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A Participatory Approach to Designing a Student-Facing Dashboard for Online and Distance Education

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Abstract

In this paper, we explore the design of a student-facing dashboard for online and distance learning with a focus on capturing and addressing specific learning needs. A participatory process involving 20 students was employed, which included a screening questionnaire and focus group discussions. The selection of data points to be displayed on the dashboard was mainly determined by student responses regarding the usefulness of a feature, and a high frequency of their agreement. The data analysis revealed that the learning needs of online students relate to course support and communication (with tutors and other students). In response to this, students expressed a desire for accessing information related to their assignments, study time, and tutorials. The data points endorsed by students related to descriptive (assignment scores, engagement with the virtual learning environment, material accessed), predictive (score prediction), and prescriptive data (material recommendations and contact information). Student choices of data points were driven by a desire to better understand their study progress and take appropriate action. These insights emphasize the need for designing dashboards that not only describe performance but foremost "prescribe" to students potential solutions to overcome performance challenges.

Notes for Practice

- Student-facing dashboards should consider specific learning needs and be designed in consultation with diverse students.
- The learning needs of online students are focused on course support and communication.
- A student-facing dashboard for online students should raise awareness of study progress and point to actions that students can take to improve their performance.

Keywords: Learning analytics dashboards (LADs), online students, participatory design, distance learning

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1. Introduction

Learning analytics dashboards (LADs) refer to online dashboards that provide information about students' study progress through a range of data visualizations and recommendations (Sedrakyan et al., 2020). LADs have been designed for two main

audiences: teachers — often coined as "teacher-facing" dashboards — and students — coined as "student-facing" dashboards. Most LADs target teachers on the premise that they are the stakeholders who can best act upon dashboard data and support students in a timely and proactive manner (Herodotou, Rienties, et al., 2020). While there are significant benefits in teachers using LADs, such as improved learning outcomes (Herodotou et al., 2019), there are often contradicting arguments related to students not being involved in processes of decision-making and thus not developing learning autonomy (Bodily & Verbert, 2017). Self-regulated learning has been frequently discussed in relation to LADs, which are seen as tools to support student development of self-regulation skills and knowledge mastery (Jivet et al., 2017); this refers to students being able to monitor and adjust their behaviour to achieve personally defined goals (Sedrakyan et al., 2020). Emerging studies also note the positive impact of using LADs on student performance, retention, and study motivation (de Quincey et al., 2019).

Several studies highlight the need for a human-centred approach to designing dashboards since student voices and needs rarely inform their design. A human-centred approach could facilitate LAD adoption and acceptance (Sadallah et al., 2022) and even result in the design of adapted LADs following student requests to access specific data sources (Oliver-Quelennec et al., 2022). For example, Bodily and Verbert (2017) noted the need to understand student perspectives when designing LADs, including capturing how students interact with them and identifying relevant support interventions (Viberg et al., 2018). Rets et al. (2023) presented an empirically validated framework of ethics for learning analytics stressing the inclusion of students in the design of tools and a consideration of diverse student needs.

In response to these criticisms, a growing number of studies started to deploy participatory approaches in the development of learning analytics tools (e.g., Sarmiento & Wise, 2022). In this paper, we present a participatory case study with 20 distance learning students and their engagement in a co-design process for developing a LAD for online and distance education. This approach enables us to consider student voices and needs and accordingly design a dashboard that will more likely be adopted and used by students (Sadallah et al., 2022). Online and distance education gained significant popularity during and after the COVID-19 pandemic, yet how students engage and progress at a distance remains a major challenge for online education. LADs could enable monitoring of student progress and provide tailored support when needed (Rets et al., 2021).

1.1. A Review of Existing LADs

Three types of learner dashboards are proposed in the literature: 1) predictive dashboards forecasting student performance; 2) modelling dashboards providing students with visuals of their learning behaviour, such as communication instances and time spent online; and 3) descriptive dashboards showing students' past learning behaviours, such as attendance rate, grades compared to other students, and whether they are on track with their studies (Bennett & Folley, 2020). LADs feature varied sets of data visualizations, such as student mastery level on a concept, class comparisons, interactivity, as well as data mining recommendations, such as suggested resources to study, informed by what other students have studied (Bodily & Verbert, 2017). It could be argued that the ultimate aim of a dashboard is to develop learner agency and empowerment. Bennett and Folley (2020) proposed that this can be achieved through four guiding principles: 1) student ability to customize dashboards, such as whether or not comparative performance data can be viewed; 2) support student sense making (interpretation) of data through design features, such as the level of aggregation and type of data; 3) enable students to identify actionable insights, such as setting a goal or changing behaviour; and 4) ensure integration of the dashboard into the broader educational process, such as to inform discussions with personal tutors.

Several studies have designed and tested student-facing dashboards. For instance, a dashboard designed to provide process-oriented feedback to 94 university students showed that students accessing this ongoing formative feedback via the LAD (as opposed to product-oriented feedback) improved their learning outcomes, with larger gains for students with lower prior knowledge as assessed by a pre- and post-experiment test (Wang & Han, 2021). In another study, students accessing a gamified performance dashboard for an undergraduate geology class reached a 13% higher final grade compared to peers without the dashboard (Alam et al., 2023). A large-scale study with more than 3,000 students and 34 university courses tested a dashboard that helped students find material they missed, plan for upcoming assignments and compare course performance with others. Students used the dashboard to monitor their performance compared to others and reflected on what to do to change or maintain their performance. Yet, social comparisons were shown to support mastery rather than performance orientation regarding learning (Teasley et al., 2021).

