Decisions, theory and data: defining the role of analytics for assessment and feedback

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Executive summary

The field of learning analytics is in its infancy. Providing actionable insights, forging greater connections with educational theory and research and developing relevant data management strategies in institutions are some persistent and interconnected challenges. Our study aims to influence the sector's agenda for the development of purposeful analytics to enhance assessment and feedback in practice.

Modularisation is a key challenge to assessment and feedback. Integrating data across modules to gain valuable information and make programme design and the student experience visible is a relatively recent area of both enquiry and development. Given the persistent challenges in assessment and feedback practice, defining the role of learning analytics in this context is important. Understanding readiness of institutions to develop meaningful analytics is also necessary. Our study focuses on laying the foundation to future analytics developments by defining:

- relevant decisions in practice, drawing from educational theory and research
- constructs, measures and define relevant data attending to theory and research
- the feasibility of a set of initial proposals by attending to stakeholder acceptance and common patterns of data availability in institutions

The project consisted of two phases.

Decisions, constructs, measures and data: analytics mock-ups

The first phase focussed on identifying the *decisions* that programme leaders and students make and that present challenges in practice. Integrating the learning designs and student experience, helping to make it more visible across modules, is a known challenge. Drawing from existing literature, the following areas of decision-making were selected:

- Programme leads' decisions at design (constructive alignment, assessment load, supporting learning) and review (assessment difficulty, impact of assessment on learning, actual student load) stages of the assessment life-cycle were chosen.
- Student decision-making in the context of a programme and focussing on self-regulation in two key areas: time management and monitoring progression towards goals.

Having identified the decision areas, we then turned to exploring research on the *measures* of the chosen *constructs,* in consultation with staff and students we developed nine mocked-up analytics examples. The resulting mock-ups provided the basis for consultation with stakeholders in the second phase. A list of *twenty data elements* required to construct the mock-ups was compiled and would be further investigated.

Validating the analytics mock-ups with staff and students across institutions

The second phase focussed on the validation of the mock-up analytics outputs in consultation with stakeholders (thirty-eight staff, sixty students) across four institutions. The consultation focussed on the need, uses and purposes of learning analytics mock-ups developed in phase one.

Our consultation with programme leads and students validated the models for their relevance in practice in order to support better decisions by both academic staff and students. Results show acceptance of the proposed analytics models, and on this basis, the twenty data elements identified are recommended as essential for institutions to access since they could be turned into valuable information in important areas of practice. Beyond the illustrative mock-ups, the data identified is more broadly valuable as it relates to key constructs of design and student learning.

Feasibility of the proposals: data availability

With the aim to understand feasibility of the proposals made, during the consultations, common patterns of availability of the twenty data elements and their structure in different institutions were investigated. The majority of data elements investigated are typically unavailable at institutional level due to various sources that cause lack of systematicity, integration and structure. Accuracy of data, administrative processes, as well as unsystematic practices (marking, design), make the majority of the data elements difficult to access in the institutional contexts at present. In addition, the same data elements are sometimes stored in multiple systems (e.g. VLE, SIS). A few (exceptional) cases were found where manual processes or changes to institutional processes had been implemented to access the data and gain greater value from it.

Conclusions and future work

Our study provides positive directions for developing impactful analytics for assessment and feedback.

- *Programme level emphasis for learning analytics.* Integration of data at programme level can generate valuable information and this can enhance staff and student decision making in important areas of practice as shown in the nine proposals from our study.
- *Theory, research and stakeholder engagement are required from the outset to create analytics that will enhance practice with improved decision-making and advance research (e.g. student load).*

In addition to understanding key purposes, institutional strategies are necessary to capture, curate and manage data. Accessing valuable data across institutions is necessary to drive analytics uses forward in the ways illustrated. Our initial feasibility study shows that institutions may not yet be in a position to provide impactful analytics in light of the challenges to locating and extracting data described. Below we recommend areas of focus for institutions wanting to overcome barriers:

- *Think valuable data and your institutional strategy.* Twenty data elements investigated have proven to be valuable since they can be turned into valuable information and inform decisions. Moreover, each data element was required for more than one purpose. Understanding *valuable data* for institutions by establishing value of the data in the ways illustrated is paramount for institutions to create effective data strategies
- *Drive analytics forward in positive ways also by enhancing practice in assessment and feedback.* Transforming practice, data awareness, systems and processes should all be a central consideration moving forward with analytics in institutions. Our study has shown that advancing analytics for assessment and feedback will also require addressing the challenges in practice that motivated our study. Theory-motivated analytics developments in assessment and feedback can be a powerful ally to support institutional plans to enhance practice, in tandem with decision-making of stakeholders.

Work needs to continue to expand the agenda for analytics, following from our study, to create principled mock-ups and investigate measures. The success of institutions to gain value from their data will require the joint development of institutional data strategies and enhancement plans.

Moving forward with analytics in higher education institutions

Learning analytics is *"the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs"* (Long and Siemens, 2011 p. 1). Retention has been the focus of many analytics developments with a number of successful examples in different institutions (Nistor and Hernandez-Garcia, 2018; Sclater and Mullan, 2017; Newland and Trueman, 2017). Developments of learning analytics in higher education institutions remain limited to date and the field is in its infancy (Gašević and Siemens, 2015; Gašević, Kovanović, and Joksimović, 2017; Higher Education Commision, 2016; Mangaroska and Giannakos, 2018; Sclater, Peasgood and Mullan, 2016; Tsai *et al.,* 2018).

Relevant and consistent institution-wide datasets are fundamental to fulfilling the aspirations of learning analytics. Institutions have an abundance of data but stablishing relevance and getting value by turning it into information are key barriers. Data driven, atheoretical analytics have been noted as a key barrier for analytics to reach higher levels of maturity (Gašević, Kovanović, and Joksimović, 2017). Firstly, learning theory needs to drive analytics since it is essential to stablish relevance of questions to answer, define constructs and data required as well as provide meaning to interpret outputs (*ibid*.). Stronger links with theory are essential to define the purpose to the point that analytics should be part of the learning designs (Gašević, Kovanović, and Joksimović, 2017; Wise, 2014; Wise and Shaffer, 2015).

Secondly, relating educational theory with analytics requires a careful consideration of the information, measures, their origin, sources and how they are derived. Moving from *clicks* to constructs is recognised as central to analytics (Knight and Buckingham Shum, 2017). A construct is the abstract idea that one wishes to measure (Dew, 2011). Prior to any data collection, the dimensions of a construct should be defined (*ibid*). The instruments we use to measure the construct must be in line with the complexity of the construct. If our measures do not reflect the construct dimensions, our results or outputs will always have limitations or risk being invalid (Messick, 1994). Understanding the complexity of the construct is essential. This is central for analytics to gain greater maturity as a field. By way of illustration, institutions nowadays have access to VLE log in data. However, if we desire to measure "student time on task" (key predictor of motivation and performance) we need to understand first the construct and define its dimensions. Careful consideration of the construct we wish to measure, the data we need for the desired purposes, in this precise order, is key. Reflecting on the construct "student time on task" may soon reveal that is multidimensional (i.e. attendance, independent study time, time to complete tasks) and that needs defining.

Thirdly, much research also warns of barriers for accessing valuable data, structured and systematically (Higher Education Commission, 2016; Newland and Trueman, 2017; Sclater, Peasgood and Mullan, 2016; Tsai *et al.,* 2018): ethics, data capability and data management procedures, leadership in the strategic planning and implementation, skills/training, funding and infrequent stakeholder engagement. Of all these challenges, institutional data strategies and data management (Higher Education Commision, 2016; Sclater, Peasgood and Mullan, 2016) are given priority as they determine the ability of institutions to obtain the relevant data for the key purposes and would require consideration at early stages of any analytics development.

In sum, for learning analytics in Higher Education Institutions (HEIs) to reach greater levels of maturity as a field requires greater links to learning research and theory, to stablish meaningful and relevant purposes, constructs, and measures. Institutional strategies for the effective gathering and analysis of data also needs careful consideration. The objective of our project is to consider these important aspects in relation to assessment and feedback, that despite being a persistent challenge for the sector has received little attention regarding learning analytics developments (Chatti *et al.,* 2012). Below sector-wide common challenges are summarised prior to defining the project aims to advance both learning analytics and assessment and feedback.

Assessment and feedback sector challenges

The challenges for assessment and feedback practice are well documented (Bloxham *et al.,* 2016; Bloxham, Hughes and Adie, 2016; Boud, 2017; Elton and Johnston 2002; Evans, 2013; Jessop and Tomas, 2017; Medland, 2016; Price *et al.,* 2012; Tomas and Jessop, 2019; Winstone *et al.,* 2017). Challenges reported in the literature concern all stages in the assessment life-cycle and different stakeholders (e.g. staff; students; assurance) (Jisc, 2015). For our project, we have selected a sample of stages and stakeholders to focus the project on and illustrate the steps proposed in the introduction of placing analytics in existing research and theory. Despite not being able to cover all stages and stakeholders in depth, the sample of stakeholders and stages is deemed as a good basis to get insights into different theoretical accounts and relevant research to date. Our study focusses on different stages and stakeholders.

