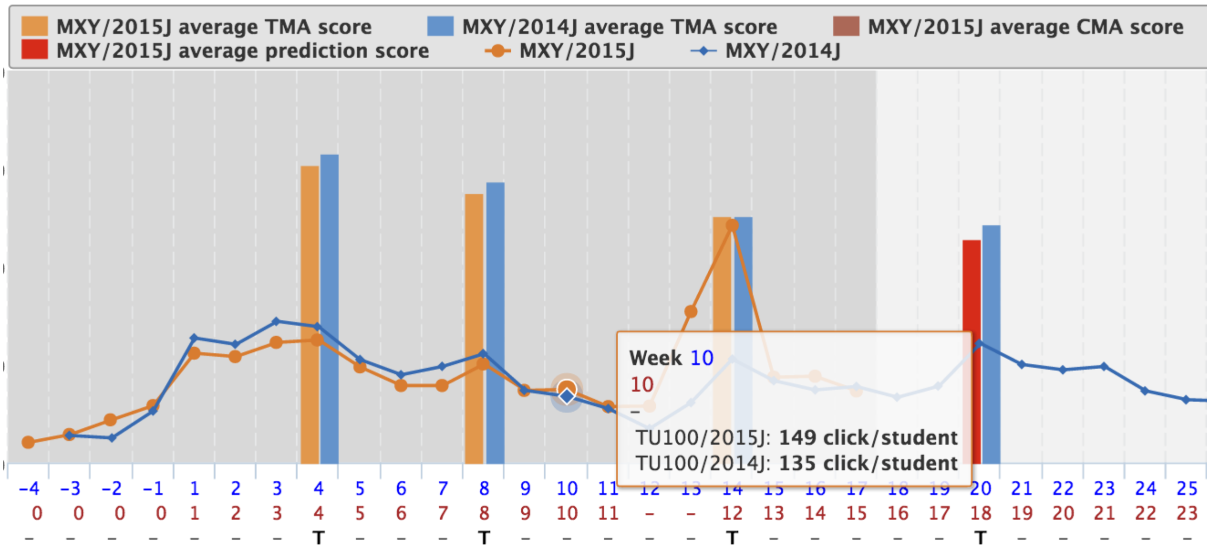
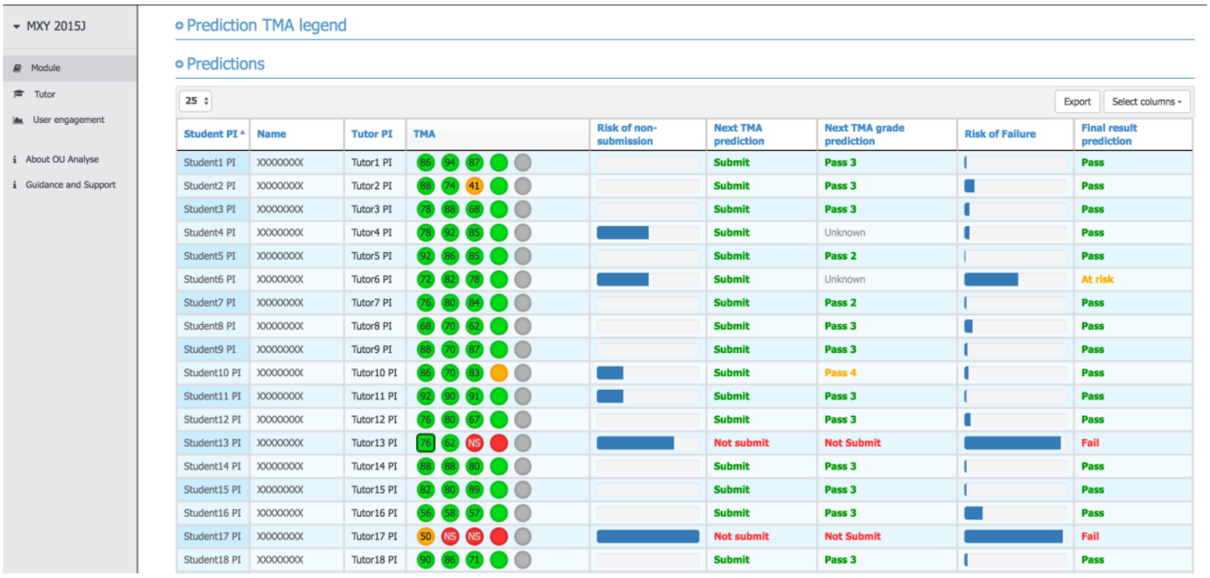