Other studies have shown the impact of LADs on student motivation to study. For example, a LAD with predictive and prescriptive elements was found to influence student engagement. Students engaged with their course significantly more after they accessed the dashboard and increased their levels of learning motivation (Ramaswami et al., 2023). In another study, students who accessed a LAD with predictive and comparative elements were found to be more motivated than those without access while they also outperformed their peers (Fleur et al., 2020). The integration of reference frames (comparative student data) in LADs was shown to have a small influence on self-perceived motivation; these should be carefully considered in LAD design (de Vreugd et al., 2025).

Some studies focused on specific groups of students, aiming to understand how dashboards may improve student performance and reduce awarding gaps. Aligning with Wang and Han (2021), Chen et al. (2023) studied 88 undergraduates

engaging with two dashboards; one providing information about how they read material online compared to others, such as time reading a page, memos on a page; and one aiming to support time management and reflections using comparative heatmaps. High-performing students conducted more monitoring and reflection strategies than the lower preforming group. Also, high-achieving students were less satisfied with the LAD than low achievers more likely due to being aware of their performance and progress compared to other students (Kim et al., 2016). In contrast, a LAD was endorsed more by successful students with more than half accessing it often as opposed to only one-third of other students (Broos et al., 2017). In another study, a dashboard showing recommended courses and a five-star rating showing subjects in which a student is more likely to achieve a good grade was found to improve course grades and graduation rates, closing the achievement gap for low-income and minority students (Denley, 2014). In relation to online students, a LAD was more appealing to students with medium-range scores, younger students (<40 years old), and those with low self-efficacy in terms of keeping track of their studies (Rets et al., 2021).

Several studies have involved students in the preliminary stages of designing LADs by asking them to identify design features about which they would like to have information. Schumacher and Ifenthaler (2018) identified 15 features that university students expect from LADs, including planning and organizing the learning process, self-assessments, adaptive recommendations, and analysis of learning activities. Droit and Rieger (2020) involved 139 business students in the process of developing a dashboard and identified that students would endorse a LAD that supports, in particular, flipped classroom courses and that has comparative student data, such as grades and time spent online, prediction of final grade, an early alert about whether they are at risk of failing, and recommendations about elective courses. Other studies identified that students (mainly high performers) favoured study recommendations and disliked peer comparisons (Rets et al., 2021; Herodotou, Boroowa, et al., 2020; Divjak et al., 2023).

1.2. Participatory Methods in the Design of Student-Facing Dashboards

Few studies detailed the use of participatory methods in the design of student-facing dashboards. Bodily et al. (2018) used a practice-centred participatory design throughout the design process. After creating a first prototype of the dashboard, they evaluated it with students and faculty members using a think-aloud protocol. This initial evaluation led to several strengths and weaknesses they considered in subsequent versions of their dashboard. It was found that university students liked unit-level feedback since they could easily see where they should spend more time to prepare for exams as well as clickable recommendations; i.e., each bar chart displayed on the dashboard was clickable and this enabled students to click on a concept they were struggling with to receive practice problems or videos to help improve their performance. Their approach did not include a needs assessment and identification of preferred data points by students.

In contrast, other studies consulted students right from the start of the design process. Park and Jo (2015) conducted a needs assessment with eight college students. This helped them understand students' perceived needs related to a student-facing dashboard and include information related to login time, login frequency, login regularity, and visits on the board. After the first version of a LAD was produced, a usability test was conducted with six students using stimulated recall. Students perceived information in the dashboard as useful, objective, and accurate. de Quincey et al. (2019) involved students in the design of a dashboard using a combination of knowledge elicitation and user research methods. To identify suitable visualization techniques and motivational metaphors to be incorporated into the LAD, a semi-structured interview technique was used to elicit students to share requirements and selection criteria. In addition to this, six focus groups with 20 students were conducted during which students shared their understanding of data metaphors, their look and feel, and whether they would use them in the future. While students endorsed a tree metaphor, they also proposed other, more personalized representations such as avatars. Finally, Gras et al. (2020) invited 100 first-year students to share their needs in relation to features and functionalities of a LAD, which resulted in a prototype. This was shared with 300 first-year students, and their feedback was also collected.

The above studies stress the importance of understanding student needs and requirements when designing a LAD and collecting their feedback on various LAD iterations. Adding to this limited body of work, in this study we engaged students in the process of a LAD design, right from the start, by asking them to identify their study needs and choose data points based on usefulness. We then examined the use of LADs in a context not previously explored, that of online and distance learning education. Next, we examined whether and how predictive data, accompanied by study recommendations, can be used by students to effectively support study practices.

1.3. Aim and Research Questions

The aim of this study was to capture the needs of online undergraduate students, in relation to LADs. A screening questionnaire (N=23) and six online focus groups (N=20), addressed the following research questions (RQ):

RQ1: What specific learning needs can a LAD for online and distance learning support?

RQ2: What data points do online students find useful in supporting their learning needs?

