OfLA Project
2018-1-UK01-KA203-048090

O16 – Final Project Report

RESPONSIBLE PARTNER:
NOTTINGHAM TRENT
UNIVERSITY

Funded by the
Erasmus+ Programme
of the European Union

Strategic Partnership: 2018-1-UK01-KA203-048090

PARTICIPATING PARTNERS:
UMC UTRECHT
ARTEVELDE UNIVERSITY OF
APPLIED SCIENCES

Description of output from the original bid

We will produce a final project report summarizing our key findings and making recommendations for future studies in these fields.

A1. We will review the findings gathered throughout the project

A2. We will conduct editorial meetings at the 5th and final transnational meetings

A3. Throughout the last year, we will review our key lessons and produce a report summarizing key recommendations. Most findings will be already included in the other outputs, but we will seek to conduct a final piece of research asking for longitudinal feedback from the staff involved.

Contents

Output 16 Report

Executive Summary

The Onwards from Learning Analytics (OfLA) project (2018-2021) was developed to better understand how to integrate early warnings into institutional support. This is a specific field within learning analytics based on the hypothesis that if students can be identified early as being at risk of early departure, then there is a greater chance to help them adapt more appropriate approaches to learning, or to be supported to overcome barriers to their success. Sclater (2017) describes this as 'student success' analytics. In our opinion, too much time has been spent discussing the mathematics involved in developing the most effective and accurate alerts and not enough time spent on what to do next. The work was framed by Clow's (2012) learning analytics. Clow suggests that there are four stages: **Learners (1)** generate **Data (2)**, institutions interpret the data using **Metrics (3)** and then if needed there is an **Intervention (4)**. The OfLA model fits into the intervention stage. It takes the leaky pipeline metaphor and suggests that there are three points at which institutions fail to support students effectively:

- **Trigger/prompt** - can institutions identify students in need sufficiently early and cost effectively?
- **Communication** - can institutions communicate effectively to those students?
- **Intervention** - can institutions provide effective interventions to help students adjust their approaches to learning, or overcome problems in their personal lives?

The project was spread over three years; broadly the work conducted was as follows:

- **Year 1** - baseline testing, student and staff views about interventions, literature review conducted
- **Year 2** - Trials - different types of interventions up to faculty scale using historical data, surveys and learning analytics early warnings
- **Year 3** - further testing of student and staff views, interventions based on self-analysis and whole institution learning analytics. Production of overarching summary reports into policy, staff development and the use of data.

It is important to stress that the Covid-19 pandemic had a profound impact upon the project. The early warnings developed as part of the project were used as mainstream components to support students through the pandemic rather than refining our approaches from year 2 as was our original plan. The project team felt that, on balance, this was a better use of time as it created new live opportunities to test the approach in the field. Instead of conducting a final piece of longitudinal research, the team consulted earlier participants in discussion and staff development activities about the findings.

Key Findings

The overall model remains useful for describing the work needed to support students at risk, although in practice the Communication and Intervention were found to merge at times. The support process cannot be followed without proper consideration of institutional policies, processes, and capacity. Moreover, it cannot be followed without the active involvement of staff users, and they require role clarity, training, and resources to use it.

Trigger/ prompt

Both staff and students are broadly in support of interventions based on early warnings. Different alerts were used including self-reflection or hard systems-based early warnings. Staff wanted more involvement in decisions about triggers, but the researchers found that there were costs associated with this including time and higher data literacy skills. Effective triggers were more complicated than simply providing a calculation: capacity and the risk of false positives needed considering.

Communication

Students told the researchers that they wanted to be engaged if they were at risk of early departure or other issue and wanted to be communicated to as individuals. In practice, they often engaged less enthusiastically with the process. Students tended to prefer ‘official’ communication channels to personal social media. There is unlikely to be a ‘correct’ form of communication, every option has challenges associated with cost and efficacy. Communication was an important record of activity.

Intervention

Our experience of the project strongly suggests that there is still a need for a staff-member intervention. One important issue for students and staff was finding the right balance of being supportive and stressing the importance of how students should change their approach to study. The team found that students wanted simple first steps to action and not to be overwhelmed by the intervention. Once again, logging the intervention was felt to be important for the next person in the support chain.

Management and Operations

The overall project focussed on the operation of the early warning. However, all learning analytics/ early warnings sits within an institutional context. Our work was framed by features such as institutional policy, data capacity, staff capacity and data literacy. Staff interviewed in the project were passionate about supporting students but acknowledged that it could be difficult and time-consuming. Staff wanted simple systems to see not just early warnings, but the full extent of support being offered to students.

Recommendations

Overarching Recommendations

Design interventions from the perspective of the intervention, not the IT system to support it. Working backwards from this starting point is essential.

Trigger/ Prompt

Different triggers can work but need to be easily explained. Design triggers based on mathematical risk, but also the institutional capacity to act. Balance the need for the quality of decision making and staff buy-in with the time required for staff to engage and analyse each trigger. Responding to early warning triggers is not ‘normal’ for most staff, they will require training.

Communication

The communication stage should be used to prepare students for the intervention. There is no perfect form of communication, the best approach is to mitigate against the disadvantages of each option. Personalise communication where possible and strive for a supportive, serious tone.

Intervention

Some students will act based on the communication stage alone, however an intervention is an essential part of the process for most. We recommend that a coaching approach is usually the best way to intervene. If possible, contact from staff known to students is likely to help. Being transparent about data is important, but an over-emphasis on risk or deficit may demotivate the student. We recommend simple goal setting and follow-on meetings.