Figure 3.1 shows a section of the OUA dashboard illustrating the average performance of the whole cohort of students in a respective module. The current module presentation (yellow) is compared to the previous one (dark blue). The bars show the average assignment marks and

the lines indicate the average number of clicks per student per week in VLE activities. Figure 3.2 shows another section of the OUA dashboard. A list of all students and their predictions of performance in the next TMA are presented. It is possible to narrow the focus to a selected group of students by applying the filter, such as selecting only students from a particular region, IMD, or prior educational qualification.

Figure 3.2. A section of OUA dashboard showing the likelihood of individual students to submit their next assignment

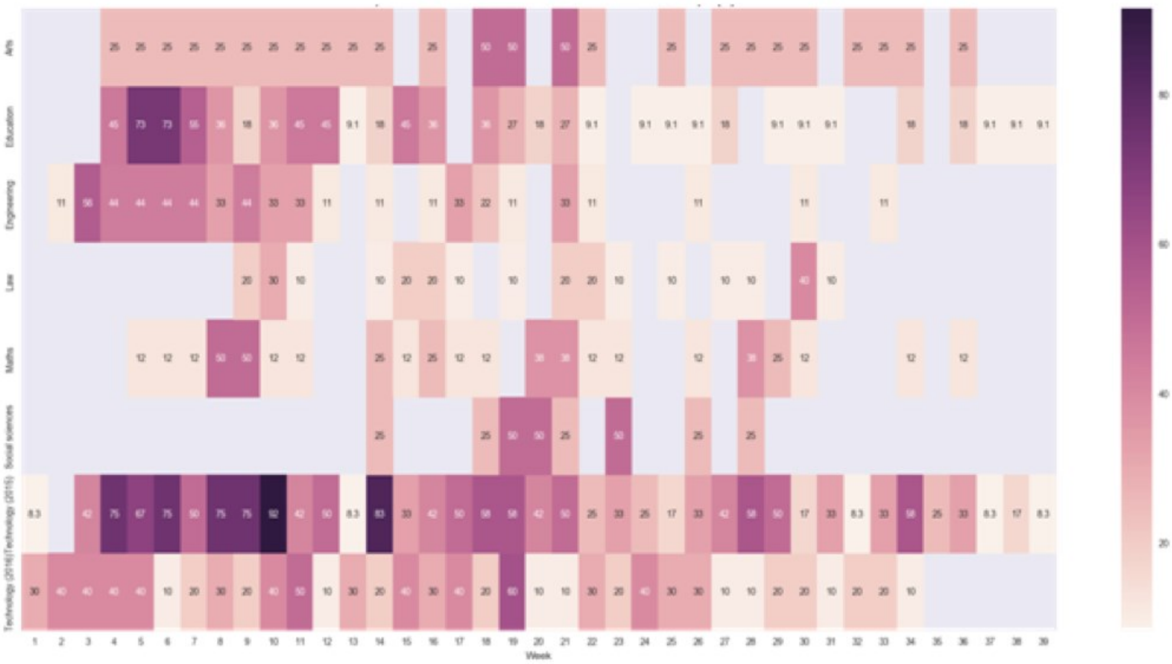


3.2 Impact of OUA on student performance in 2015

In our first large-scale implementation of PLA, OUA was originally piloted with 10 modules (Arts, Social science, Education, Health care - two presentations, Maths, Engineering, Technology - 2 presentations, Law) and 240 ALs, of whom 171 accessed predictions via spreadsheets sent to their emails and 69 via the OUA dashboard (See also Herodotou et al., 2017). At early stages of development, OUA could be accessed remotely through a VPN connection, an issue that raised concerns by some ALs who had difficulties accessing VPN, who asked for predictions to be sent to their emails. The logging in activity of those ALs who were given access to OUA through the dashboard (and not via emails) (N=67) was examined to identify how often and when ALs accessed the system. Weekly usage statistics were gathered and aggregated on a module level to guarantee anonymity of respective participating ALs. The majority of ALs logged into the system at least once.