RQ3: What types of visualizations could be used to visualize predictive data about student performance?

RQ3 makes particular reference to predictive data about student performance. In the context of this study, this refers to the use of machine learning algorithms to forecast student performance in an upcoming graded assignment. It builds on our earlier work of designing, testing, and deploying at scale a teacher-facing dashboard — the Early Alert Indicators dashboard (Herodotou et al., 2023). Given the availability of predictive data, this was included in the list of data points students assessed in terms of usefulness for succeeding in their studies.

2. Methodological Design

2.1. Sample

We circulated an email announcement to 791 students in one faculty ("Business and Law") at an online and distance learning university. Students were recruited from the School of Business where there was management commitment to the use of learning analytics in supporting students, particularly those subject to inequitable outcomes and where university funding was available for one academic year. A pilot course was selected based on the timing of the course presentation and most of its content being online. The only requirement for students to take part in the study was the completion of at least one online course to ensure that students already had experience studying with the university. We encouraged (and to a certain extent received) participation by students from disadvantaged or less represented backgrounds with the intention of designing a LAD that can best meet diverse study needs and increase chances of success for a range of students. Online students at the university under study access class materials through a virtual learning environment (VLE) and receive synchronous online sessions, grades, and any support needed from their tutors. They study at their own pace and manage personal and professional responsibilities alongside their studies. A £20 Amazon voucher was offered to each participant.

Twenty (N=20) students expressed interest in the study, completed the screening questionnaire, and participated in the focus groups. Seven were male and 13 were female. Eight declared a disability. Three students were 22–29 years old, 14 were 30–49 years old, and three were 50–59 years old. Sixteen were white, three were Asians, and one was Black. Ten students had completed less than A-levels, five had A-levels or equivalent, and five had a higher education qualification. (A-levels are required for entry into many universities and professional training opportunities in the UK). All participants completed at least one course at the university under study with seven of them withdrawing from at least one other course in the past.

2.2. Methods of Data Collection

To assess student learning needs in relation to LADs (RQ1) a short screening questionnaire (Appendix 1) was emailed to focus group participants beforehand, asking questions such as these:

- What information (data) about your studies would you like to have access to in order to complete and succeed in your studies?
- How would this information (data) help you to succeed in your studies?
- What would you say your main learning needs are when you are studying a new course?

To address RQ2 and RQ3, we followed a "grounded data exploration" approach, similar to the work described by Villalobos et al. (2023) in which participants were asked to sort cards with data indicators (in text and visual form) according to their interpretability and actionability. In our study, the sorting process was based on "usefulness," following other studies that explored usefulness (such as Schumacher & Ifenthaler, 2018, Rets et al., 2021, Droit and Rieger, 2020). Participants joined six online focus groups (three to four students each) with one facilitator drawn from the research team. In the focus groups, lasting two hours each, we explained the aims of the project, the norms of discussion and key terms. Two activities followed:

Activity 1: Drawing from Villalobos et al. (2023), a range of data points (textual form) in the form of virtual cards were presented to each focus group using an online board. These points were selected based on 1) insights from the analysis of the screening questionnaire and 2) availability of student data at the university under study. Data points were mapped under the following categories based on relevance:

1. Assessment e.g., score on your assignments
2. Progression e.g., number of credits passed
3. Virtual learning environment (VLE) e.g., type of material I visited
4. Tutorial e.g., number of tutorials I missed
5. Forecast e.g., what my score in my next assignment is likely to be
6. Recommendations e.g., material to study to complete my next assignment
7. Contact with your tutor
8. Comparisons e.g., any data point to be compared with others

Since our focus was to understand data usefulness as perceived by students, two prompting questions were used:

1. Which of the data points are more useful and why?
2. Which of the data points are less useful and why?

Activity 2: Two mock-ups of dashboards (visual form of data points, following Villalobos et al., 2023) were presented to students — one for a well-performing "imaginary" student and one for a student who faced study difficulties (Figure 1). Three different metaphors (weather change, tree growth, smiley faces) were used to visualize predictions of whether a student will submit their next assignment (Figure 2). Metaphors provided a user-friendly way of visualizing predictive data about student performance and a means to prompt discussion. As with Activity 1, prompting questions were used:

1. Which data visualizations do you find useful and why?
2. What features would motivate you to study more and why?
3. What features do you find less useful and why?
4. What is missing/should be added to these visualizations?

Focus group discussions were video-recorded and Microsoft Teams automatically generated transcriptions. The university's student panel gave ethical approval for these.