Management and Operations

Institutional policy, guidance and staff development is needed to embed effective early warnings. Clearly articulate expectations for staff and students. Effective record-keeping about interventions is essential for all staff supporting students; staff users must be supported with training in privacy and confidentiality.

Project Goals

The original project goals were:

- To build up a body of knowledge amongst practitioners about ways to use data to improve the quality of interventions
- To produce reports, briefings and staff development materials and disseminate them through internal and external events
- To have used staff development and guidance to increase staff capacity in data literacy and advising using learning analytics
- To have shared these resources through national and international conferences

(Summarised from original bid page 19)

The OfLA Model

Learning Analytics/ Early Warning Systems

Institutions possess large quantities of data about students. This data can be used to generate early warnings that a student may be at risk. Data points include both fixed characteristics (for example background or entry qualifications) and dynamic data (for example attendance or computer use). There are associations between data and student outcomes. In the UK, the Office for Students shares sector wide data showing the relationship between socioeconomic backgrounds and student outcomes. Early warning systems have been built around measures such as attendance and show an association with academic outcomes (Romer (1993). The project team worked on an earlier study to show an association between satisfaction with academic experience in a first-year survey and academic outcomes (Foster et al., 2012). Finally with the onset of more computing power, the sector is experimenting with bringing together multiple sets of data and using algorithms to demonstrate risks associated with different levels of academic related activity (Arnold & Pistilli (2012), Jayaprakash (2014)).

Learning analytics present several ethical issues. These arise from issues such as accuracy, transparency, and the consequences of operationalisation (e.g., failing a student who does not work in a way described by an algorithm). There are also strong concerns that algorithms may reinforce existing social injustices, or simply identify problems that institutions are not able to resolve.

Students at risk

For this project, we view the phrase 'students at risk' to mean one of the following:

- Students at risk of withdrawing from their course early
- Students underachieving against academic potential
- Students encountering difficulties such as anxiety or mental health problems brought on by struggling to cope

There is one very important ethical consideration with this approach. Early warning systems are based on evidence from students. These may be qualitative (e.g., self-reflections in surveys), or more likely quantitative (e.g., attendance monitoring, or a basket of different measures). They are normally derived from individuals, but cohort level data is possible. This means that the focus is the individual student, not on any problems with learning and teaching, or the institutional milieu more broadly. We believe that this is a legitimate approach, but it's essential that students aren't blamed by the process. In most institutions we would expect that holistic work in areas such as making the curriculum and estate accessible to students will also be taking place in parallel to this intervention-based approach.

Onwards from Learning Analytics

Onwards from Learning Analytics is based on the leaky pipeline metaphor. Even if institutions can identify students at risk, this clearly does not automatically mean that the risk can be mitigated or resolved. Therefore, the project team proposed that institutions can miss opportunities to support students at three stages:

- Trigger/prompt
- Communication
- Intervention

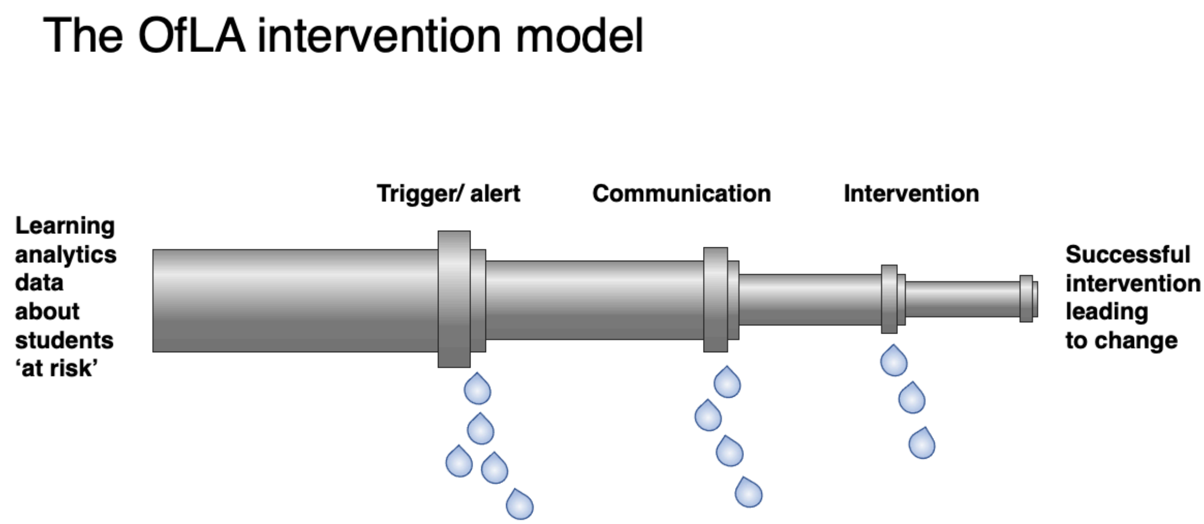

Figure 1: the OfLA leaky pipeline model

Stage 1 - The Trigger/Prompt

The trigger/prompt is the specific trigger for action. During the project one issue that arose from staff interviews was that often they had a sense that students were struggling or disengaging, but that this was not always so serious that they needed to intervene immediately. Triggers are therefore potentially useful as an unambiguous trigger to act. However, there are numerous challenges with triggers, all of which could mean that students are missed:

- Firstly, is the trigger accurate? Does it identify students in need of support?
- Can it be produced in a timely fashion? As the term or semester progresses, alerts are likely to be far more accurate, but later alerts are likely to be less useful for instigating changes in student behaviour.
- Is the alert unambiguous? Almost any missed session, or low use of a resource is likely to show some degree of risk, but should tutors/ advisers follow up every alert? Most are likely to be false positives. An early intervention might be transformative for one student, but a waste of time for ten others. Chasing every possible early warning will be very expensive to facilitate.
- What power do staff members have? Many of the people who will be using alerts are likely to be higher education professionals used to exercising autonomy over their working lives. An overly prescriptive system raises issues for these staff.