Design

The effects of modularisation[1] and assessment *of* learning cultures are visible in heavy summative assessment loads, exam heavy assessment diets, low presence of formative assessments raise concerns sector-wide over alignment, authenticity of assessments (Harland and Wald, 2020; Jessop and Tomas, 2017; Tomas and Jessop, 2019; Wu and Jessop, 2018). Regular diets with high summative and low formative are problematic for learning. Sector-wide efforts are directed towards improving programme level design (Dochy, 2009; Evans, 2013; Jessop and Tomas, 2017; Van der Vleuten *et al.,* 2015). Data has already been an area of focus as part of the sector-wide efforts to address these challenges using descriptive statistical summaries (TESTA, Transforming the Experience of Students Through Assessment; Jessop 2017) and visualisations (e.g. Walker 2019). Our project builds upon this previous work in relation to programme level design.

Review

The review stage of assessments, whilst essential, presents many challenges in practice that are manifested overall as lack of transparency of criteria and standards (Bloxham *et al.,* 2016; Bloxham, Hughes and Adie 2016; Boud, 2017; Elton and Johnston, 2002). The review stage in the assessment life-cycle, in principle, should focus on checking on many of the assumptions made at the design stage (see Messick, 1994, 1995, 1996). For our study, we are selecting a few challenges: impact of assessment on learning, understanding difficulty and finally checking aspects of the design such as load. This is a less well-explored area and our project makes some initial proposals to support practitioners with data at this stage.

Engagement of students in learning: planning stages and reviewing progress

Assessment *for* learning cultures (AfL) have student learning and self-regulation at the heart. Literature abounds calling for greater emphasis on learning rather than selection (Biggs and Tang, 2011; Boud, 2017; Boud *et al.,* 2018; Elton 1987, 1998; Elton and Johnston, 2002; Medland, 2016). Many efforts in the sector address student engagement in learning and frameworks for practice are available (Boud *et al.,* 2018; Winstone and Nash, 2016). Still supporting students to answer three key questions in learning continues to be subject of much research and developments in practice. The three key questions that students ask in practice (Hattie and Timperley, 2007; Sadler, 1989) that

[1] See glossary

are fundamental to self-regulation (Zimmerman, 2000) are: *Where am I going?* (setting goals), *How am I going?* (reflection), and *Where to next?* (actions).

Elements from the design and review stages discussed are part of the barriers to the full development of assessment *for* learning cultures. Challenges around design, culture and lack of transparency all have an impact on student engagement in learning and assessment as many of the reviews quoted highlight. For this reason, our project will concentrate on programme level views of the student experience of learning and how students manage these aspects. Multiple research reviews highlight similar challenges for students to engage with assessment and feedback: time management, understanding progression, identifying what to do next (Black and Wiliam, 1998; Evans, 2013; Hattie and Timperley, 2007; Winstone *et al.,* 2017).

Developing analytics that fully embrace the tenets of self-regulation is well established with formulation of the principles (Wise, 2014), desirable features (Schumacher and Ifenthaler, 2018) and even some attempts to define key constructs (Lee and Recker, 2017). Our study will concentrate on programme level views to facilitate student time management and progression. This focus will complement much research and developments by addressing some of the central sector-wide challenges in this broad area.

Project aims and research questions

Sector-wide efforts are directed towards improving programme level design (Dochy, 2009; Evans, 2013; Jessop and Tomas, 2017; Van der Vleuten *et al.,* 2015;) and engagement of students in assessment and feedback (Boud *et al.,* 2018; Price *et al.,* 2012; Winstone and Nash, 2016;). The project aims to advance the application of learning analytics to assessment and feedback by exploring purposes, constructs and relevant data with stronger links with learning theory and research (Gašević, Kovanović, and Joksimović, 2017).

The project will answer the following questions that define learning analytics (Chatti *et al.,* 2012):

- *Who* are the analytics for and *why*? What are decisions by stakeholders we want to address with the use of analytics? (Objectives of analytics and stakeholders)
- *What* data is needed? (constructs, measures and data)
- Is the data required available in HEIs? What is the institutional readiness to start addressing these challenges? (sources and availability of data)

Approach and methods

A case study approach offered the flexibility to achieve the project goals. There have been two different phases. The first phase has consisted of a literature review to draw from educational research and theories:

- the purposes (why)
- stakeholders (who)
- constructs and the data that would be required (what data).

Drawing from the review, a set of analytics mock-ups were created as a way of exemplifying possible analytics types. These were developed in collaboration with the Head of User Experience, students and staff at the University of Nottingham. Analytics mock-ups were created as a way to contextualise discussions with stakeholders about data relevance in phase 2.

The second phase sought to validate the proposals with key stakeholders of the project focussed on the validation of the proposed purposes and the data models created in phase 1. Separate student and staff focus groups were designed to last up to one hour. The focus groups were designed to validate the models proposed with relevant stakeholders and to hold discussions about availability of data sources. The data collection during the focus groups consisted of a mixture of discussions and recorded responses via using a questionnaire. Students and staff focus group covered different analytics mock-ups and they were asked to rate the likelihood that they would use this for specific tasks (i.e. when deciding number of assessments).

The participation of a range of HEIs was sought to obtain a representative perspective but also to investigate common approaches and patterns of data availability across institutions. To finalise, key institutional leads were invited to confirm details about availability and structure of data in their institutions to confirm insights obtained during the focus groups and discuss aspects of systems, processes and practice that played a role.

Gaining access to participants

During phase 1 academic staff and students in the main institution (University of Nottingham) were consulted during the development of the initial learning analytics mock-ups. Students were recruited through an institutional programme for student engagement at the University of Nottingham (*Students as Change Agents*). Students were involved in the design as part of their collaborative remit.

Participants in external participating institutions were obtained through the collaboration of key institutional leads. Initially up to six institutions were contacted to take part. Four HEIs were able to arrange the focus groups within the project deadline. Participating institutions were: University of Nottingham, University of Hertfordshire, University of Lincoln and Nottingham Trent University. Key institutional leads arranged staff and student focus groups following the ethical guidelines from the project lead. Students received vouchers for their participation in the study.

Ethics

All participants received information relating to the project in advance where the purpose, aims and data collection details were explained. Participants were invited to take part voluntarily. Upon arriving to the focus groups, participants signed the informed consent declarations. They were given the opportunity to withdraw and ask questions at any stage. An ethics committee at the University of Nottingham approved the ethical procedures.

Sample

60 students (43 female; 17 male) took part in the student focus groups exceeding the proposed target of 40. The student sample covered a range of:

- *Institutions* (46 University of Nottingham, 8 University of Hertfordshire; 6 Nottingham Trent University)
- *Discipline* areas: 2 Engineering; 9 Social Sciences; 22 Medicine and health sciences; 21 Science subjects, 4 Arts; 2 not declared
- *Years* of study: 12 year one; 21 year two; 18 year three and 6 year four.

Thirty-eight staff members attended the staff focus groups (16 female; 21 male; 1 undeclared) from four different HEIs: 12 University of Hertfordshire; 15 University of Nottingham; 3 Nottingham Trent University; and 8 University of Lincoln.

The focus groups were attended mainly by programme leads and academic staff (n=29). Nine other participants represented relevant professional services (e.g. Teaching and learning development, institutional analytics projects and student wellbeing).

PART I Programme level design: staff decisions in practice, constructs, variables and key data

Programme level design of assessment determines student learning and experience of assessment (Jessop and Tomas, 2017; Tomas and Jessop, 2019). Modular degree summative assessment and feedback design is disconnected and compartmentalised which tends to obstruct learning (Harland *et al.,* 2014; Harland and Wald, 2020; Jessop *et al.,* 2014a, 2014b). As a result, multiple frameworks for practice emphasise the role of the programme leader (Baartman *et al.,* 2009; Bearman *et al.,* 2014; Dijkstra *et al.,* 2012; Dochy, 2009; Evans, 2018; Hartley and Whitfield, 2012; Price *et al.,* 2012; Van der Vleuten *et al.,* 2015). Overall, many of the principles and considerations relate to the validity of assessments (Messick, 1994, 1995, 1996) that considers design, implementation and review stages as a whole with reference to all stakeholders (staff, students, employers). The current case study selects examples of decisions that programme leads make in practice with reference to a broad range of frameworks for practitioners that fundamentally, overall, impact on the validity of assessments.

In relation to design, a few key sector-wide challenges are selected (Evans, 2013; Medland, 2016; Jessop and Tomas, 2017) as key examples for our case study:

- Constructive alignment between tasks and outcomes: *Does the programme assessment align with the programme intended learning outcomes?*
- Student assessment load: Is the programme load well balanced in the programme? Are we bunching assessment deadlines? Is the diversity of assessment types sufficient and aligned?
- Developing an assessment *for* learning culture: *How is student learning supported?*

Practices in review and moderation stages are not very well developed (Bloxham, Hughes and Adie, 2016). All practice frameworks suggest checking sources of difficulty and assumptions made at the design stage. For illustration we propose the following as a focus at the review stage for programme teams

- Student performance and sources of difficulty: *Are assessments well aligned in terms of difficulty? What aspects of assessment students find more difficult?*
- Impact of assessment on learning: did the students appreciate the intention of the assessment and value? Was purpose and value clear to students?
- Assumptions about load: is the load aligned (e.g. are weightings of assessment accurately reflecting the effort/time required?)

This section describes the existing literature in relation to these key decisions in practice for programme leads at two important stages of the assessment life-cycle. Literature on measuring these constructs is also reviewed. The mocked-up analytics proposals for each purpose are discussed. Finally, results from stakeholder consultations on the analytics proposals are presented.