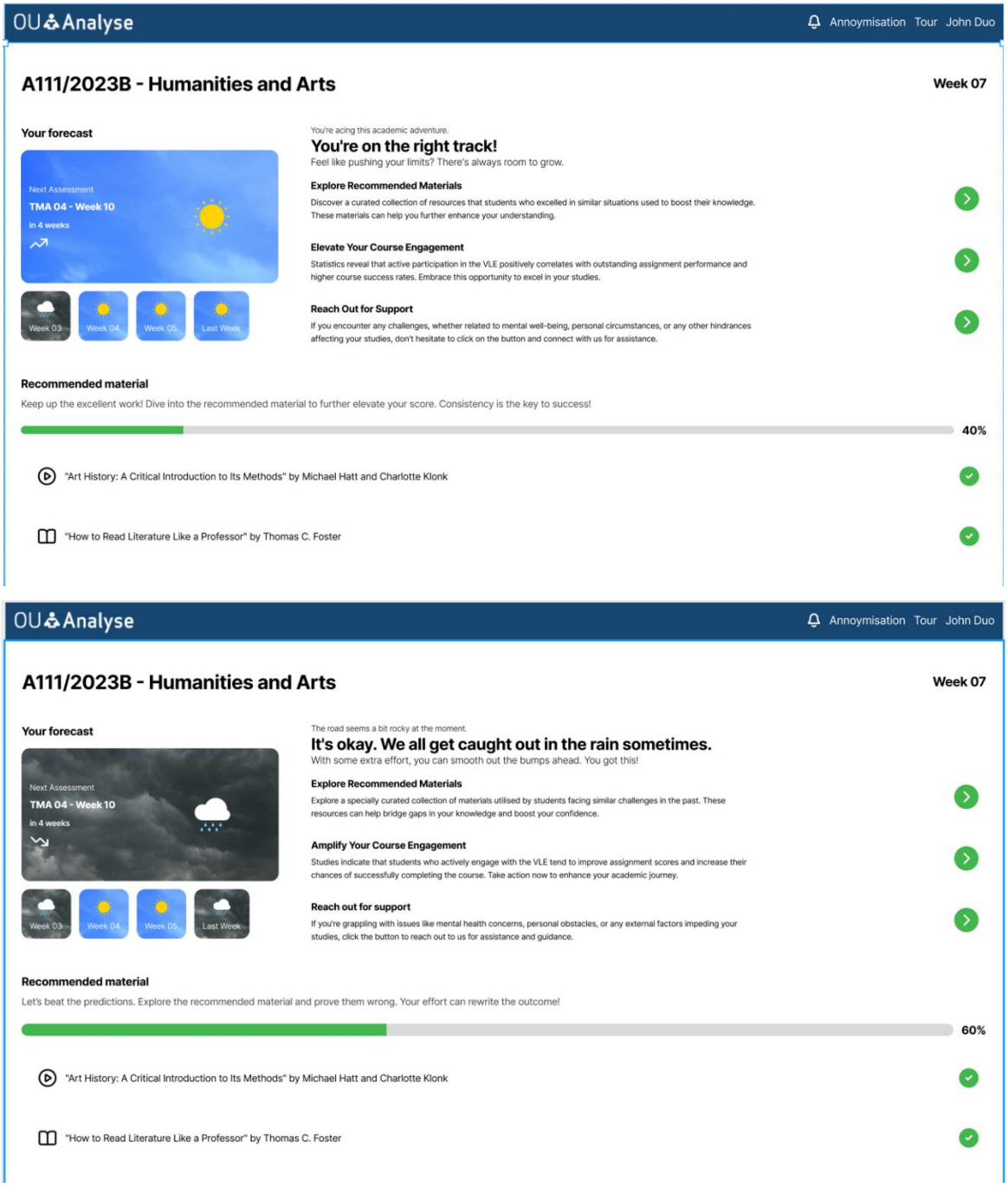

Figure 1. A hypothetical dashboard using a "weather" metaphor.
Top: a high-performing student; bottom, a low-performing student.