Stage 2 – Communication

Once any system has identified a student is at risk, the next stage centres on decisions to contact the student.

- Does the student need contacting? The staff member who has received an alert may be fully aware of the student's circumstances and there may be good reasons to not contact the student
- What media is used to communicate to the students? Throughout the project, the team have found some ambiguity and complexity about students' perceptions about being contacted.
- How much effort should be put into communication? Students can be reluctant to answer emails, pick up the phone or respond to other communication.
- What tone should be adopted? The media is important, but if this communication is designed to change behaviour, there's also the challenge of breaking through into the student's consciousness that motivates the student to act and doesn't destroy their confidence along the way.

Stage 3 – Intervention

Finally, we suggest that an intervention is required. For the most part we argue that this is likely to be some form of conversation between the student and the relevant member of staff (although in practice, it could be with a more-experienced student). It is likely that in some instances, the communication is the intervention: i.e., sending an email to a student may be all that is required for them to change behaviour. However, we would argue that it would be a mistake to assume that an email from a tutor is an effective intervention in all cases. Issues at this stage include:

- Who delivers the intervention? It appears from our surveys, that students would prefer to be supported by someone who knows them personally, likely someone connected to their programme. However, these are often the most time-poor colleagues in the institution and many of the most important interventions are with those students who may never have formed working relationships with staff.
- How much support is appropriate? It may be that a single conversation is sufficient, but students' needs are varied and more may be required.

It is important to stress that, even after all these processes, the correct decision may be for the student to leave their course or take a break from their studies. The issue, we would hope, is that students can be supported to make and act on an informed choice sufficiently early, not simply fail their programme because they had not understood that they were at risk.

Starting Assumptions

Literature Review Summary

Our work was influenced by the following key themes from the literature (summarised in output 4 on the project website).

Literature Review

- Institutional framework
- Bound by legal, ethical, and institutional considerations (pedagogic and organisational)
- Ought to involve users in the design of interventions and systems

Prompts/ triggers

- Data needs to be actionable and in operation needs to be accessible to all partners in the process. Triggers can come from a range of sources, ethical considerations about choice of triggers

Communication

- Personalise as far as possible, role of the communicators
- Communication needs to be action-oriented
- Communication is complex, careful not to overload students

Intervention

- Timing is critical
- Data can be a route into dialogue
- Evidence limited about efficacy of early warning approaches
- Blackstone's formulation – better to intervene with false positives than miss a true positive

Project Activity

The project can be described in broadly two phases.

Phase 1

The first set of outputs were a series of case studies carried out at each partner institution. These explored different aspects of early warnings and success interventions and were delivered across all three years (Outputs O6, O9 and O12). Earlier in the project, the focus was testing existing systems, testing the views of staff and student users. Later in the project, the focus was on trialling early warning interventions. It is important to note that Covid-19 significantly disrupted the second half of the project, but this provided the opportunity to use student success analytics as part of the institutional response to the pandemic. These outputs are summarised in the section below. The literature review (O4) was conducted as part of this phase.

Phase 2

The second phase was to provide a series of focussed summary reports and resources to help colleagues at other institutions develop their own learning analytics and early warning resources. These reports were O13 Staff Development and Organisational Development Resources, O14 Policy recommendations for integrating data, learning analytics and the advice-giving process, O15 Guidance on using Institutional Data and this O16 The Final Project Report (this document). The findings from these reports are included in the Findings and Recommendations of this report. Most of this work was conducted in the final year of the project.

NTU Student Transition Survey and a note about names of outputs

In the original bid, the project team planned to include a research tool used by NTU, the Student Transition Survey. This survey is a large online survey conducted in February and March each year amongst first year students with a response rate of approximately 1,000 (10% of the cohort). This was not funded. Nonetheless we used the survey to gather data about student views and these helped shape our findings and recommendations. We have included a summary of findings from the three surveys in the appendix at the end of this report so that a reader can see the source of our thinking. Sharp eyed readers will notice that there are some outputs missing (there is no O5 for example). This is because not all our proposed outputs were funded and to make sure that we met the funding requirements we have kept the original names. We promise that we have included work for all the projects that were funded.

Summary of activity 2018/19

In the first year of the project, the project team focused on better understanding the baseline activities taking place at each institution. This included both understanding where opportunities might arise to conduct further early warnings trials and to test the end user's views on this approach (students and staff). A literature review was conducted to help the project team focus on priority areas.

Key findings have been grouped using the OfLA model.

Trigger/Prompt

At NTU, staff members felt that one of the main benefits of learning analytics was that early warnings provided a strong prompt to act. They may be aware that a student may need support, but an early warning was a specific nudge to act immediately. In the two institutions not using learning analytics (AHS & UMCU), staff reported that they felt able to spot students who needed further support using background and behavioural indicators. Several interviewees acknowledged that doing so could be time-consuming. The staff at UMCU were interested in early warning approaches that included qualitative data such as surveys and self-reflections, not just quantitative data such as grades. Students at AHS reported that they were interested in the potential of early warnings.

Communication

Staff at NTU reported how they personalised their communication and used the strengths of their relationships with students to encourage them to seek help. Students at AHS were clear that they wanted communication to be clear and timely.