1 Design stage: Constructive alignment decisions

Biggs (1996 p. 2)*: "'Constructive alignment' has two aspects. The 'constructive' aspect refers to the idea that students construct meaning through relevant learning activities [.22] The 'alignment' aspect refers to what the teacher does, which is to set up a learning environment that supports the learning activities appropriate to achieving the desired learning outcomes."*

Constructive Alignment (CA) (Biggs, 1996; Biggs and Tang 2011, 105) proposes four steps to address construct validity as part of the alignment of teaching and assessment: define intended learning outcomes (ILOs); embed in chosen teaching and learning activities; embed assessment tasks that enable judgements as to how well a student met the ILOs. In the context of programmes of study, the sample of tasks in a programme that address the same competence (Dochy, 2009) are also essential (Baartman *et al.,* 2007) to assure representativeness and content validity. Assessment drives learning and therefore, this balance in assessment design is sometimes termed as the hidden curriculum. Poor alignment is known to result in poor learning and poor student experiences (i.e. lack of purpose, unidentified value) (Dijkstra *et al.,* 2012).

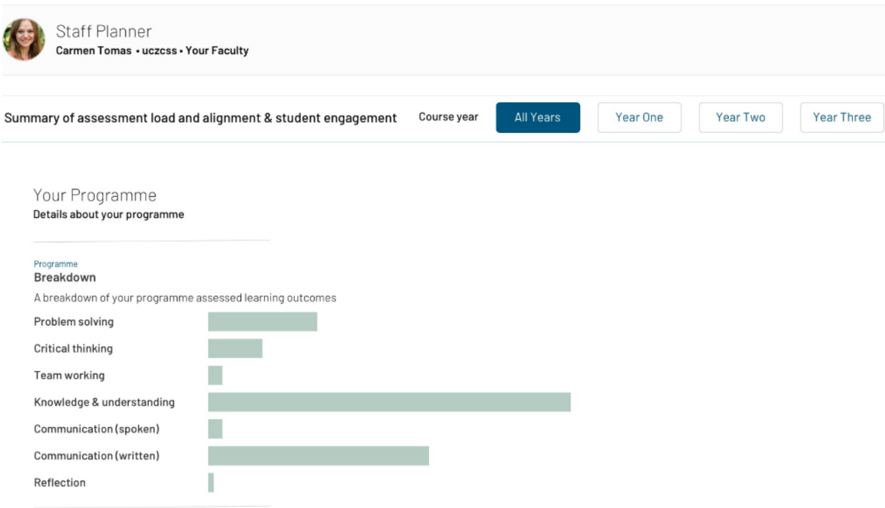
1.1 Measuring constructive alignment: construct, variables, data

A proposed descriptive measure of constructive alignment in a programme is based on the frequency with which ILOs are assessed and supported (Gottipati and Shankararaman, 2018). Generating an accurate summary of the balance with which certain LOs are assessed would require the following data:

- Student pathway(s) information (derived from student enrolment data)
- Learning outcomes (LOs)
- Tasks (formative) (mapped to LOs)
- Tasks (summative) (mapped to LOs)

Figure 1 below offers an example of a mocked-up descriptive summary proposed as an output that would present how frequently a learning outcome is assessed in the programme, both in total and by year.

Figure 1 Constructive alignment across a programme expressed as frequency of LOs assessed



2 Design stage: Student assessment load decisions at programme level

Student assessment load defined as the total number of summative, formative assessments, number of concurrent deadlines and lastly, the diversity in the assessment types all contribute to the notion of student assessment load (see TESTA project for full description). Assessment load is relevant to student learning in a number of ways (Jessop and Tomas, 2017):

- superficial learning and grade orientation
- lack of clarity about goals and standards (due to poor coordination) can stem from having too many different assessment types
- formative presence can promote learning

Student assessment load at programme level has gained increased prominence in many practice frameworks and regarded as a necessary consideration reflected in frameworks for practitioners (see literature review references).

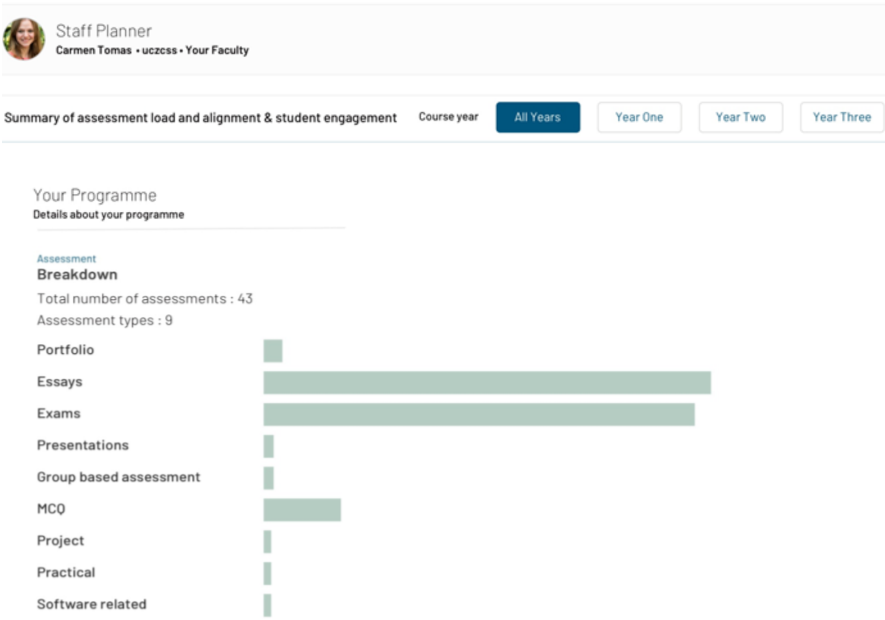
2.1 Defining the construct and variables of student assessment load

The TESTA project provided a definition of the construct of student assessment load. Measuring assessment load involves collecting data on the following dimensions of practice (TESTA) in relation to a programme of study and selecting the most common pathway:

- number of summative tasks (tasks that carry a weighting)
- number of formative-only tasks (compulsory, no weighting and there is feedback)
- varieties of assessment
- proportion of examinations

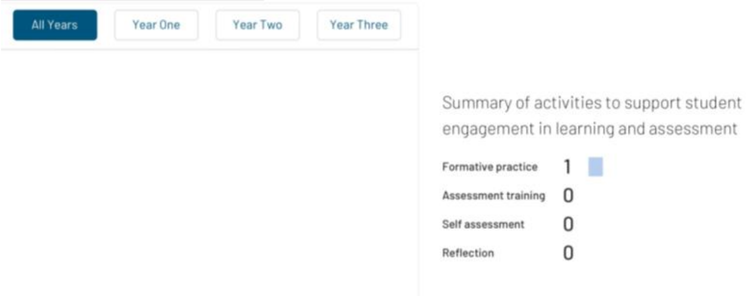
A mocked-up summary was constructed reflecting this element of assessment load (Figure 2 below) very much in line with the TESTA approach to summing up assessment load. Summaries of the total number of assessments and by type are given for an entire programme and per year of study.

Figure 2 Summary of total number of assessment and different types in a programme



Establishing how programmes support learning by engaging students actively in assessment is also dealt with in several frameworks but we draw from TESTA (TESTA; Baartman *et al.,* 2006, 2007; Dochy, 2009; Messick, 1994, 1995, 1996). The TESTA method measures this element by summing up the total formative opportunities in the programme. Formative tasks are those both compulsory and with zero credit weighting. The TESTA method, as an initial measure, proposes to check the total number of times when formative opportunities are practiced as an indicative measure of offering support to student learning by helping them gain insights into the task format and standards which is central to student learning. Operationalisation of this aspect has been widely discussed and accepted in much of the work on assessment life-cycles that emphasise learning (Price *et al.,* 2012). In line with much literature, that operationalizes formative assessment (Carless, 2007; Boud *et al.,* 2018; Evans, 2018; National Union of Students, 2015), most frameworks converge on: the need for clear communication, practice of the assessment type to familiarise students (formative practice), helping students to understand standards with exercises such as marking exemplars (assessment training) and lastly, supporting student reflection on progress (self-assessment and reflection). Figure 3 below exemplifies how, at programme level, a range of different activities aimed at engaging students in learning, could be specified and measured using descriptive frequency summaries.

Figure 3 Formative assessments



In addition to total numbers of tasks, load at different points in the year is an important challenge in practice frequently referred to as "bunching of assessments". Chronological representations of student assessment load have been explored (e.g. Map my assessment by Walker 2019).

In line with developing visualisations of load, current developments (e.g. Programme landscape, University of Hertfordshire; some Schools at the University of Nottingham) are seeking to integrate delivery (teaching load) and assessment in a new development that is now under construction and in pilot phase. In consultation with colleagues at the University of Nottingham and Hertfordshire, greater integration between the teaching (delivery) and assessment timetables offers greater power in terms of visualising student learning and load at programme level. It appears that developments in practice to support programme visualisations aim at the development of the construct of student load beyond assessment only to integrate teaching, assessment and independent study.