Figure 3.3 shows the percentage of ALs who accessed the dashboard per week per module. At this moment in time, the OU does not consistently track whether accessing the OUA dashboard also led to action by the respective AL. The two modules with the highest frequency of access were Technology (2015) and Education. During the first weeks of the module presentation, an average percentage around 80% (8 out of 10 ALs who had access to dashboard) made use of OUA. Accessing the OUA dashboard was substantially lower for Law, Maths, Social sciences, Technology (2016), Engineering (week 12 onwards), and Education (week 16 onwards). This trend indicates that, although ALs had access to PLA, they did not access OUA predictions systematically. This trend raises questions as to why ALs did not engage with predictions throughout a module presentation and what obstacles may inhibit a more systematic engagement with OUA.

Figure 3.3. Percentage of ALs accessing OUA dashboard per week per module



Two binary regression analyses were performed to identify whether and how the actual usage of predictions by ALs relates to student pass rates and completion rates. The following variables were the factors entered into the regression analysis possibly explaining student performance (predictors): student demographic data including, gender, age, disability, ethnicity, education level, IMD band, whether the student was new at the university (new vs continuous), best overall module score from previous study, sum of previous credits achieved, and type of module, ALs' number of students per module presentation (as a proxy of workload), number of module presentations each AL attended (as a proxy of teaching expertise), and weekly usage of OUA (divided by length of each module to account for different size modules).

A binary regression analysis with the above-mentioned predictors and pass rates as the dependent variable was performed. A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between students who pass and students who fail a module (chi square = 83.98, $p < .001$, df = 24). Nagelkerke's R2 of .176 indicated a moderately weak relationship between prediction and grouping. The model explains 18% of the variance in passing rates and correctly classified over 68% of the cases. In particular, prediction success overall was 68.5% (34.1% for not passing a module and 86.8% for passing a module). The Wald criterion demonstrated that only OUA usage (p=.002) and best previous module score (p=.003) made a significant contribution to prediction. All other predictors were not significant. In terms of effect size, the odds ratio was examined. Exp(B) value indicates that when OUA usage is raised by one unit (increase in average weekly usage by one unit) the odds ratio is 7.1 times as large and therefore students are 7.1 times more likely to pass the module. Also, Exp (B) value indicates that when the best overall previous module score of a student is raised by one unit, the odds ratio is raised by one time and therefore students are one time more likely to pass the module. These findings indicate that two factors - increasing use of OUA predictions and greater best overall module score from previous study - are associated with an increase in the likelihood of passing a module. Similar results were identified for completion rates (chi square =80.79, $p < .001$, df = 24). The Wald criterion demonstrated that only OUA usage (p=.003) and best overall module score from previous study (p=.004) made a significant contribution to prediction. All other predictors were not significant. **In plain English, these findings indicate that increasing use of OUA predictions and greater best overall module score from previous study are the factors associated with an increase in the likelihood of completing a module.**

Impact of OUA on teaching practice

Six in-depth interviews with ALs who made use of OUA in their practice were conducted and qualitatively analysed. Data revealed a shared perspective amongst ALs that OUA is a useful tool for understanding students and their participation. All six interviewed ALs found the tool quite accurate in predicting which students were at risk of not submitting their next TMAs (Herodotou et al., 2017). One AL noted that "I love it, it's brilliant. It brings together things I already do [...] it's an easy way to find information without researching around such as in the forums and look for students to see what they do when I have no contact with them [...] if they do not answer emails or phones there is not much I can do. OUA tells me whether they are engaged and gives me an early indicator rather than waiting for the day they submit". Second, there was a consensus that OUA predictions agree with ALs' experience and intuition of which students might potentially be at risk. One AL noted that: "It's brought together all the little ways I have of checking on a student without constantly phoning them and presented it in a very useful way. I'd love to see this used throughout the OU." Another AL described OUA as a "proactive tool" that complements existing teaching practices, such as emailing students and participating in forums, by giving an indication of how much work students are doing.

3.4 Follow-up evaluation of OUA with 21 modules in 2016

After the initial positive findings of PLA and student retention when teachers were actively using PLA, in 2016 we extended both the reach and scale of OUA. OUA was piloted with 21 modules in 2016 presentations (1 x Arts, 6 x Business, 4 x Education, 4 x Health care, 1 x Language, 1 x Science, 1 x Engineering, 1 x Technology, 2 x Law), whereby more 251 ALs volunteered to use OUA. While in 2015 ALs had to log-in via VPN to access the OUA dashboard, in 2016 with enhanced security protocols students could directly access the OUA dashboard from Tutor home.