Intervention

Staff at NTU found that using the quantitative data from learning analytics was one method that could help open up a dialogue with students and enabled the tutors to work with the students rather than confront them.

Management

Staff across the partner institutions reported that reaching students in need of further support could be time-consuming and personally draining. Staff felt that they were encountering more frequent and complex issues associated with mental health and wellbeing that tested the limits of their personal capacity and roles.

Summary of activity 2019/20

In the second year of the OfLA Project, the partners conducted a series of research trials, testing different approaches to learning analytics. Arteveldehogeschool conducted two trials to test whether institutional systems could generate meaningful early warnings. Both approaches: answers to a personal reflective survey and attendance monitoring generated effective early warnings. UMCU conducted a study using historical data to identify whether students from particular entry routes were more at risk of early departure or underachieving. NTU's work was split across three areas. Firstly, the team continued with the work of the previous year asking personal tutors to reflect on their experiences of supporting students in a series of reflective diaries. They also sought students' views on receiving automated early warning alerts. The team analysed two pilots in which learning analytics data was integrated into school-wide pastoral interventions. Finally, the team experimented with the early warning alerts, searching for an alert time period that balanced the need for meaningful alerts that did not generate too many false positives.

Trigger

All three partners successfully used data to identify students in need of further support using a range of approaches: surveys (AHS), student engagement data (NTU & AHS), historical data analysis (UMCU). Several key issues arose from this work including staff reluctance to rely on abstract data alone and needing to integrate such data into their mental models. Even when data can provide unambiguous evidence of risk, the rules for triggers need to consider the culture of the institution and issues such as duty of care. Early warning systems generate false positive alerts and this needs incorporating into any support systems. AHS students continued to express interest in being contacted using data from early warning systems remained generally favourable about risk being communicated to them.

Communication

Students expressed strong views about being recognised, and communicated to as individuals, for example, AHS students felt strongly that if a risk had been identified about them personally, it ought to be communicated to them privately. There was a role for generic communication, particularly for pushing students to further sources of support.

Intervention

NTU staff described a variety of skills used to build rapport with students, for example sharing examples of times they had struggled. Researchers at NTU found a weak association between using letters as a communication channel and subsequent re-engagement. Students reported that the role of the tutor was important for helping them to re-engage. Students wanted the next steps to be kept simple. They did not want to be overloaded by choices about which actions to take.

Management

The NTU researchers found that factors such as role ambiguity continued to impede tutors' capacity to support students and a number reported that they felt emotionally burdened by the complexity of students' support needs. Two of the case studies at NTU involved sharing large data sets with academic colleagues. It appeared that both required extensive management including clear communication about roles and responsibilities, training and record keeping.

Summary of activity 2020/21

In the final year, the project team conducted three different trials to explore the issues associated with using early warning systems: two coaching approaches from central call teams (NTU) and a survey nudge tool (UMCU) to support students. AHS carried out further analysis of the issues of integrating data and early warnings into support processes.

Trigger

All three of the interventions successfully targeted students at risk. Two interventions used learning analytics data to identify students, one used a survey to nudge students to seek help. The largest case study took place late in the 2019-20 academic year and there were significant challenges about balancing the trigger's statistical accuracy, the scale of the work (in response to the COVID-19 pandemic) and timely interventions. The UMCU survey approach showed the potential of using gentler triggers to change behaviour.

In the AHS student surveys, students told the researchers that they had put off seeking help and what lowered this barrier, reinforcing to the project team the potential benefits of early intervention. The AHS staff surveys showed that staff were amenable to the idea of data-driven early warnings, but wished to retain the autonomy to act, rather than be mandated to do so by automatic early warning systems.

Communication

In the first of the NTU coaching interventions, students were sent emails informing them that they would be subsequently contacted. In the evaluation, it was clear that some were unaware that they had been sent emails prior to the phone call. When students were contacted by the call team, they were sometimes defensive about being told that they were at risk, this led to the team softening their opening communication.

Intervention

AHS students told the researchers that they preferred higher-quality personalised interventions such as face-to-face support. They also stressed the importance of discipline-specific support, preferring support materials to be course-specific.

Management

The NTU call centres needed to be fitted around existing support systems (partly due to the challenges of the COVID-19 pandemic). Fitting around such processes was difficult and required significant change management, more consultation and ongoing dialogue with stakeholders. Importantly, the interventions required a multidisciplinary approach, joining together experts in retention, coaching, and student support with those with project management, data, and communications expertise. These are complex change management programmes.

In the AHS, staff survey, staff members told the project team of the importance of being able to see holistic data about students. In both the call centre case studies and staff surveys, staff members felt that it was extremely important to have dynamic information about students, for example records of support being provided.

Main findings

With multiple surveys and studies at the different partners, we found that some of our evidence was, at times, contradictory. In particular, we found differences between the way that students wanted to be treated in surveys and some of the ways they responded to interventions in real life. Clearly this can be accounted for by the fact that these were not necessarily the same students (or even in the same institutions) and students receiving support were in a potentially more delicate and stressed space. Anyone reading the individual case studies will be able to see these contradictions for themselves. We have tried to accommodate differing views in the main findings and recommendations, but want to make clear that for most findings, it will be possible to find contrary views from both students and staff. These findings are therefore our best attempt to demonstrate the balance of views expressed.

At the end of the project, is the model still valid?