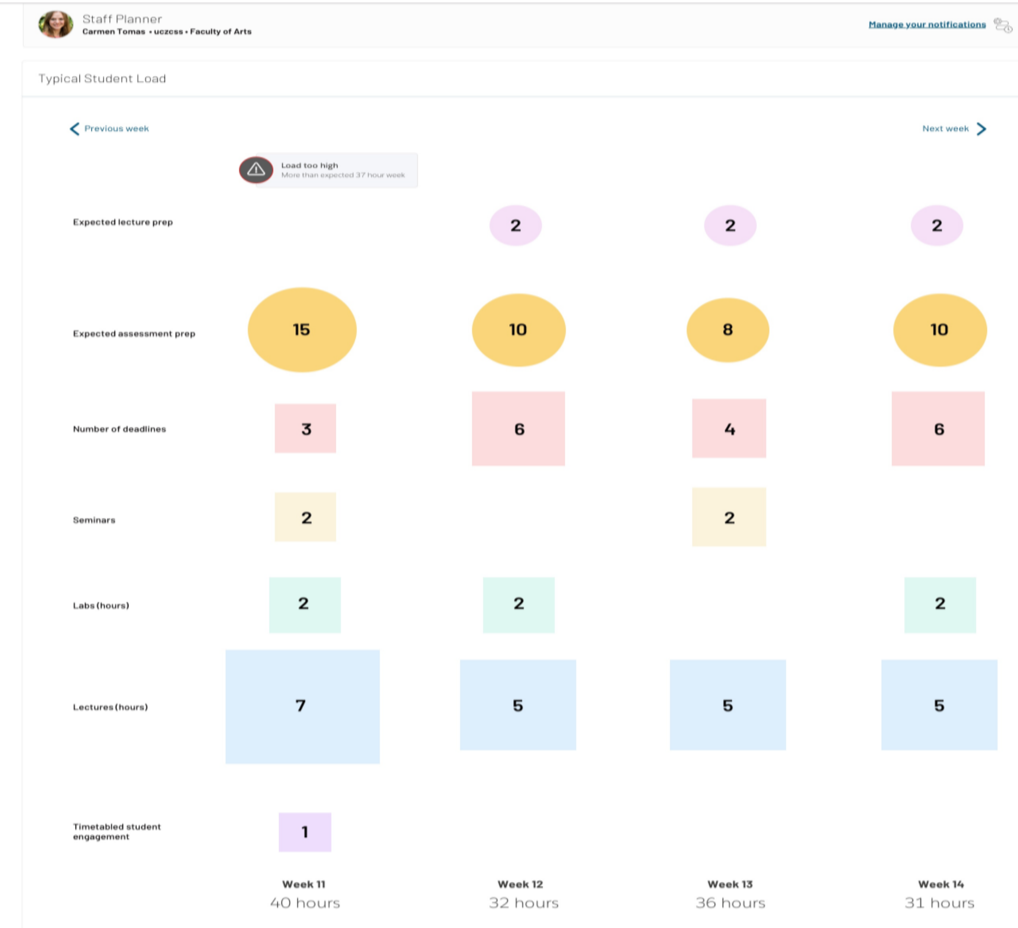
However, previous work so far has not considered student load in the round, that is, including delivery and assessment. Week by week visualisations for a typical student pathway with the total number of hours including the following elements:

- Timetabled activities [academic]: seminars, laboratories, lectures, tutorials
- Timetabled assessments: coursework deadlines, exams
- Expected estimates: expected assessment preparation time, expected lecture and seminar preparation time

- Timetabled return of feedback (to ensure it can be used before next assessment)[not included]

Figure 4 exemplifies a mocked-up output providing a visual summary of student load in the programme for a given pathway. As explained, this was created to illustrate an idea rather than as an exact representation (at this stage). The idea is to provide weekly summaries of load including assessment expected preparation, total contact hours and associated lecture preparation. Squares and circles were used to illustrate estimated time (circles) and fixed time commitments (squares). Squares for known scheduled elements (e.g. contact time) and circles for estimates (e.g. expected assessment preparation and lecture preparation). Shape sizes were also used to indicate visually the number of hours. Figure 4 below is a mocked-up visualisation of student load for staff.

Figure 4 Student weekly load in the programme

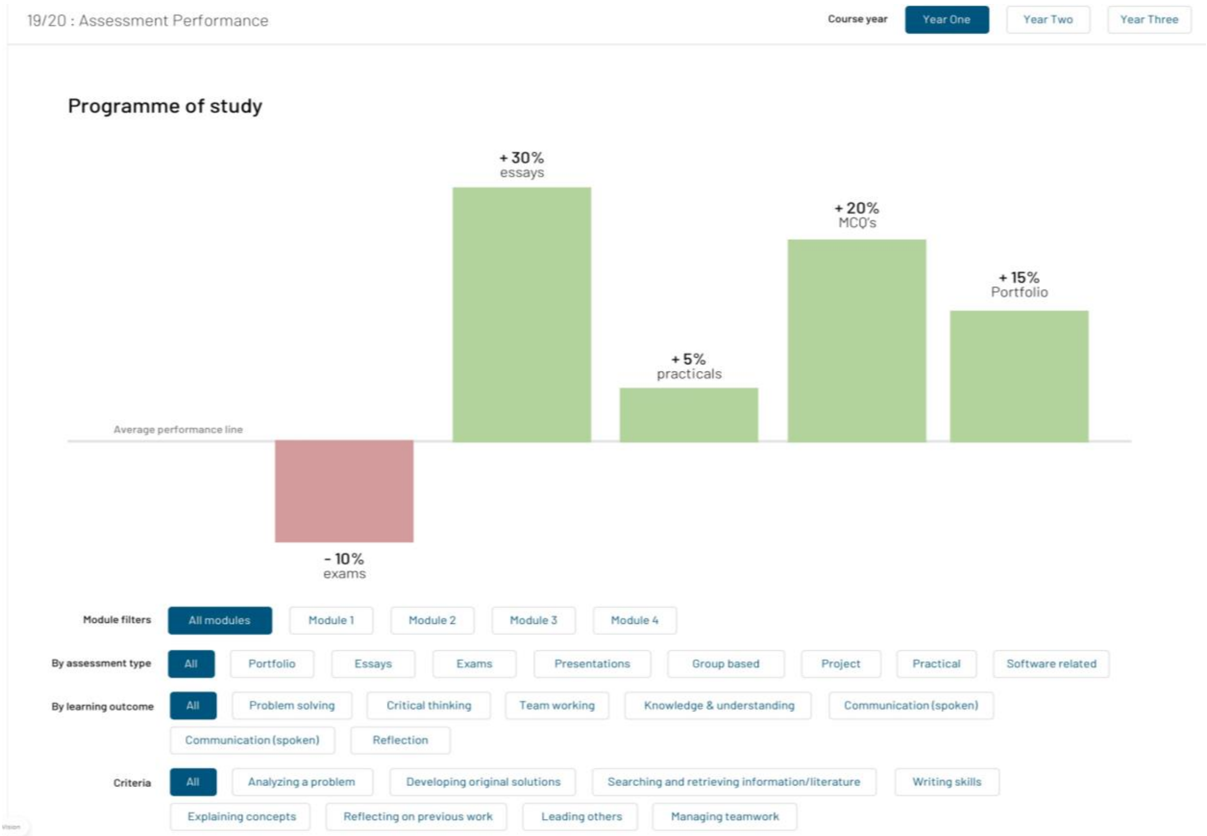


3 Review stage: Identifying sources of difficulty in assessment

When choosing assessment types or designing an exam, assumptions are made about the difficulty. Identifying and understanding sources of difficulty in our assessments and performance is key to the ability of practitioners to understand and review the design. The literature on standard setting and review of assessments is extensive and requires much technical knowledge (Cizek, 2012; Tavakol and Dennick, 2017). Whilst this is beyond the remit of our exploratory study, this would be relevant in more advanced discussions. For this exploratory study, the assumed audience is a generic one to get some interpretable output to any practitioner (without technical knowledge).

The proposal consists of a descriptive summary with filters that draw attention to aspects of design. Overall, identifying difficulty of assessments is proposed to be made up of key aspects that could influence difficulty. Figure 5 therefore presents a cohort's average performance summarised against a number of aspects that should drive design – assessment task types, learning outcomes, criteria, and modules. This is illustrated in figure 5 below with a mocked-up impression of a descriptive summary of a cohort's performance by different filters relevant to design: module, assessment type, learning outcome, and criterion.

Figure 5 Overview of cohort's performance by assessment type, module, learning outcome and criterion



Additional measures that would complement the analysis of marks would be students' perceived difficulty of assessments (Messick 1994, 1995, 1996). Difficulty as a construct needs to be understood from many angles. Adding student perception to a quantitative analysis (such as figure 5) would provide enable a better understanding of difficulty for practitioners' interpretation (*ibid*.). This is explored in the section below and figure 6.

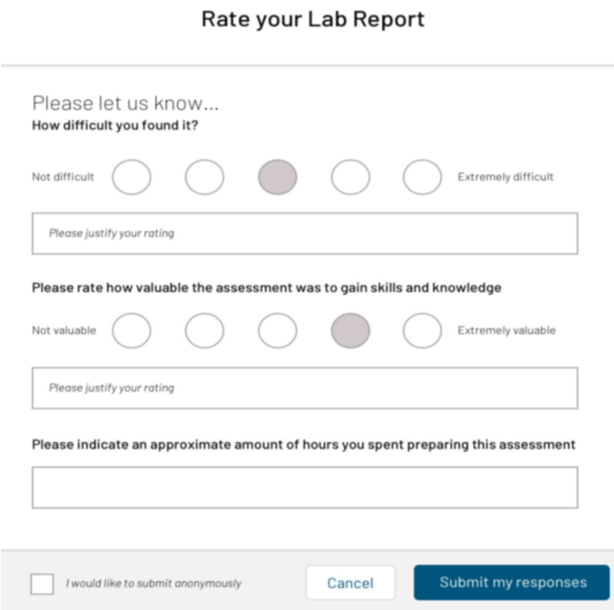
4 Review stage: Checking assumptions about load and student perception of assessment

Lastly, in line with elements highlighted in our exploratory case at the design stage, we illustrate the principle of reviewing assumptions made at the design stage. Estimates of assessment load (hours expected to complete an assessment) and programme teams' understanding of constructive alignment need to be checked. Obtaining actual student preparation time and students' perceived value of an assessment is a proposed initial measure to check our initial assumptions.