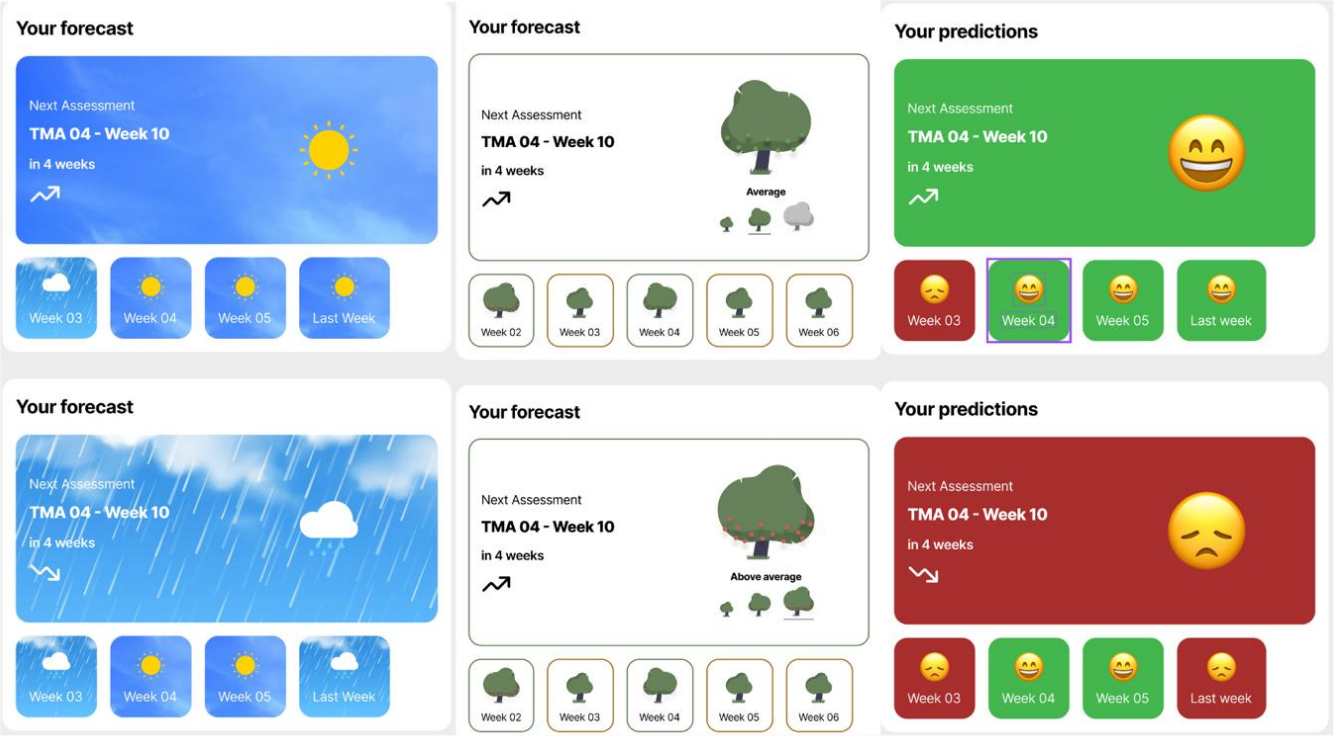

Figure 2. Metaphors used to visualize predictions of future student performance.

2.3. Methods of Data Analysis

To analyze the questionnaire and focus group data, we followed a bottom-up thematic analysis or "grounded data exploration" approach (Braun & Clarke, 2006; Villalobos et al., 2023). Analysis of RQ1 and RQ2 was combined. For each data point mentioned, an explanation was given as to why it can help the participant succeed in their studies. RQ3 was analyzed independently. Emerging codes were grouped into conceptually similar categories (themes). Focus group discussion data were also analyzed quantitatively, using descriptive statistics (frequencies for each data point; see next paragraph).

To analyze the first workshop activity, we created a matrix listing data points against individual students. Using the transcripts from each focus group, we recorded the number of students who agreed that a specific data point was useful and should be displayed on the dashboard, disagreed with it, as well as those who remained neutral or did not have an opinion. In addition, self-reported reasons explaining choices were added to the matrix. Frequency tables for each data point were produced using SPSS. The second workshop activity regarding proposed mock-ups of a dashboard was analyzed using thematic analysis; transcripts were imported to NVivo and coded inductively. Altogether, 31 codes emerged that were grouped and categorized into 12 themes. To ensure inter-rater reliability, two researchers (Herodotou and Shrestha) conducted the analysis of the focus group transcripts; the two coders agreed on most codes assigned. Cases of disagreement were discussed one by one until agreement was reached.

3. Findings

To document the participatory process of data collection and analysis, we present relevant data in a sequence of tables showing what data have been collected from each activity and how this informed certain design decisions about the dashboard.

3.1. Screening Questionnaire

The analysis of student responses showed specific sources of information and reasons why these were perceived as significant by students (Table 1). Different sources of data could support students in different ways. For example, comparisons of student assignment scores could put performance into perspective (especially given that they study in isolation from other students), help them to visualize their study progress, and manage their expectations. Overall, insights about a student's learning journey — such as assignment outcomes, forecasts, time spent studying, and tutorial attendance — are seen as beneficial since they could enable progress and help students to stay on track with their studies while also boosting their confidence and motivation.

Table 1. Critical Information for Student Success

"Information about my studies I would like to have access to, to succeed"	**Reasons why specific information could help students to succeed in their studies**
Assignment-related data — Comparisons	• Performance in perspective (overcome isolation) • Study progress • Manage expectations
Assignment-related data — Individual scores	• Study progress
Assignment-related data — Highest assignment score across students	• Improve study skills: better preparation for next assignment
Assignment-related data — Forecast of next assignment outcomes	• Self-improvement • Being on the right track • Greater confidence • Improve study skills: better planning
Example assignments	• Better performance • Get help from it
Time studying	• Being on the right track • Greater confidence • Meet personal targets • Motivation • Improve study skills: focus on studying
Tutorials attendance	• Improve tutorial attendance
Re-sit data i.e., data related to resitting or retaking an exam	• Greater confidence • Motivation

The learning needs of online students, when they are studying a new course, are related to course support, communication with tutors, tutorials, individual help, motivation, and induction (see Table 2). For example, in terms of course support, students asked for information about background knowledge related to a course, specific guidance on what is needed to complete it, support to understand the content, and guidance on how to study (read and gather information). Learning needs related to live communication and interactions with others, such as tutors and other students, and induction events could be seen as beyond what a dashboard could address. Overall, it could be argued that a dashboard could meet student needs, including motivation and course support.

Table 2. Learning Needs of Online Students

Theme	**Explanations**
Module support	Background knowledge (prior concepts, knowledge, etc., required for understanding the module content) Guide on what is needed and by when Understanding the module content How to read and gather information How to sustain motivation during studies
Communication with tutors	"Keep in touch" sessions with tutors Accessible and informative tutor
Tutorials	Discussions with other students and tutor Additional tutorials Recorded tutorials
Individual help	Additional help for students with disabilities
Induction	As a face-to-face event

3.2. Focus Group Activity 1: Selection of Data Points by Students

Table 3 presents student evaluations of different data points in terms of usefulness. Regarding assessment, students mostly agreed that the following data points were particularly useful: teacher-marked assignment (TMA) score, overall assignment average, and ratio of submitted assignments in a course. Assignment scores were perceived as useful as students can use these to determine how they are progressing in a course, what they need to do further to pass, and to help them predict their final score. An assignment average can inform future performance; a good assignment average means that they should not worry about their performance in upcoming assignments. Having information about the ratio of submitted assignments in a course can work as a source of motivation and engagement.