However, as was previously found in 2015 ALs' engagement with OUA revealed that only 22% of ALs with access to OUA made some use of it. T-tests and chi-square analysis between ALs who made frequent use of OUA and ALs who made little or zero use revealed statistically significant outcomes in favour of ALs who made frequent use of the system. T-tests with dependent variables (a) average continuous assessment and (b) end-of-course assessment showed significant differences for average continuous assessment (p=.007), yet not end-of-course assessment. The 'high usage' group had a higher mean score (M=47.78, SD=36.07) in average continuous assessment as opposed to the ‘zero/low usage’ group (M=41.77, SD=34.06).

Table 3.1. Comparative analysis between ALs who used frequently OUA and ALs who made little or zero use of the system

Variable	**N**	**M**	**SD**	***p* value**
Continuous variables				
Average continuous assessment (assignments)				
High usage	274	47.78	36.07	.007*
Low/zero usage	17948	41.77	34.06	
End-of-course assessment				
High usage	274	60.53	20.55	.860
Low/zero usage	17948	60.30	21.34	
Dichotomous variables				
Pass rates				
High usage Passed	154	73%		.203
Failed	57	27%		
Low/zero usage Passed	9866	75.7%		
Failed	3167	24.3%		
Completion rates				
High Usage Completion	296	77.1%		.033*
Non-completion	88	22.9%		
Low/zero usage	19903	72.8%		
Completion	7454	28.2%		
Non-completion				

Chi-square analysis with pass and completion rates as dependent variables showed significant differences in only completion rates (*p*=.033). A percentage of 77.1% of the ‘high usage’ group as opposed to 72.8% of the low/zero usage group completed their course (See Table 3.1). These findings suggest that usage of OUA can positively affect average continuous assessment and tackle retention by raising the number of students who complete a course. In addition and aligning with findings from the original piloting of OUA with 10 modules, the majority of ALs was found to be reluctant to using the system, an area that necessitated further research to unpack reasons explaining ALs' behaviour and potentially tackling it.

3.5 Conclusion and Implications

The evaluation of OUA with overall 31 modules and more than 500 ALs with access to the system revealed that systematic use of PLA can have a positive impact on student performance and retention as well as enhance and facilitate the teaching practice. At the same time, it highlight complex and myriad relations between PLA and retention, which in part as explained by the voluntary nature of using OUA, in part related to a lack of consistent policy what ALs are expected to do in terms of PLA, and in part related to a lack of consistent tracking of what ALs actually do based upon PLA. In modules where ALs are actively using PLA in general there seems to be a relatively positive effect on progression and retention, while the effects amongst modules with low PLA usage indicate limited to no effects. At present ALs are not "forced" to use PLA in their AL contract, and therefore uptake and usage of PLA is solely dependent on the goodwill of ALs and module teams.

What this data suggests is that: (a) PLA should be used by module teams, ALs and Student Support teams to support students at risk of failing their studies. (b) ALs need to be systematically engaged with predictive data to make a difference to student performance and retention. (c) Engagement of ALs with PLA can predict student performance. (d) Predictive data can inform ALs about their students' online behaviour, complement and strengthen existing teaching practices. (e) Research is still needed to identify which interventions should be used by ALs to effectively support students at risk. (f) Research is still needed to identify why a majority of ALs is found to be reluctant to use OUA in their practice along with strategies as to how to best support ALs when using PLA. An alternative approach that will need to be tested in the near future is whether providing PLA data in a sensitive, inclusive, and positive manner to students could have a more direct, positive effect on progression and retention. Of course given the sensitive nature of PLA and the context of our OU students, this will need to be tested extensively and carefully.

4 WHAT IS THE IMPACT OF FIRST PRESENTATIONS OF NEW MODULES ON PASS RATES AND SATISFACTION?

Highlights
1. Some students seem to avoid first presentations of new modules.
2. Comparing 68 new modules over three consecutive implementations in terms of pass-rates and satisfaction showed no significant impact of new modules
3. Substantial changes in follow-up presentations based upon learning experiences first presentation

4.1 Introduction

Anecdotal evidence suggests that some students avoid first presentations of new modules and that some staff advise students - particularly those with disabilities - to avoid taking new modules. There is, however, a lack of understanding of the impact of a module being in its first presentation on performance and satisfaction. While there could be various challenges raised by the production and presentation of new modules, it has not been clear how these emerge in practice at a university-wide level.