We would argue that the model (trigger/prompt, communication, intervention) is an appropriate way to plan the use of early warnings for interventions. The main reason is that it focuses on not just identifying students at risk, but on what to do at the point where those students have been identified. We would argue that the instinct in many higher education institutions is, rightly, on uncovering new knowledge, in this case 'why are students at risk?'. This quest for truths does not necessarily prepare institutions for making the operational changes needed, particularly where changes to working practices may be required. Therefore, mapping out the stages in more detail is important. We acknowledge the work of Clow (2012) in our approach but feel that adding detail to his model's 'intervention' stage is essential. Although the model is drawn in a unidirectional flow, it is important that we see it as a cycle. Even the best interventions may require repeat activity to help students to continue to grow and develop.

The OfLA Project model was developed specifically to explore the process of supporting students. In our original bid, we attempted to focus on process, not on the supporting infrastructure and management processes as we had investigated this in previous projects (ABLE, 2018, STELA 2018). In practice, this model cannot be separated from the surrounding infrastructure. Any early warning system much above the scale of single course cannot be implemented without carefully considering (and, if needs be, changing) institutional processes. These institutional processes include policy, data processes, staff development, resources such as software, meetings space and experts in specialist support. Most importantly, an agreed strategy that clearly articulates the role and responsibilities of those involved.

At the start of our work, the project model did not sufficiently address some of the issues of stakeholder capacity: what do those staff using the system and supporting students need? Through the course of the project in our interaction with staff, staff need resources such as time, but also skills such as data literacy and knowledge of further support. We feel that one area that requires further consideration is the issue of role clarity. Tutors/ advisers often have well-defined roles in theory but enforcing the limits of these roles with distressed students can be difficult and stressful. Tutors reported that they did not feel comfortable or equipped to support issues such as mental ill health and were also uncomfortable telling students that this was the case. Within resource-limited systems, it may never be possible to completely address these issues, but if we expect staff to support students at risk, then every institution needs to keep in mind the stresses this can cause.

The project model focused deliberately on institutional processes, not on the psychological requirements of students to change during the period from alert to intervention. In practice, those needs were considered at every stage, but they are not the focus of the project. We strongly believe that future work in learning analytics/ early warning systems needs to spend much more time in this field. Not just with surveys of students asking about how they would feel if an alert were raised, but alongside students as they are coached, or nudged through change.

Trigger/ Prompt

All three partners ran successful early warning alerts. NTU expanded its existing learning analytics work by conducting two trials into learning analytics call centres (O12), UMCU used a survey to nudge students towards seeking support (O12) and Arteveldehogeschool used both attendance monitoring and a self-reflective survey to identify students at risk (O9).

Key findings

Staff and students were in support of early warning alerts (both in principle and practice). Staff at NTU found the alerts useful because they were unambiguous. Alerts usually coincided with staff perceptions of students (they were rarely a surprise) but they were useful because they moved the tutor from a general sense that something may not be right to a specific need to investigate further.

Different alerts are possible. The team used a range including self-reflection surveys prompted student actions, showing students their own data instigated further engagement, and both engagement and attendance-based early warnings instigated staff interventions. Views varied between institutions about the role of fixed characteristics such as socio-economic status in the alert. Some academics wanted to have access to this information as a factor to consider when considering an intervention. Where learning analytics is used at an institution, the alert explicitly only uses dynamic activity data to avoid the risk of unconscious bias or other unintended outcomes. Fixed characteristics such as entry qualifications can be used as part of any evaluation or impact assessment but require very careful consideration when used as a trigger for action.

Early warnings contain profound tensions. Fundamentally, a very early alert will be accurate: some of the students identified will withdraw/ achieve poorer grades etc. However, the cost is the number of false alerts: most students identified will succeed and so don’t need an intervention. Spending time supporting them also has a cost. Similarly, telling students at the very start of a module that they are at risk of failing is unlikely to resonate very effectively. They are likely to discount early warnings that are too early, believing that they will have time to catch up. Delaying the early warning trigger will reduce the number of false positives, but it will also reduce opportunities for meaningful interventions. An alert generated on the very last day of term is likely to be extremely accurate, but functionally useless. Similarly, self-identified alerts are likely to be most useful amongst students who already possess a degree of self-awareness and understand what is required of them. We found that triggers/ prompts are therefore a combination of mathematical risk, organisational capacity and, to a lesser extent, what staff and students will accept.

Some of the biggest issues were about the autonomy of staff users. Academics are professionals used to using their judgement about offering support to students. There were noticeable tensions: staff not currently using learning analytics triggers were reluctant to give up their autonomy, and even where automatic early warnings are used, staff wanted to add personal knowledge and judgement to the decision to act. Or not act. Giving staff the autonomy to act may be important for staff buy in, but it also adds time which has consequences. In a term or semester of 12 - 15 weeks, waiting a week for staff to make more sophisticated, personalised decisions is quite a large delay and may take them away from other tasks. Of course, this needs balancing against the opportunity cost of intervening unnecessarily.

Staff were also keen to understand the nature of the alert. They wanted any calculations to be transparent. This is both important for their buy in, but also for student buy in. If a staff member did not understand the nature of the trigger, they would not be able to defend it to a student who may be defensive or indignant about being challenged. This is potentially more important due to the nature of early warning alerts: asking to speak to a student after they have failed an assignment is quantifiably very different to asking to speak to a student who is at risk of failing an assignment.

Staff also discussed the need for data literacy. Issues such as odds of progression are not natural for most people. We have written before if five students have an 80% chance of passing the programme, in all likelihood one will drop out. The nature of humans means that often staff remember the student who dropped out, not the students who didn’t.

Finally, triggers/ prompts need institutional infrastructure. Programme or module teams can manage early warnings and develop learning analytics, but there is a point of scale where this work requires institutional commitment.