- Expected preparation time vs actual student preparation time
- Student perceptions of learning gain and value of assessment tasks

These various measures relating to aspects of the student perception of assessment were represented in the dialogue box (also including the element of difficulty) (fig. 6) below as a way of eliciting valuable information from students at the point of submitting an assessment.

Figure 6 Students' perception of difficulty, learning value and load



5 Consultation with programme leads on design and review related analytics proposals

Academic colleagues were shown the proposals described in this section (except for figure 6). The presentation involved contextualising the figures and asking them to reflect on their practice. For each of the proposals, they were asked to rate the likelihood that they would use the representations for their programme design and review stages. A five-point likert scale was used: 1 Not likely – 5 Very likely that I would use. The responses from the total of 38 participants are summed up using median and interquartile ranges (IQR).

Table 1 Summary of programme leads and staff ratings of the value of the analytics proposals

Construct	Proposed analytics		Median	IQR
Constructive alignment	Constructive alignment across a programme expressed as frequency of LOs assessed (fig. 1)		4	3 - 5
Load	Summary of total number of assessments and different types in a programme (fig. 2)		4	3 - 5
	Formative assessments (fig. 3)		4	3 - 5
	Student weekly load in the programme (fig. 4)		4	4 - 5
Identifying sources of difficulty in relation to assessment design	Overview of cohort's performance by assessment type, module, learning outcome and criterion (fig 5)		4	3 - 5
	Filters of cohort performance summaries (fig. 5)	Criterion	4	2 - 5
		Learning outcome	4	3 - 5
		Assessment type	5	4 – 5
		Module	5	4 – 5

Overall participants rated all the figures highly, medians of four and above, suggesting a high likelihood that having information represented would be valuable when making decisions about design and review. This view was reinforced by comments in the discussion that suggested that participants understood all the insights would be valuable to inform their decisions about programme design and review. The most highly valued figure is the visual representation of load (overall). Some filters to review a cohort's performance in figure 5 were the most highly valued: filters by assessment type and module.

In relation to reviewing assessments, participants were asked to rate additional measures that we were not able to illustrate in the proposed mock-ups but are recommended in theory (Messick 1994, 1995, 1996). Participants were also asked to select which potential additional information would be important for reviewing assessments. Due to time constraints, this was a final generic question where colleagues indicated which measures would be important to develop. Table 2 shows out of the 38 participant how many indicated those measures as potentially useful.

Table 2 Additional analytics for review stage

Measures for programme review	**Total**
Expected preparation time vs actual student preparation time	20 (52%)
Student perceptions of difficulty of assessments	16 (42%)
Student perceptions of learning gain and value of assessments	25 (66%)

PART II Student decisions in practice, constructs, variables and key data

Student self-regulation (Zimmerman, 2000) is at the heart of transitioning towards an assessment *for* learning (AfL) culture (Elton, 1998; Elton and Johnston, 2002; Biggs and Tang, 2011; Medland, 2016; Boud *et al.*, 2018). Self-regulated learning (SRL) defines learning as students' understanding of their own abilities and themselves (metacognition) (Zimmerman and Kitsantas, 2002) and is linked to success and achievement (Clark, 2012; Dignath, Buettner and Langfledt, 2008; Sitzmann and Ely, 2011; Zimmerman, 2008). Self-regulation are self-generated thoughts, feelings, and behaviours that are oriented to attain goals (Zimmerman, 2000). Motivation and self-perceived abilities play a fundamental role for success (Zimmerman, 2000; Bandura, 1982) since they determine students' time on task (Zimmerman and Kitsantas, 1997). Self-regulation involves:

- self-awareness of own abilities
- the ability to self-assess in relation to a task in order to self-correct
- motivation to engage.

Self-regulation is central to many frameworks for instructional design (Winstone and Nash, 2016) and programme level considerations in particular (Bearman *et al.,* 2014; Boud *et al.,* 2018; Dijkstra *et al.,* 2012; Evans, 2018). Similarly, self-regulation is at the heart of preliminary research on desirable LA features for students (Schumacher and Ifenthaler, 2018). Frameworks for the design of LA emphasise the centrality of SRL (Wise, 2014) to learning design but also to embed LA. LA should aim towards supporting SRL but also providing relevant insights into learning. Student self-regulation is a persistent challenge for instructional design and practice (Evans, 2013; Winstone *et al.,* 2017). Understanding how analytics further supports student decisions in learning needs careful consideration and integration with instruction and programme designs.

The challenges of programmes of study to student learning and self-regulation are well documented (Evans, 2013; Jessop and Tomas, 2018): understanding what is expected (what good looks like, criteria, levels and standards); anticipating and managing load and effort; seeking help; understanding feedback and knowing how to improve on feedback and monitoring progression. Schumacher and Ifenthaler (2018) suggested top features that students expected (in principle) to receive support from analytics. From a list of thirteen identified features (qualitatively) students desired support with time management, revising learning content, self-assessment, receiving feedback on drafts and learning recommendations. This study is valuable but needs to be complemented with studies on the feasibility and modelling that would be required (e.g. might just not be possible to meet the desirable features).

In line with maintaining a consistent focus on programme level overviews, the proposals of analytics for students are aimed at bringing together the student experience and overview of the programme of study. Two specific areas are selected: time management and student progression and reflection. Student questions in practice are:

- *Time management*: how best should I allocate my time and when?
- *Progression monitoring*: how well am I doing?

1 Student time management and programme overview

Students having an understanding of how things fit together (Evans, 2018) and having indications of how long to allocate to an assessment are some of the concerns raised in the student experience of the programme. The same initiatives discussed in part I regarding load and design, also encourage use of the visualisations (Walker, 2019) for student planning. The assumption is that having an integrated overview can support student decision making about time management and allocation. Similarly, to the proposed analytics for academics (Figure 4), a version was created for students that also included

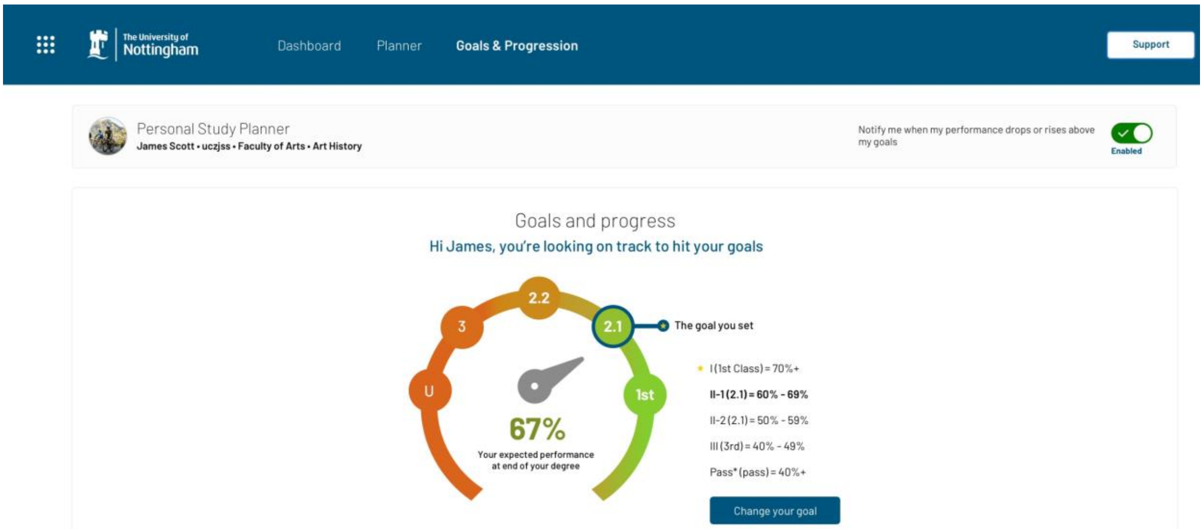
- Student timetabled activities [personal, extracurricular]

2 Students' self-regulation: how well am I doing and where to next?

Student monitoring of own learning is challenging for instruction and hardly understood at programme level. How this significant concept is translated into practice is challenging for researchers and practitioners. For our case study, initial tentative proposals are made keeping the focus on programme level views. A reference framework for students to reflect is proposed by using students' own prior activity, information from the self (Winstone *et al.,* 2017; Wise, 2014) and with reference to the learning design aspects emphasised at programme level.

Figure 7 below was developed to reflect student's own prior activity. Quantitative summaries of student performance have already been suggested as a valuable feature for students in previous studies (Bennet, 2018). This idea was further developed to require students also to set goals making connections with the idea of also obtaining insights into students' goals but equally keeping a record for their reflection. This is an important aspect related to motivation and self-efficacy. Figure 7 fulfils two functions: providing a summary of a students' performance across the programme and would provide a possibility to input students' intended level of performance and other interactions such as changes to it (boosts and lows).

Figure 7 Progression tracker and setting goals



Understanding and interpreting the quantitative summary would require additional information for students' to self-assess and identify actions. Figure 8 below emphasises a programme level overview of performance linking to learning outcomes (generic for illustration). Similar developments have been reported elsewhere (e.g. Hilliger et al. 2020).