With a more agile and just-in-time production process with OU Redesign/Student First Transformation, we need to unpack whether (or not) the OU indeed might disadvantage some or all students who join a first presentation. We also need greater understanding of the issues faced by students and staff when modules are first presented. This report provides a quantitative and qualitative analysis of these issues.

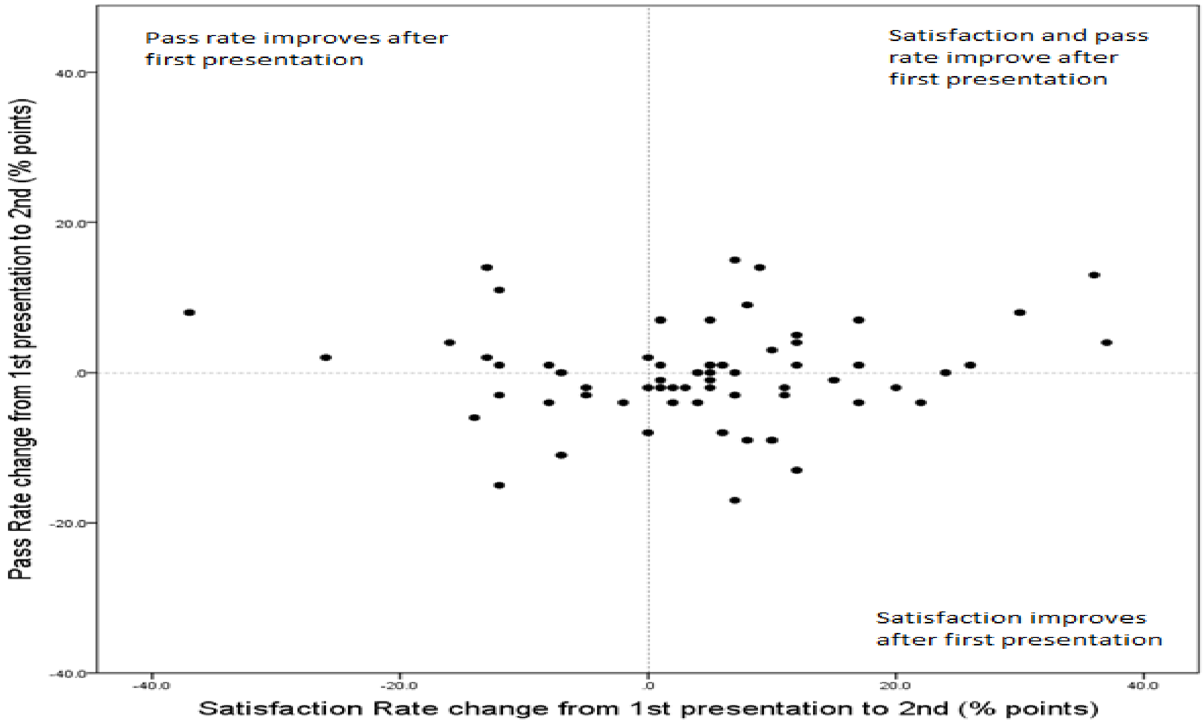
1) Overall, does performance and satisfaction with modules change after the first presentation of a new module?
2) Are there modules in which the first presentation has had a negative impact on performance and satisfaction? What issues occur in these cases?

We conducted an analysis of university-wide data from modules first presented in 2013 and 2014, for which there is now data to compare the first and subsequent two presentations. Using this analysis, we identified ten modules as case studies where a change was apparent that could be attributed to problems with the first presentation in section 4.1. In section 4.2, themes from discussions with the module teams, and SEaM comments, are used to explore the issues that occurred in greater detail.