Communication

The project team communicated early warnings to students. In practice, there are only a limited number of routes to communicate early warnings to if students are not regularly engaged in class. Much of our work therefore concentrated on the use of official university email and telephone calls.

Key findings

Students repeatedly told the project team that they wanted to be warned if they were at risk. However, in practice, some students ignored such communications. This difference is perhaps to be expected. Students in surveys are perhaps more likely to describe how they would like to act. Students who actually receive communication following an early warning alert are perhaps in a more difficult situation, facing a range of complex issues.

Often, the project team felt that the communication and intervention stages merged. An email to students could lead to changes in student behaviour. All three project partners had examples where the communication alone achieved a change in behaviour. However, just because communication alone was enough for some students does not mean that it is enough for all students, particularly those most at risk.

The project team found that different communication media have different strengths and weaknesses. Official emails appear popular with students, certainly over options that require them to log in to access. The practitioners on the team raised concerns that students often failed to respond to official email communications. Email should perhaps be the baseline for all communication, but it is probably not safe to assume that it will reach all students, particularly those most at risk. In the final transition survey, text messages appeared a popular communication option and this is an area for future development, perhaps as a step between email and an attempt to talk to the student. Other media such as Microsoft Teams or students' own social media were less popular. It may be that students are keen to receive communication via social media in the future[1], but it may also be that students want to manage their communication into personal and official streams. Telephone calls were used in two case studies. As we shall show at the end of this report, they may be more effective than email at triggering a change in behaviour, but are substantially more expensive and were not perfect communication channels. Ultimately, the team felt that there was no perfect communication channel, but steps could be taken to mitigate the risks associated with each.

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[1] At the time of writing, Facebook was 17 years old. Although students are more likely to use other social media channels now, they have grown up with social media and there's no particular reason to assume that they will be more comfortable using whatever new tools come online in the future.

Students repeatedly told the researchers that they wanted to be recognised as individuals in the process. They preferred to be contacted by people that they knew and knew them. We believe that there are benefits for most students to be provided with such personalised support, however, we also recognise that there are logistical limits to such an approach. It may be that a personalised approach using student data can partially compensate in situations where the student is not known by the person offering them support. It is also important to note that students who may benefit most from an intervention may be those students who have not yet formed such personal relationships with university staff.

Finally, the team noted that communication is a record of activity. Given the scale of many institutions and the complex interplay of agents who could be supporting a student, leaving a record of interventions is essential. This record is helpful for the next person who supports the student and as a record in case of complaints.

Intervention

The project team delivered a range of interventions: these included email early warnings, self-reflection tools and telephone calls.

Key findings

Firstly, we believe that interventions from a professional staff member remain essential. Of course, students are autonomous adults with a range of skills and talents, however, for whatever reason, at the point where an early warning alert was generated, many appeared to need more support than they possessed themselves. Our experience suggests that whilst a minority of students were facing significant challenges such as mental health crises, many more were unaware that their behaviour might put them at risk or had temporarily dipped in their motivation or engagement. At the point where an intervention was made, these students needed someone to help them adjust their approach, encourage them, or perhaps simply remind them that the institution had noticed their lack of activity. For whatever reason, students often told us that the interventions helped them to re-focus and re-engage. A range of colleagues delivered the interventions: academic advisers, personal tutors, course teams and call centre staff all successfully communicated with and coached students. All were able to successfully re-engage students in the different pilot studies. It may be that using more-experienced students would have the same impact, but this was not tested due to the ethical complexities of sharing data with fellow students.

The project team spent some time exploring the ’tone’ of interventions. There may be a case for shocking or scaring students to act. However, at the point where a staff member first speaks to a student, it is impossible to tell whether the student is blithely unaware that they are risk or are fully aware and in the midst of a crisis. On balance, we believe that the right approach is to adopt a positive coaching tone.

There were challenges about transparency. At NTU, risk was made very clear at the start of the call centre trials. Early in the phone conversation the callers informed the students that the call was because of ‘low engagement’. It was felt by the callers that this was too confrontational, and the script was changed, students were instead told that they were receiving a coaching call. Only if asked, was low engagement explicitly explained during the intervention. In theory, students in surveys wanted to be informed that they were at risk, but in practice, the team were concerned that doing so could be paralysing rather than motivating.

Academic staff explained that they sometimes used engagement data in an interesting way to motivate students. They would treat the early warning as something to ‘beat’. They would offer to work with the student to help them overcome the abstract system, siding with them against the faceless university bureaucracy.

In a situation where students may not be clear what to do differently, the data from learning analytics systems appeared to help staff set goals with students. If, for example, the student had ‘low’ engagement, focussing on getting ‘partial’ or ‘good’ engagement was a realistic goal to work towards.

Our research was focussed at the start of the process of identifying a student at risk and supporting them. Students told the researchers that they wanted first steps to be simply explained and wanted that advice to be made available in writing. This advice could be personalised, but students appeared to be happy to receive group advice about studying or seeking help. There was a preference for academic advice to be offered within the context of the programme, not generic institution-wide advice.

The project team only considered positive interventions, for example coaching conversations. The team did not consider the role of learning analytics or early warnings as part of disciplinary, or 'fit to study' procedures. Adding consequences such as withdrawing funding puts additional pressure on any trigger. It may be that whereas ambiguity is possible for a positive support trigger, it is not for one with negative consequences.

Finally, once again logging the intervention activity was felt to be essential. It helped the student to have a written agreement about the next step and helped the next person in the support queue to know what had gone before.