Table 3. Frequency of Agreement with Each Data Point

Data point	Useful	Less useful	Neutral	Reasons explaining preferences	
Assessment					
Teacher-marked assignment (TMA) score	8	1	8	Useful:	Know how far one has come and how far one is away from in the module Helps to predict the final score
				Less useful:	No reasons mentioned
Overall TMA score average	4	3	10	Useful:	TMA average will help one to plan during some life events (such as family bereavements) and not to worry if some unexpected things happen
				Less useful:	Showing that one hasn't performed well can cause stress
Ratio of submitted TMAs on this module	4	1	12	Useful:	Motivating aspect to know how far one is in their module
				Less useful:	No reasons mentioned
Ratio of submitted TMAs during studies	0	4	13	Useful:	No reasons mentioned
				Less useful:	Duplicates information related to submitted TMAs
Number of extensions obtained	1	6	10	Useful: Less useful:	No reasons mentioned Students already have a knowledge of extensions
Progression					
Ratio of successfully passed credits out of all registered credits	2	4	11	Useful:	Information about how credit completion helps achieve certain grades
				Less useful:	Takes space of the screen and the time from IT technicians
Qualification studying	1	7	9	Useful:	No actual qualification listed on other online platforms, so it can be useful to mention on the dashboard
				Less useful:	Listed on the certificate Students already aware
Number of credits passed	6	3	8	Useful:	Indication about how far one is through a qualification Builds confidence Motivating positive message
				Less useful:	No reasons mentioned
Number of credits studying	3	5	9	Useful:	Information not available on the website with student information ("studenthome")
				Less useful:	No reasons mentioned
Last time active on module	5	5	7	Useful:	A student is not running behind or not doing enough Some pressure, become faster, become more efficient
				Less useful:	Machine cannot track whether someone is active just by logging in
Qualifications other students registered at the module study	4	2	11	Useful:	No reasons mentioned
				Less useful:	No reasons mentioned
Number of credits failed	4	2	11	Useful:	Credits passed and failed as a balanced view
				Less useful:	No reasons mentioned
Virtual Learning Environment (VLE)					
Days visited VLE since start of the studies	2	6	9	Useful:	No reasons mentioned
				Less useful:	No reasons mentioned
Type of material least interacted with	6	6	5	Useful:	Module material one is struggling with Information about what students spend their time on
				Less useful:	Focus on the positive side is more important
Type of material mostly interacted with	5	5	7	Useful:	Understand the mode of study one is best engaged with
				Less useful:	Students have their own way to interact with module material
Days/weeks visited VLE	0	8	9	Useful:	No reasons mentioned
				Less useful:	Days or weeks are never the same — no single pattern of studying
Days visited VLE since module was opened	4	6	7	Useful:	Helps to understand if one is falling behind
				Less useful:	Work done outside the VLE cannot be captured
Tutorials					
Number of tutorials missed	4	4	9	Useful:	Check what one has covered or not
				Less useful:	Self-understood by looking at tutorials one has attended No need to highlight the negative aspect
Number of tutorials cancelled	1	6	10	Useful:	Greater awareness
				Less useful:	No reasons mentioned
Ratio of tutorials attended	4	4	9	Useful:	A more comprehensive picture of what one has attended Provides an indication of how active one is Acts as a secondary prompt or a reminder
				Less useful:	No reasons mentioned

Data point	Useful	Less useful	Neutral	Reasons explaining preferences	
Forecast					
Forecast of next TMA	5	7	5	Useful:	Know whether a student is going to fail as they haven't covered certain module contents Trigger to make one revise module content
				Less useful:	Not an accurate reflection if assignments are based on essays Cannot predict the life situations one might come across that can impact assignment writing
Forecast average TMAs	5	5	7	Useful:	Know where one is in relation to their overall performance in the module
				Less useful:	No reasons mentioned
Recommender					
Contact student support team	6	1	9	Useful:	First point of contact Available 24/7
				Less useful:	No reasons mentioned
Recommendations on materials to study to complete TMA	9	1	7	Useful:	Pinpoint specific chapters or pages to read
				Less useful:	No reasons mentioned
Contact to tutor	8	1	8	Useful:	All communications in a single platform Report issues directly
				Less useful:	No reasons mentioned
Comparison data (in relation to varied features)	7	3	7	Useful:	Specific chapters or pages others read A comparative picture showing materials accessed vs. not accessed A comparative figure of who attends a tutorial and who does not Ratio of how well students perform who attend the tutorials compared to those who do not Comparison of student performance this year with that of last year
				Less useful:	You don't feel good if you are not performing well when compared to others

Regarding **progression**, there were mixed findings about the number of credits a student has passed/failed. Students who perceived this as a useful feature declared that this information could increase their confidence and motivate them to study more. Regarding the **VLE**, mixed opinions were observed related to information such as the last time students were active on a course. Those who found it useful explained that such data will keep them on track with their studies. Those who did not perceive such information as not accurately reflecting the extent to which they are active on the course. Mixed preferences were also captured for material students interacted with the most. They would like to see the kind of materials they mainly interact with so that they can infer the best approach for studying.