In developing these, we have attended to the principle also of integration that analytics are not simply about presenting information but can be embedded in learning (Wise, 2014; Gašević, Kovanović, and Joksimović, 2017). In line with much literature figure 9 would capture students self-assessed and self-perceived abilities at different times of their student journey (e.g. Boud, Thompson and Lawson, 2015; Ibarra-Sáiz and Rodríguez-Gómez, 2017). The lists of learning outcomes used were generic and used for illustration. This idea is inspired in existing frameworks (Boud *et al.,* 2018; Winstone and Nash, 2016). This example is selected for the significance of capturing this information about students self-perceived abilities in order to support reflection, especially in contrast with performance as seen by the tutors (in this case).

Figure 8 Progression (qualitative)

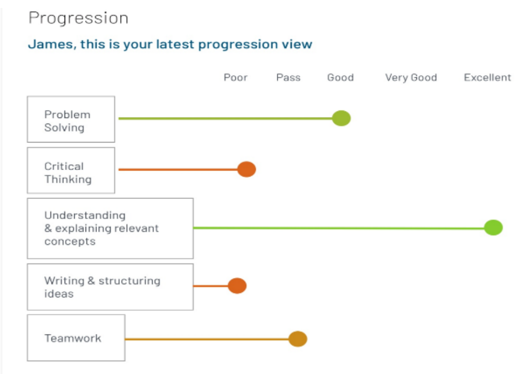
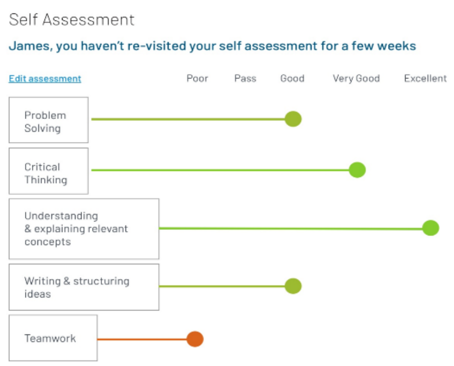


Figure 9 Self-assessment



These examples of analytics would require certain data:

- LOs
- Criteria
- Marks
- Marker recorded judgements on criteria (marks*criteria)
- Combination rules (assessments at module level and programme level rules)
- Student goals (student generated)
- Student self-perceived abilities (student generated)

3 Consultation with students

Participating students were shown the proposals described in this section as well as the student version of figure 4. They were asked to rate the likelihood that they would use the representations, on the assumption that they would be available and accurate. Students were asked to rate the likelihood that they would use each figure for a relevant task (e.g. to plan; to review progress). A five-point likert scale was used (1 Not likely – 5 Very likely that I would use). Table 3 below shows descriptive summaries of the student ratings (n = 60) for each analytics proposal using median and interquartile ranges (IQR).

Table 3 Summary of student ratings of proposed analytics

Construct	Proposed analytics	Median	IQR
Time-management	Student weekly load overview in the programme (student view of fig. 4)	3	2 – 4.5
Self-assessment	Progression (quantitative) (fig 7)	5	4 - 5
	Progression (qualitative) (fig 8)	4	3 - 5
	Self-assessment (fig 9)	3	2 - 4

Some features presented would require students' providing information as part of identified tasks (figure 6, 7 and 9). Students were asked whether they would or would not give consent to uses of their data. It is important to note that the proposals were contextualised as helping the programme teams to understand really important aspects of the student experience and learning. The purpose of gathering information in that context was explained to the students. Students expressed agreement with sharing their responses to questions presented in figure 6, 7 and 9 but equally they would only agree if the data was handled in an anonymised format.

Generally, students felt these questions were important to feedback on. Some comments were made in particular in relation to figure 6 where students are asked to feed back on aspects of their assessments.

"This info is really helpful as it helps lecturers focus on what students need more lessons on" (Student 56)

"Important. This is so good as especially in Biology I don't think they appreciate the difficulty of some assessments to give us proper feedback as to why they set it or care about our opinions." (Student 59)

PART III Data, structure and sources

The first two parts of our case study selected a sample of common, sector-wide challenges relating to assessment and feedback, reviewed literature and made proposals about analytics purposes. Example analytics outputs (fig. 1-9) were mocked-up for the consultation with stakeholders (programme leads, students). The consultation with stakeholders was positive and supported the notion that the proposed analytics outputs would be valuable, in principle, to assist stakeholders in making better-informed decisions. Beyond the specific mocked-up analytics or future solutions, at this stage the focus is on establishing overall feasibility of developing any of the proposals by first establishing, in broad terms, the availability of the relevant data to generate meaningful information. As a result, this case study has identified key data elements that are related to a range of significant aspects of practice also sampling different perspectives and stages of the assessment life-cycle:

- Design: constructive alignment, student load (design)
- Student self-regulation (time management, student progression)
- Performance and review (difficulty, impact on learning, load)

Our proposals included gathering data generated by students (part of figures 6, 7 and 9) that could generating valuable information about student experience and learning. In this section, we examine the availability of fourteen data elements that would need to be used from institutional systems in order to create the proposed outputs. The consultation with stakeholders established that the data elements identified are valuable, in principle.

The third objective of our study was to provide an initial insight into the availability of the data in institutions. Our initial analysis considers systematically available data and its structure. The source was from the staff focus groups where academic staff were asked to provide information about sources to some data (LOs, criteria). Also, these were complemented with discussions with key contacts in two of the institutions to verify emerging results. This initial exploration of data resulted in the following categories to describe availability:

- *Systematically available* data: in order to stablish this we considered the data sources that were centralised where data would be stored.
- *Structured/unstructured* data – *structured* data is easily searchable and identifiable this would be typically stored in a database, validated and labelled which makes it more consistent and accessible for reporting or analytics. *Unstructured* data is typically embedded in text files, emails or other media (e.g. social media). Lack of standardised formats and content might make it difficult to use for any reliable reporting.
- *Unsystematic*: this category was created to indicate data elements that could potentially be systematically available across an institution, sometimes even structured, but are commonly left to School based decisions or individual modular choices
- *Unavailable*: data that is not often defined or recorded.

Table 4 sums up common patterns of data availability across all HEIs. Figure 10 complements this table with a high level summary showing a range of locations of data and systems. Common challenges are discussed from the point of view of accessing and processing the data to generate the analytics proposed in this study. Finally, exceptions at particular HEIs are discussed for their approaches to making data more consistently available.

Systematically available and structured data are held in the Student Information Systems (SIS), VLEs, and timetabling. Table 4 reflects data elements that despite being in this category, presented various challenges:

- *Integration* of data is challenging (marks and assessment deadlines) given that exams and coursework follow separate processes (central and local) for scheduling and similarly, for processing of marks. Separate processes also result in different timings for when these data are available. Data format and level of detail are also casualties of differing processes.
- *Accuracy* of data held in SIS about summative tasks (coursework) that might not reflect the actual number of assessment tasks (VLE or elsewhere). An assessment component labelled as coursework in the SIS may in effect contain different assessment components (e.g. presentation and essay). These inaccuracies also impact on the availability of an accurate set of combination rules for assessment in a systematic way.

Learning outcomes, which played a significant role to many of the proposals in this study, are available but are largely unstructured. Typically, learning outcomes, with different levels of detail, are embedded in text files (programme specification documents). This poses barriers to using this data for any processing and meaningful reporting certainly such as the one exemplified in our proposals.

A whole range of data elements was potentially structured and systemically available, but choices in approaches to practices made this unsystematic in HEIs quite typically. A key example here is data that reflects tutor judgements against criteria which are typically generated as part of analytic marking. Marking practices can vary from module to module (holistic or analytic marking) (*see glossary*). Whilst criteria might exist, use of criteria as part of marking and recording explicitly the judgements against the criteria (e.g. to justify the mark and provide feedback) is inconsistently applied in marking. Similarly, marking criteria (e.g. rubrics, marking schemes) may be available depending on local/individual choices and their structure will be variable (depending on the individual or local choices).

Lastly, some data elements were deemed broadly unavailable. For example, students described using multiple locations for managing their time including paper based diaries and calendar apps so comprehensive personal schedule data would be unavailable. Some data which would be required related to data that would be elicited from programme teams at design stages such as expected time to complete an assessment, prepare for, and review lectures. Other valuable data such as how assessments map onto learning outcomes and criteria is unavailable in the light of common practices. These examples of valuable data that could be turned into valuable information in the ways exemplified are broadly unavailable.