4.1 Quantitative analyses of impact of first presentation on satisfaction and pass-rates

A sample containing all modules that were first presented in 2013 or 2014, which also had two subsequent years of completed presentations[1], and have SEaM results available, was identified. This sample totals 68 modules and includes 3 Access modules, 14 Level 1 modules, 20 Level 2 modules, 12 Level 3 modules and 19 Postgraduate modules. Furthermore, we included 11 modules from FACULTYA, 11 from FacultyB, 3 from LTI, 31 from FacultyC, and 12 from FacultyC. Figure 4.1 represents all of these modules in terms of the change to pass rate[2] and satisfaction rate from first to second presentation[3]. This shows a wide variability in the changes in satisfaction and pass rate from 1st to 2nd presentation.

Figure 4.1 Changes in pass rate and satisfaction rate from 1st to 2nd year of presentation



Note: Data based upon all modules with three years of available performance and SEaM data with a first presentation in 2013 or 2014 (n=68 modules)

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[1] Where there were multiple presentation start dates in a year, module presentations were compared on like-for-like start dates (e.g. if the first presentation was a B presentation, it was compared to the B presentation in the next year, rather than a J presentation). This bypasses any effects caused by differing presentation start dates to provide the most suitable comparison.

[2] Students achieving a pass as a proportion of those registered at 25% fee liability. Drawn from SAS-VA Hub

[3] Proportion of the responses that agreed or strongly agreed with Q31: "Overall, I am satisfied with the quality of this module". Drawn from SAS-VA Hub.

Table 4.1: Descriptive statistics for changes to satisfaction and pass rate from 1st year of presentations to 2nd or 3rd year for the sample of modules that were first presented in 2013-2014

	ΔRange	**ΔMean**	**ΔMedian**	**ΔStd. Deviation**
Satisfaction change from 1st to 2nd year	-49 to +37	+3.32	+5.0	14.45
Satisfaction change from 1st to 3rd year	-64 to +51	+3.52	+2.5	15.30
Pass Rate change from 1st to 2nd year	-17 to +15	-.04	0.0	6.53
Pass Rate change from 1st to 3rd year	-32 to +17	-.94	-1.0	7.51

n=68, change in percentage points.

Table 4.1 provides a view of change over both year 1 to 2 and year 1 to 3 for the sample of modules. Both paired-t-tests and separate change analyses between the various presentations showed that there is no significant change, on average, in pass rates between first presentations and subsequent presentations. Separate analyses on changes in satisfaction rates indicated that first presentations had on average lower satisfaction rates compared to the second year of presentation of the same module (Z= -2.325, p=.020). The same result, lower satisfaction in first presentations, is also present and significant between first and third year of presentation (Z= -2.697, p=.007). This occurs in a context in which the overall average satisfaction rate either fell, or was static, for all Central Academic Units between 2013/14 and 2015/16 (Ullmann, Marsh, Slee, Cross, & Rienties, 2016). However, in both cases, the effect size is small and the variation between modules makes the result relatively weak. The analysis therefore showed a small improvement in satisfaction rates between first and subsequent presentations, but with very high variability between modules.

However, prior research has found no relationship between satisfaction and performance in OU modules (Rienties & Toetenel, 2016), and also in this data set no significant correlations where found between satisfaction and pass-rates across any of the three presentations. As the effect identified for satisfaction is not substantial in size and the satisfaction rates are extremely variable, the pass rate finding should arguably be prioritised. This suggests that there is no overall effect of first presentation modules on performance.

4.2 To what extent are there modules that have faced first presentation challenges?

While there is no performance impact on average across the modules, the top-right quadrant of Figure 4.1 does show a number of modules that saw large increases in pass rate and satisfaction after the first presentation. Does this indicate that they had challenges during the first presentation that were subsequently resolved? If so, these challenges would be useful to understand in order to support improved module production and presentation processes. In order to answer this question, we investigate changes to pass rate and satisfaction at the level of individual modules.

There are 47 modules where satisfaction improved (69%) and 30 modules where pass rate improved (44%). Of these, there are 20 modules where both the pass rate and the satisfaction improved after the 1st presentation (29%). However, if improvements were due to changes after the 1st presentation, it would be expected that these improvements would persist into the 3rd year of presentation. Also, some changes to modules made after review of first presentations may not be in place until the 3rd presentation. While other factors could cause these changes, this presents itself as a reasonable measure through which to identify modules with potential first presentation challenges. For 11 modules (16%), there was a persistent improvement to pass rate and satisfaction after the first presentation. For 17 modules, there were pass rate-only improvements that persisted after the first presentation (25%). For 37 modules (54%), there were satisfaction rate-only improvements that persisted after the first presentation.