Regarding **tutorial attendance,** preferences were mixed with some students considering that it is useful to know how many tutorials one has attended as it can prompt them to find what is covered and what is not in the course; others saw it as less useful since they can highlight how many tutorials they have missed by knowing how many they attended. Regarding **forecasting** performance on a next assignment, some students found such data useful to help them to keep track of their performance; for example, a negative forecast would motivate them to do better. Some students questioned the validity of any forecast as it cannot predict unforeseen circumstances that emerge in one's life and can have an impact on performance.

Regarding **recommendations,** students perceived **contact** points as useful features since they would allow them to contact the student support team (SST) of the university and their tutor via a single system rather than using different platforms. They explained that any issues or needs could be discussed with their tutor, such as seeking extensions for submitting an assignment. Regarding **material recommendations**, these were perceived positively and viewed as a means to improve performance, such as recommendations for specific chapters or pages to study. Regarding **comparisons,** mixed opinions were captured in relation to which of the mentioned data points should be presented in a comparative manner. Some students found benefits in comparing their assignment performance to that of other students; others found it useful to see the materials they have accessed versus those they did not, who attends or does not attend a single tutorial, and how tutorial attendance relates to performance.

3.3. Focus Group Activity 2: Visualizations of Data Points

Themes emerging from the analysis of student perceptions of data visualizations can be found in Table 4. In some cases, the discussion around data visualizations was found to relate to specific data points, similar to Activity 1. These issues were reinforced and explained further in Activity 2. In relation to proposed metaphors, student preferences were a matter of personal choice. For example, a student showed a preference towards the smiley face metaphor since a yellow frowning face means that a student needs to work further, whereas a happy face means they are doing well (W2B2S14). The weather metaphor was seen as more neutral than other metaphors, yet it was noted that different people can interpret it differently, especially if rainy weather is desirable: "Some people might like the rain" (W1B1S3). The tree metaphor was seen as "less judgmental" as it shows progress rather than whether performance is good or not (W2B1S12). The tree metaphor was perceived as a growth continuum that can show where the student is currently at in their learning trajectory. As explained: "You can see your growth […] It's kind of more positive to see […] I need to make improvements there and where I am, whereas with the smiley faces, if I saw a frown, I'd be a bit upset that there's a frown there" (W2B2S16). In terms of the language used to describe a student's

performance that is not so good ("It's OK! We all get caught in the rain sometimes"), this was positively perceived: "It gives an understanding perspective as opposed to 'you're in trouble'" (W1B1S3). Overall, it was noted that the choice over which metaphor to be used should be made by each student.

Table 4. Emerging Themes from Activity 2

Themes	Relevant codes	Explanation of codes
Metaphors predicting assignment submission	Opposing views	Metaphors can be misleading as they do not reflect the exact performance of a student
	Supporting views	Metaphors deliver information subtly, helpful
	Choice over metaphors	Choice of metaphors by students
	Opposing views: smiley face metaphor	A sad face can be upsetting
	Supporting views: smiley face metaphor	Communicate well how one is doing in a module
	Supporting views: weather metaphor	A weather metaphor is less harsh
	Supporting views: tree metaphor	Tree metaphor shows where the student is currently in the learning trajectory and denoted growth
	Supporting views: actual scores	Percentage and scores as forecast instead of having metaphors on the dashboard
Predictive data	Contextual information	Predictions cannot capture the impact of personal conditions on performance
	Suggested changes	Forecast should capture how a student will perform in the whole module in addition to assignment specific forecast
	Opposing views	No need to rely on predictions
Support	Reach support	Easy reach for support through the dashboard
	Tutors	One-to-one feedback via a dashboard is helpful
Recommended materials	Supporting views	Recommended materials are useful, yet students perceived this feature as material they forgot to read or skipped accidentally
	Opposing views	Not being able to study recommended material
	Suggested changes	Addition of short video clips of tutorials
Activity progression	Suggested changes	Green ticks used to show the progress of students through activities
	Progress bar	Progress bar indicating how far a student is through the module
	Time engagement with activities	How long a student is engaged in each activity
Time studying	Time spent on each activity Comparison to a recommended study time	Record of time spent on each activity on VLE and how their engagement on each activity compares to a minimum study time for each activity set by a tutor
Badges	Aesthetic tools	Some value to the dashboard's layout, not useful
	Prompts, incentives, showing achievements	Progression shown through badges
Offline activities	Capturing offline activities on a dashboard	Inability to capture offline engagement, reading from printouts
	Capturing additional materials	Record of additional materials students choose to study (beyond VLE)
Access to dashboard	Early access	A dashboard should be available when a module is launched

For visualizing predictive data, students raised some concerns regarding predictions not being able to capture the context of studying and the potential impact of personal conditions on performance. It was explained that being in a difficult situation, and thus not interacting with the course material, may not have a negative impact on performance: "I was in the hospital … I did very well, and I deserve recognition" (W2B3S18). It was also suggested that predictive data should capture how a student would perform in the whole course in addition to forecasting performance on assignments.