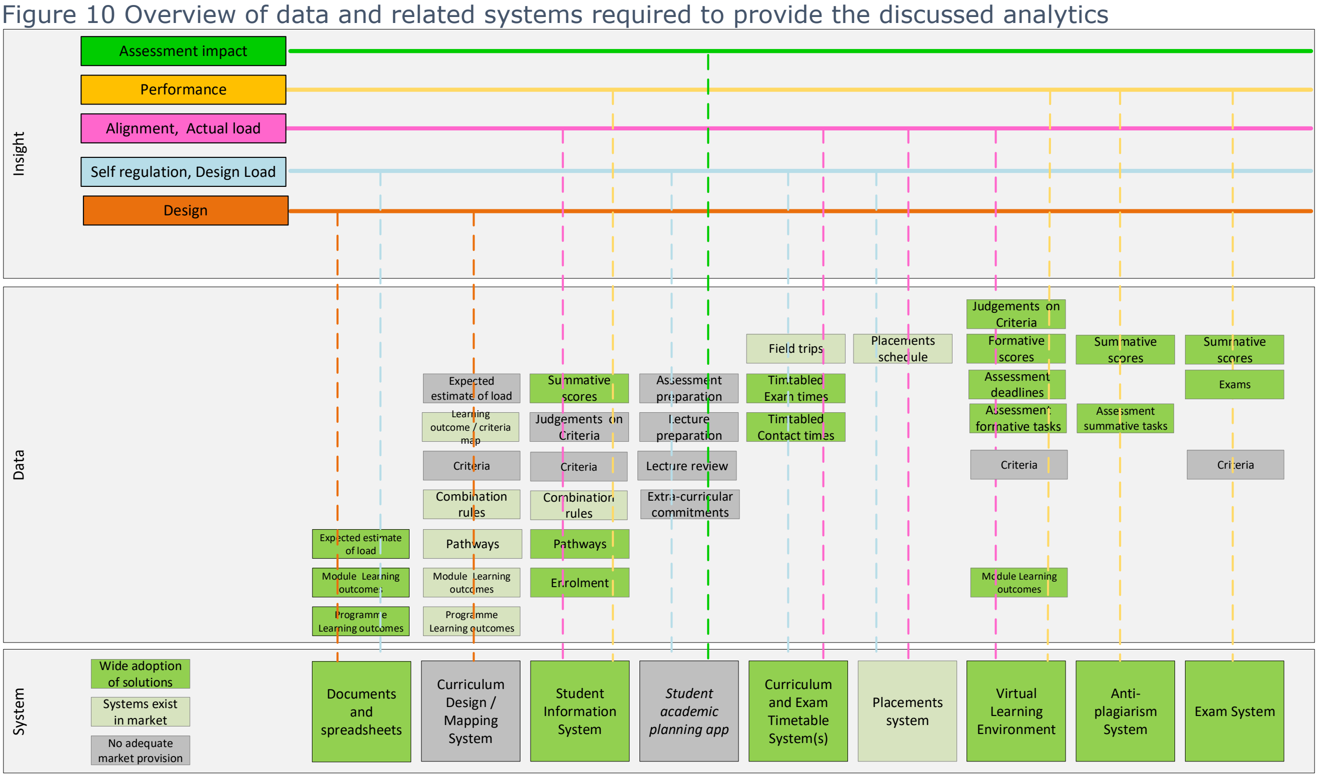
Some exceptions were found in discussions with some participant institutions. One department was already integrating (manually) the suggested data and creating similar outputs to the ones proposed regarding programme level overviews of load and alignment (Figure 4) (University of Lincoln). A university-wide initiative at the University of Hertfordshire is planning to overcome these common barriers discussed and are attempting to make the VLE assignment tool the central location for all scheduled assessments (coursework and exams). Regardless of the assessment type (i.e. whether it is submitted in the VLE or performed physically), they are proposing to set up and mark all assessments in the VLE assignment tool. This way the institution will access assessment schedules and marks more systematically.

Table 4 Data availability - common patterns

Availability	Data elements		
		Accurate	*Challenges*
Systematically available	*Structured*	Student pathways *(Derived from SIS enrolment data)* Timetabled contact time *(Central timetabling)*	***Inaccuracies*** Assessment tasks (summative) Combination rules (to derive marks) *(Assessments within a module; across modules)*
			Integration of data Assessment schedules *(coursework and exams)* Marks (SIS, VLE or other)
	Unstructured	Learning Outcomes (programme level; module)	
Unsystematic (School or Individual module approaches)	*Structured*	Assessment tasks (formative) Assessment formative tasks – subtypes Recorded judgements against criteria (Criteria*Marks) (also unavailable)	
	Unstructured	Criteria (e.g. rubrics) Timetabled other (field trips, group work, placements)	
Unavailable	Learning outcomes mapped to assessment tasks and criteria Expected estimates time to: 1) prepare and review lectures; 2) prepare assessments Student timetable – extracurricular commitments (societies, other employment, extracurricular activities)		

Lastly, figure 10 represents the multiple systems where relevant data can be found. This figure was elaborated based on the University of Nottingham as a case and the discussions with other institutions. It highlights the range of university systems that exist typically to keep data. More importantly, at a high level, it points out where solutions do not exist to capture the data proposed in this study.

Figure 10 Overview of data and related systems required to provide the discussed analytics



Summary

Our case study aimed to advance the understanding of the role for learning analytics to support improvements in the sector for assessment and feedback. With a view to helping advance this agenda in a relevant and strategic manner, the project asked who, why, what data and which sources and their availability. A literature review, analytics proposals and a stakeholder consultation have all been carried out. The study has provided a test of the proposals and ideas that would add value to decision making (i.e. providing actionable insights). Secondly, initial feasibility insights regarding data availability in institutions has been gained.

Who are the analytics for and why? (Objectives of analytics and stakeholders)

A literature review of the common challenges relating to assessment and feedback led to us focussing our research on programme level design, review and student engagement. As a result, the main stakeholders identified were programme leads and students. The study has considered a set of decisions that these stakeholders make in practice and that pose challenges across the sector. Whilst the study could not explore a wider range of challenges (e.g. marking, moderation), our choice, by exploring different stages and stakeholders, brings together design and student learning which is fundamental to the purposeful development of learning analytics (Gašević, Kovanović, and Joksimović, 2017).

A more focussed review of the literature in the specific selected areas, led to developing a range of analytics mock-ups. The definition of the constructs attended to theory, research and also an exploration of practical developments in collaboration with staff and students. As a result, the proposed mock-ups are varied in their nature including

- descriptive summaries of constructive alignment, performance review and student progress
- visualisations of load built from previous work

Our proposals have gone beyond summing up data but have illustrated purposeful ways in which really important information could be elicited from students in meaningful contexts.Paying attention to particular purposes for review of assessment designs (Messick, 1994), other analytics mock-ups enabled the collection of meaningful data by gathering student feedback at the point of submission of an assessment (fig. 6). Other analytics proposals were both offering a summary and enabling gathering of valuable student information such as their goals (figs. 7) and self-perception of their abilities (fig. 9) (Zimmerman, 2000; Boud *et al.,* 2018).

Stakeholder consultations on the analytics mock-ups (60 student and 38 staff) aimed to test the ideas in principle by obtaining their views on the value of the proposed analytics. These stakeholders rated the likelihood that they would use the proposed analytics outputs and their ratings confirm that better decisions could be made in practice if the proposed information was available.

What data is needed?

Having established that the purposes and ideas were, in principle, valuable for stakeholders the next aim of the project was to offer insights into a range of valuable data. The project also considered the breakdown of data elements that would be required to create the proposals. Our exploratory case has identified a total of 20 data elements that would be needed to create the proposals. Of these, some would be drawing from university systems (14) and some other data would be elicited from students (6). Our study proposes this initial list of data elements as valuable overall and important for institutions to consider pursuing them since they bring together key constructs of design and student learning.

The initial idea testing with stakeholders has helped to confirm the importance of the data for institutions as it could be turned into valuable information. This is important for institutions to consider pursuing as part of wider analytics institutional strategies that support enhancement of assessment and feedback practices. As a result, a set of data elements is identified that are valuable for institutions and these relate to a selection of stages, tasks and stakeholders in the assessment life-cycle

- Design: constructive alignment, student load (design)
- Student self-regulation (time management, progression)
- Performance and review

Is the data required available in HEIs? What is the institutional readiness to start addressing these challenges? (sources and availability of data)

Thirdly, our study considers the feasibility of the proposals made by considering the availability of key data and its sources. This was investigated as part of the consultations with institutions and stakeholders. A high-level summary of the availability of data in institutions reveals some common challenges to accessing valuable data in structured formats.

Only a few data elements in our proposed list are systematically available. Most of the elements that are systematically available relate to design. The majority of data elements explored presented different kinds of challenges

- *Accuracy* of data held in Student Information Systems. Discrepancies between the data recorded in the SIS and actual practice are well known (e.g. coursework assessment design)
- *Administrative processes are not aligned with learning design constructs*: where we need to understand 'assessment load' processes in practice, we found as an example, assessment scheduling, treats exams and coursework separately and this leads to challenges for data integration (for the purposes we describe)
- *Unstructured valuable data*: learning outcomes are fundamental to many of the proposals in our case, yet they tend to be unstructured, albeit systematically.
- *Inconsistent practices*: individual module leads' choices in practice impact availability or structure of valuable data in our list (e.g. rubrics; criterion based judgements during marking) that would play a role in understanding performance and also student progression (e.g. fig. 8).
- *Unavailable data*: data that is not typically captured relates to design (e.g. expected time to prepare an assessment) and hard to get data relating to student load (extracurricular).

Moreover, our initial high level overview also considers the multiple systems where data tends to be held in and also, of our valuable data, software solutions to capture it do not exist.

Lastly, in terms of accessing the data that based on our proposals would be elicited from students, our study also elicited students' reactions on giving permission to institutions to use data provided (assessment experience, personal goals etc). In general, students responded positively since the purposes of the data gathered were clear. Students felt particularly strongly about feeding back on their experience of assessment (value, difficulty, load) since they felt tutors needed to know about these aspects. Anonymity would be a precondition to all data uses.

Discussion of findings: contributions

Our study aimed to make a valuable contribution to the current approach and development of analytics for assessment and feedback practice. In this section, we discuss some valuable contributions for the sector and institutions from this study.

Our findings can offer a basis to drive forward the developments of learning analytics in relation to assessment and feedback. Our study confirms that analytics have an important role to play to support staff and students in making better decisions by bringing together visualisations at programme level and gaining important insights into the student experience. Regarding the specific proposals, the project makes some valuable contributions. The analytics mock-ups proposed were developed in consultation with staff and students and wider stakeholder consultations confirmed generally that these would support better decision making in the areas explored.