Case studies using student and module team feedback

To identify whether these changes are really due to first presentation issues, and what these issues entail, we used qualitative data to investigate the student experience in modules where satisfaction or pass rate saw a substantial and persistent improvement after the first presentation. In addition, attention has been drawn to issues faced by disabled students and others with additional needs, such as offender learners, such as the lack of module materials in appropriate formats in good time for study on a first presentation. A full analysis of these issues is beyond this report, but we include in our case studies modules where the disabled student attainment gap[4] narrowed substantially after the first presentation and this change was persistent.

In order to understand what happened in these specific cases, we communicated with module teams where possible and asked them to summarise the challenges of the first presentation and any changes that were made afterwards. We also analysed SEaM survey open comments from disabled students. Where there were a large number of comments, word frequency comparisons were used to identify any major differences between comment sets from first and subsequent presentations. Where there were not, a manual analysis identified themes and sample quotes representative of these.

The Appendix identifies the seven case study modules. It provides data on the three markers that suggest that challenges may have been faced in the first presentation (improvement in the pass rates or satisfaction rates, and / or a decrease in the disabled student attainment gap). The selected modules had relatively large and persistent improvements in at least one of these indicators. The final column at Table A.4.1 shows the themes that were identified as challenges

[4] Attainment gap measured as the difference between passes for students declaring a disability and those who do not, as a proportion of those registered at the 25% fee liability point. Derived from QELA (SSST) Module Profile Tool.

based on the qualitative analysis of these modules. More details of these are provided in the case study descriptions the Appendix.

Conclusion

This analysis suggests that concerns of a general trend of poor student performance in first presentations are not founded. For the majority of first presentations, a student's chance of achieving a pass is not significantly different to subsequent presentations. There is a small improvement in average satisfaction after the first presentation, but this is against a background of high variability in these ratings.

This is not to suggest, however, that some individual modules do not face challenges during first presentations. Our analysis has identified modules where performance, satisfaction, and/or disabled student attainment showed sustained improvement after the first presentation and investigated some of these cases to provide recommendations. Common challenges faced include: A lack of accessible materials; Issues concerning assessment; Online learning and technical issues; and Errors in the materials and activities. These should be a focus for module production in order to ensure quality from the very beginning, and should be particularly relevant as we redesign course production processes and tools.

This analysis has focused attention on modules where changes have occurred in response to problems with the first presentation. While these offer lessons for improvement, it would be fruitful in future work to identify modules where there were little or no changes required and a positive student experience and performance was achieved from the very beginning. Further work could also apply the methods used here for identifying persistent improvements on particular indicators, and by grouping modules according to these, identify whether the types of challenges and responses from module teams have an impact on pass rate, satisfaction, attainment gap, or other outcomes.

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PREVIOUS SCHOLARLY INSIGHT REPORTS AND FOLLOW-UP PUBLICATIONS

Previous Scholarly insight Reports

1. Rienties, B., Edwards, C., Gaved, M., Marsh, V., Herodotou, C., Clow, D., Cross, S., Coughlan, T., Jones, J., Ullmann, T. (2016). *Scholarly insight 2016: a Data wrangler perspective*. Open University: Milton Keynes. Available at: http://article.iet.open.ac.uk/D/Data%20Wranglers/Scholarly%20insight%20Autumn%202016%20-%20A%20Datawrangler%20perspective/DW_scholarly_insight2016.pdf
2. Rienties, B., Rogaten, J., Nguyen, Q., Edwards, C., Gaved, M., Holt, D., Herodotou, C., Clow, D., Cross, S., Coughlan, T., Jones, J., Ullmann, T. (2017). *Scholarly insight Spring 2017: A Data Wrangler Perspective*. Open University: Milton Keynes. Available at: http://article.iet.open.ac.uk/D/Data%20Wranglers/Scholarly%20Insight%20Report%20Spring%202017/DW_scholarly_insight_31_05_2017.pdf

Follow-up publications from Scholarly insight Reports

3. Rienties, B., Cross, S., Marsh, V., Ullmann, T. (2017). Making sense of learner and learning Big Data: reviewing 5 years of Data Wrangling at the Open University UK. *Open Learning: The Journal of Open and Distance Learning*, *32*(3), 279-293. Available at: http://oro.open.ac.uk/49085/
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