Management & Operations

Key findings

Using learning analytics and early warning systems provides institutions with opportunities to intervene earlier than was historically the case. However, it is clear from the project that institution-wide initiatives require significant managerial and operational support. The first key finding is therefore that early warnings are shaped by each institution's culture and capacity to maintain and use them.

It was clear during the project that any early warning system needed to be clearly articulated within institutional policy. Decisions, particularly those with consequences, needed to be transparently and comprehensibly described. Furthermore, ethical decisions about data use, storage and privacy need to not only meet legal requirements but sit alongside existing institutional policies.

The whole intervention process remains more complex than the OfLA model suggests. Many students need repeat interventions from teams of multi-disciplinary experts. The work can be stressful and draining. Staff need proper support including time, training (see below) and the resources to conduct interventions effectively. It may be that institutions consider new support models, for example, academic advisers and personal tutors may need to become the second line of support rather than the first.

Staff require training to use early warning systems and intervene effectively. Staff development should include how to use any systems, data literacy, what the processes and policies are, how to support students with skills such as coaching and mental health first aid and how to make referrals to other more specialised support.

Those staff involved in the interventions felt strongly about their role. They wanted the right information at the right time and often wanted the autonomy to choose to act or not. They are legitimate stakeholders and decision-makers in this intervention process. However, data-driven systems such as learning analytics can legitimately spot students at risk. If the data is simply just another decision point for already busy and stressed staff, it does not add anything helpful, it simply adds complexity.

In some respects, the system that staff wanted to see was a single point of information about students. This could include background information, entry qualifications, programme and module information, grades, attendance and features such as interventions and support already being offered. Ideally, this would be accessible by all staff who could potentially support the student. Clearly, greater access would raise further ethical issues such as privacy.

Role clarity was identified by both staff and students as an issue. For example, staff needed to know what their boundaries were and when it was appropriate to refer students on to more specialised support. Similarly, students needed clarity about what was expected of them.

Recommendations

Overarching Recommendations

- Design all learning analytics/ early warning systems from the perspective of the intervention you want to happen (in the case of the OfLA project, this was often a face-to-face conversation). The IT system that drives the intervention is not the outcome.
- All processes need to be built to facilitate this outcome. These will include data, policy, IT systems, staff development, estates, and other resourcing

Triggers/ Prompts Recommendations

- Different triggers/ prompts can work. These need fitting into the institution's ethical and operational framework. They must be transparent and easy to explain to staff and students.
- Triggers/ prompts are a combination of mathematical risk, organisational capacity and to a lesser extent what staff and students will accept. Institutions need to design them accordingly
- Institutions need to consider the role of staff involved: giving them autonomy about acting is likely to improve buy in, but, at the very least, will add time to the process
- Responding to early warning triggers is not a natural way of thinking for most people. Training, including data literacy, is important.

Communication Recommendations

- The communication stage must prepare the student for the intervention to come or be sufficiently detailed for them to act alone.
- Some students will be able to act simply based on the communication stage, do not assume that all students can
- There is no perfect communication media; institutions need to consider how to mitigate against the disadvantages
- Students want personalised communications. At the very least, data should be used to give the appearance of such personalisation.
- As it is impossible to know the mindset of a student receiving a communication, it is best to retain a supportive, but serious, tone.
- Institutions should have a way to record the communication and insist that it is recorded.

Intervention Recommendations

- Whilst some students possess the capacity to act simply from the communication, assume that most students at risk require an intervention.
- If institutions have the data to show that a student is at risk, not intervening is an ethical consideration.
- The tone of the intervention should be a coaching one designed to help students understand what they need to do differently and building their confidence and skills to do so.
- Students prefer academic support to be made in the context of their programme.
- Data can be used to help students understand what they need to do differently
- At the end of an intervention staff should try to make the next steps clear and easy to take for students, ideally there will be an opportunity to review progress.
- Staff should always log interventions, to help the next person supporting the student.

Management and Operations Recommendations

- Learning analytics and early warnings must be built into institutional policy, guidance and staff development
- Staff roles and responsibilities in the intervention process need to be clearly articulated
- Student roles need to be clearly articulated and implications of these approaches made clear
- The intervention process should be supported with a single spine of information accessible to all staff who could support the student. Staff with access to this information will require additional training in privacy and confidentiality.

Conclusion & Discussion

The project set out to better understand the issues of operationalising ‘student success’ learning analytics and the role of early warning alerts. The three partners Arteveldehogeschool, Nottingham Trent University and UMC Utrecht consulted staff and students, reviewed existing systems, and trialled a range of interventions against the original three step model.

We would argue that the fundamental approach provides value insights for anyone considering the steps involved in operationalising learning analytics. Anyone taking Clow’s (2012) learning analytics cycle needs to give far more attention to the steps between receiving an early warning and effectively supporting students. There is no automatic link between identifying the student and changing their approaches to study, helping them deal with problems in their personal lives or whatever other barriers prevent them from thriving. Prompt/alert, communication and then intervention provide a useful series of steps to consider how to structure these approaches. In practice, the boundaries blur, but anyone planning interventions needs to be able to visualise or describe how digital intelligence is turned into actionable intervention. The OfLA model provides one way to break these steps down.

When the project was planned, the team planned to focus as tightly as possible only on the intervention steps. In practice, the issues of management, organisation, staff development and IT were always at the forefront of our minds. Learning analytics and early warning systems are inherently scalable approaches, but even small-scale interventions require some information technology, legal agreement, and organisational buy-in.

The project team would like to thank all the students and staff who participated in our research. Their insights led directly to this report and all the preceding reports, resources and workshops delivered.