The analytics proposals provided a context to consultations. Nevertheless, whilst only mock-ups, they could inspire institutions to consider needs of key stakeholders in assessment and feedback. More important than each individual proposal, institutions are encouraged to consider the connections illustrated in the case study between design intentions, student perceptions and performance data (Messick 1994). One of the key challenges for analytics, in general, is investigating the modulating effects of learning design on learning (Gašević, Kovanović, and Joksimović, 2017). Our case illustrates how understanding design and measuring learning requires multiple data sources to get meaningful outputs and interpretation (e.g. example of understanding impact of assessment and difficulty). Beyond each individual proposal, at this idea and feasibility testing stage, institutions are encouraged to consider the greater power of analytics if they could indeed have these ranges of data available to make connections between design, learning, performance and student experience. Future work is discussed below.

Knight and Buckingham-shum (2017) encourage the field to move from clicks to constructs. Our case has illustrated this in a principled manner for each of the purposes specified, constructs and measures have been explored in connection with existing theory, research and consulting with stakeholders. Most of the measures in the study are very basic and all require further in-depth development moving forward. Nevertheless, the project has illustrated how to approach the development of measures by starting from the construct and developing it.

Despite the exploratory and tentative nature of all the proposals, some valuable insights have been gained in terms of specific contributions in developing measures. The study has advanced the notion of student assessment load (TESTA) to "student load" bringing together delivery (e.g. timetabled contact hours) and assessment. This illustrates the powerful integration of educational research and also consultation with stakeholders to advance analytics so that they can provide actionable insights.

A construct explored in-depth in our study has been learning design by exploring assessment design. Our study has attended to key constructs relating to learning design (constructive alignment, load, supporting student learning). These additional aspects expand the measures used in many analytics studies to date (e.g. Laurillard's conversational framework in Rienties *et al.,* 2017). Still the construct of learning design and its measurement needs to be further expanded in line with existing frameworks on assessment design (Messick, 1994).

Furthermore, in line with suggestions in the literature (Gašević, Kovanović, and Joksimović, 2017; Wise, 2014) we have illustrated how working to specific tasks and purposes, resulted in embedding elements that were part of learning (e.g. self-assessment). This serves to illustrate how analytics may play an essential role in the learning design.

More broadly, our findings also provide a basis for institutions to consider the readiness to start using analytics to support some of the sector challenges for assessment and feedback. The study establishes an initial list of twenty valuable data elements and some insights into what would be required to gaining access or making them available systematically.

Our case further illustrates why data strategies are necessary at the outset of any analytics initiative. The same data elements are valuable for analytics for staff and students as demonstrated in our case. We have shown how some key data (e.g. Learning Outcomes) would be required to create valuable information to staff and students. Considering this would be important to institutions to develop a fuller understanding of data requirements, so that an informed and credible strategy to create and capture data can be devised. Whilst taken in isolation, each isolated proposal might not seem worth the effort to overcome the challenges described (e.g. change of practices in marking or design). However, taken together, the potential impact indicated by this study is significant and should encourage institutions to adopt strategic approaches to understanding how their data can bring value to multiple stakeholders therefore rendering some data highly valuable and worth pursuing.

The project has identified initial valuable data for HEIs and identified some common barriers. Our case echoes previous findings and known limitations to accessing data due to systems and processes (duplication, inaccuracies, fragmentation) (Sclater, Peasgood and Mullan, 2016). Our particular theoretical focus on student learning and validity of assessments, suggests that the limitations to accessing some of the valuable data identified are related to the challenges that motivated the study (e.g. lack of transparency in design and marking; a predominant assessment *of* learning culture; modularisation). Our preliminary study, offers insights into what might be required in institutions not only to advance analytics but also to enhance assessment and feedback practices. Accessing valuable data relates to practices referred to as challenging in our high-level summary of assessment and feedback practice. Enhancement of practice and analytics projects are inextricably linked and institutional projects should design analytics into enhancement plan to drive changes in practice. If considered in a principled manner, analytics developments have the potential to support better practices in assessment and feedback (e.g. better designs and student engagement in learning, as illustrated). Institutions should develop visions for analytics that speak to their enhancement plans in key challenging areas of practice.

Lastly, our study illustrates that currently unavailable data, that would be very valuable (relating to student learning), might indeed be accessible if presented in relevant contexts and students understood its purpose.

Limitations

The project focussed on breadth rather than depth in line with its exploratory remit to define widely the role of analytics for assessment and feedback practice. We are mindful that the exploration of purposes needs expanding also to include a wider range of stakeholders. Our exploration has laid a foundation to be further developed.

Our study has offered some positive stakeholder responses confirming that the proposals were in principle perceived as valuable to support decision-making. This is really important to develop analytics that will provide actionable insights. Nevertheless, more developed mock-ups will require wider consultation and refinement with stakeholders.

The definition of some measures of important constructs (load, design) has been advanced in our study. Nevertheless, other constructs have only been superficially explored (e.g. assessment difficulty and student self-regulated learning) which also coincides with these areas being somewhat less well understood and implemented in practice. This limitation is a wider limitation in the practice in the sector, the analytics we can expect can only be as sophisticated as our practices allow them to be. As suggested earlier this will require a close understanding of models of practice (theory an research driven) in addition to changes to practice.

Conclusions

In sum, our case has identified a valuable role for analytics to support enhanced programme level designs and improve students' experience. The project has defined a range of key constructs linking design and student learning and developed impactful mocked-up analytics visualisations. These can provide a basis and inspiration for future developments. The barriers to analytics that we have found, unsurprisingly, echo previous findings (Sclater, Peasgood and Mullan, 2016; Higher Education Commission, 2016).

The most important contribution of our project has been in integrating a range of theoretical accounts (design, learning) to frame analytics for the complex stages, tasks and stakeholders that make the assessment life-cycle in practice (Jisc, 2015). Lastly, the case offers insights into common challenges institutions may face to access key data. Culture and practice changes will be central to getting more impactful analytics moving forward.

Future work

Whilst the project selected a sample of relevant questions in practice, the literature review has pointed out key works and frameworks that already connect practice with theoretical frameworks. These should inform the wider developments of analytics for assessment and feedback at least as the starting point. These works give an insight into challenging areas of assessment and feedback practice (Bearman *et al.,* 2014; Boud *et al.,* 2018; Dijkstra *et al.,* 2012; Evans 2018; Jisc, 2015; Messick, 1994, 1995, 1996; Van der Vleuten *et al.,* 2015; Winstone and Nash, 2016). Future work, in addition to formulating a more comprehensive set of institutional purposes should include:

- consulting with a wider range of stakeholders
- creating a vision for the integration of analytics with the design of systems and formulation of institutional design and assessment practices
- refinement of the constructs and measures proposed in greater depth by both linking existing research and stakeholder consultations
- Piloting advanced analyses of the proposed data. As illustrated, some of the proposals made will not have been investigated (e.g. load). The research base to modelling and analysing data listed in our study and their integration is scarce or inexistent. Therefore modelling and analysis work will be required to understand their potential.

At the University of Nottingham we are following this work up to develop a vision for analytics in line with a transformation of practices. Next generation systems and software requirements need to be geared more explicitly to supporting student learning. The pointers offered in this study need to be fully developed to guide institutions to overcome the challenges in practice, systems, processes.

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Glossary

Academic standards
The standards set by degree-awarding bodies for their courses (programmes and modules) and expected for their awards (QAA 2018).

Criteria
The knowledge, understanding and skills that markers expect a student to display in an assessment task, and which are taken into account in marking the work. These criteria are based on the intended learning outcomes (QAA 2018).

Marking scheme and rubric
A detailed framework for assigning marks, where a specific number of marks is given to individual components of the answer (QAA 2018).

The term 'rubric' is also used sometimes interchangeably with 'marking scheme' (in practice) to refer more generally to guides for assessing student work. Rubrics may be holistic and analytic and tend to describe traits and performance levels. Analytic rubrics display pre-set criteria and defined levels of performance using matrices. Holistic rubrics describe performance with broad statements of quality (see Hunter, Jones and Randhawa, 1996).

Formative assessment
Feedback on students' performance, designed to help them learn more effectively and find ways to maintain and improve their progress. It does not contribute to the final mark, grade or class of degree awarded to the student (QAA 2018).
The TESTA project described formative assessment as tasks that are compulsory and carry no weighting. Their purpose is to familiarise students with the task and standards expected (TESTA).

Holistic and analytic marking
Holistic marking consists of forming overall judgements on student work. Links to standards are implicit (e.g. broad statements of quality in a rubric). In analytic marking, judgement on individual criteria provide a basis for deriving marks using explicit rules. However, differences between these two terms are better understood as an spectrum of options (e.g. holistic scoring may be done with implicit reference to analytic criteria) (Hunter, Jones and Randhawa, 1996)

Learning outcomes (LOs) (also Intended learning outcomes, ILOs)
What a learner is expected to know, understand and/or be able to demonstrate after completing a process of learning (QAA 2018).

Module
A self-contained, formally structured unit of study, with a coherent and explicit set of learning outcomes and assessment criteria. Some institutions use the word 'course' to refer to individual modules (QAA 2018).

Modularisation
A reform of programmes that took place during the 90s. It consisted in the division of a course/programme into separate elements (modules). Each presented to the student with separable learning aims and objectives and assessment (Harland and Wald 2020)

Summative assessment
Formal assessment of students' work, contributing to the final result. See also 'formative assessment' (QAA 2018).