At the end of the project, one issue stands out, for all the inherent flaws (false positives, issues of timing etc.) it *is* possible to construct usable early warning alerts from complex data processes or even manual checks. However, the process of engaging with students is messy, contradictory, and complicated. It may be possible to generate a perfect alert, it may be possible to find the perfect point to intervene or even design the perfect intervention, but when we deal with tens, hundreds or even thousands of students at a time, there must be compromises. The ‘best’ will be shaped by the experience of each student, their confidence and motivation. Most importantly, the best is shaped by their confidence and motivation at the precise moment they receive the communication.

We would argue that learning analytics remains primarily work in the field of psychology, not technology. Technology enables the process of change to take place, but any change is psychological process. We therefore end with four student success conditions that we will consider in our future work. For a student to adapt their approach based on any alert or early warning, they need to overcome four barriers:

1. Do they know what needs to be different?

    a. Does the student understand that their current approach to learning may not be appropriate?
        i. Does the early warning intervention help them understand what they need to do next?

2. Are they motivated to change?
    a. Are they really committed to this subject, does passing matter to them?
        i. Can the early warning do anything to help?

3. Do they have the confidence that they can change?
    a. They may want to change, but may not believe that they can learn the difficult topic
        i. Can the intervention process help build their confidence that they can change?

4. Do they have the capacity to change?
    a. The student may be committed to change, but doesn't understand a core topic, or may be committed to change but be facing profound difficulties associated with their personal life
        i. Can the intervention process provide sufficient support (academic or pastoral) to help them thrive?

OfLA Project Team, 2021

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To cite this report:

Onwards from Learning Analytics (OfLA). (2020). *O16 – Final Report*. Retrieved from https://oflaproject.eu/outputs/output-16-final-project-report/

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Appendix – Key findings from the NTU Student Transition Surveys 2019, 2020, 2021

The NTU Student Transition Survey is an online survey conducted each year in late February and early March (response rates are around 10%). The survey includes operational questions about services delivered and questions to understand how students feel they are integrating into university life, coping with adversity and expectations about how NTU could better meet their needs. We have included only those responses relevant to the project here.

2019 Student Transition Survey (February-March, n=1,401)

There were three points to note:

- Students valued having access to data about themselves. Almost 3/4 of students reported that they found using the NTU Student Dashboard learning analytics resource useful (74%), 57% felt confident after using it and 45% felt motivated after using it. They also reported that they found it useful when tutors used the Dashboard during 1-1 meetings.
- The project team asked who students would like to be contacted by if an early warning alert was raised. The most popular responses were by their personal tutor (89%), the University's Student Support Services (74%) or direct from the system (71%). Interestingly, they would most like to be contacted via their university email address (83%)[2] or by text message (58%), letters and other methods less popular.
- Students were generally happy for the University to use data about them. This appeared to be context-specific, for example, 90% of students expected tutors to have easy access about their academic data (for example if they had failed an assignment), but only 27% wanted Student

[2] The project team spent a lot of time considering this answer. The lived experience of researchers and academics is that students often don't appear to respond to emails. The conclusion reached by the team is that email can be managed: students can choose when and how to respond to a university email, whereas a phone call is much more 'invasive'.

Support Services to have that information. However, 73% of students expected Student Support Services to have information about their mental health (88% wanted their tutors to have this information).

2020 Student Transition Survey (February-March, n=1,312)

Once again, students reported that they valued having access to the Student Dashboard learning analytics resource: 81% felt confident using it, 45% felt that it had helped them understand what they needed to do to succeed at university and 38% increased the amount of time they spent studying after logging in. However, 14% felt stressed or anxious after doing so. The impact of seeing one's own data appears to be shaped by students' engagement, for example 43% of students with 'high' engagement were more likely to increase their study time after logging in, compared to 15% of those with 'low' engagement. Similarly, 10% of students with typically 'high' engagement felt stressed after logging in, compared to 38% of students with typically 'very low' engagement. The focus of this project is the intervention process, this finding appears to suggest that students who need support the most may be least able to simply respond to data. They need some guidance and support.

Students overwhelmingly reported that they were satisfied with their personal tutors. However, 22% of students reported that they had missed a 1-1 appointment with their personal tutor - reasons for missing included other commitments, illness and mental health/anxiety. Students perceived some differences about how they should be supported with academic and pastoral problems. When presented with preferences about multiple options (results add up to more than 100%), students mostly expected to be coached to solve academic problems (84%), but a minority still expected the tutor to solve academic problems for them (27%). When facing personal problems, students expected to be signposted to services that can help (79%), although 61% expected to be coached by tutors on personal problems and 19% expected personal tutors to solve the problems for them.

2021 Student Transition Survey (February-March, n= 1,504 students)

Once again, students reported that they found access to their data in a learning analytics resource useful, 62% of students found the Dashboard to be useful. The team also analysed the background of respondents and noted that Black, Asian and Minority Ethnic (BAME) students slightly more likely to find it useful (66%) than white peers (60%). In the final year of the project, the team asked further questions about communication, asking how students should be contacted once an alert had been generated. The team had already agreed that an email would be sent to the students (See NTU case study O12) and so were interested in the next step. Students were asked to choose one option and the following were most popular: text message 32%, phone call from call centre 18%, Microsoft Teams chat 13%, call from a mobile 12%, Microsoft Teams video chat 12%. Communicating via students' social media was not a popular option. When presented with options about meeting a personal tutor for support, 82% were happy to meet in a private meeting room, 65% were happy to meet via MS Teams and 64%, happy to meet in a public space such as a cafe.