In terms of support, students find features that allow them to contact someone for support helpful. They value the ability to contact someone who can promptly assist with their queries. Students pointed out the need for one-to-one feedback, which can guide them to do better in their studies especially when they struggle. It was stated: "anybody who's struggling, they can always […] ask one-to-one help from the tutors" (W1B3S8). In terms of recommended materials, these were seen as very useful: "I think and if you ever skip any of those … or you're moving around like you can miss some things, it would be good to see that like highlighted or recap there where you can see that there's things that are really recommended not to miss and have them like right in front of you" (W2B2S14). Such materials could help students identify challenging content and enhance their study rigour (W2B2S16).

In terms of features showing activity progression, students believed that the activity graph on the VLE effectively indicates their course progression, strengths, and weaknesses. They suggested that such a graph should be enhanced to depict how much time a student is spending on which components of a course so that students can have a good understanding of their ongoing performance: "The graph is quite good because you can just see what your strengths, your weaknesses are" (W1B1S3). In addition, they noted that green ticks are useful to denote the progress of students though activities: "update which courses I've

done and which bits I've done and like sort of do a tick box exercise. That's going to [free] quite a lot of my planned study time" (W2B1S14).

Regarding information about time studying, students would like to know how the time they spend on each VLE activity compares to the tutor-recommended minimum study time: "I have to do a minimum of 16 hours study. If then I look at that chart goal, I've done my 16 hours but that score doesn't quite look right. So, is it telling me I need to do a little bit more? [...] So rather than clicks, time would be more beneficial" (W2B2S15). Knowing the minimum hours required to spend on each activity would also help students.

While some students see badges as aesthetic enhancements to the dashboard, others find them motivational, as they prompt action and highlight course progress and achievements. As explained: "It's … a recap of where you are, what you have already completed and it's there to show that you've done it" (W1B1S1). Another student suggested that the bottom area of the dashboard might be better utilized if it showed what is needed to complete a course: "I would find it useful if it showed everything that I need to achieve for the particular course" (W2B1S13).

Several themes not directly related to the use of specific data visualizations emerged. Students raised a concern that a dashboard cannot capture their offline engagement, such as when they use printouts: "You can't capture everyone engaging with the material because … some people … print out, so you won't be capturing these and they might feel a bit dismayed" (W2B1S12). Also, students would like to have a way of showing additional materials they have engaged with. Another theme emerging from the data was that students should be able to access the dashboard early on in their studies, when a course starts, so that they can use it to improve: "if it's there staring you in the face when you first log in […] you got things coming up […] you'll have no choice but to look at it and delve into certain aspects of it" (W1B2S7).

3.4. Reaching Consensus on Features to Include in the Dashboard

Our findings revealed which features are useful for inclusion in a dashboard, along with the reasons for their importance. Given the small, self-selected sample size, we could not make a valid decision about which features to include or exclude from the dashboard based solely on frequency across each feature. Therefore, we reached a consensus on the features to include by considering a combination of factors: 1) the usefulness of a feature, as explained by students; 2) a high frequency of agreement; and 3) feasibility in terms of retrieving relevant data. Table 5 presents the data and features selected for inclusion in the design of a dashboard for online students.

Table 5. Dashboard Features Selected for Inclusion

Features	Included	Excluded	Reasons
Assessment			
Assignment score	X		It was deemed useful by many students It can show progress
Assignment average		X	It depends on the feasibility of retrieving further data
Ratio of submitted assignments in a module		X	Duplication of assignment-related information
Ratio of submitted assignments across modules		X	Looking for an option to include submitted scores on the timeline instead of the ratio of assignments
Number of extensions		X	It was deemed not useful by many students
Progression			
Ratio of credits out of all credits		X	Too much information on dashboard It may not be directly relevant
Qualification studying		X	It was deemed not useful by many students
Number of credits passed	X		Builds confidence, a positive message
Number of credits studying	X		Students cannot access this information via other platforms
Last time active on module	X		Triggers continuous student engagement
Other qualifications students registered		X	Not relevant information
Number of credits failed		X	Negative information
Virtual Learning Environment (VLE)			
Days visited VLE since start of the studies	X		It can be technically shown via a VLE graph
Which days/weeks students visited VLE in a graph	X		It can be technically shown via a VLE graph
Materials least interacted with		X	Negative information
Materials most interacted with	X		Aware of how students interact with specific materials
Number of days students visited VLE out of all days since the module was opened	X		It can be technically shown via a VLE graph
Tutorials			
Number of tutorials missed	X		Prompts students to find what tutorials they have missed
Number of tutorials cancelled		X	Negative information
Number of tutorials attended	X		Highlights the positive side of learning
Ratio of tutorials attended	X		This data point is congruent with the "number of tutorials attended"

Features	Included	Excluded	Reasons
Forecast			
Forecast of next assignment	X		It is a key component of the dashboard Help with study planning
Forecast of average score on assignments		X	Average in relation to any data point should not be included
Recommender	X		Many students strongly highlight its usefulness
Contact Student Support Team (SST)	X		Many students strongly highlight its usefulness
Contact tutor	X		Many students strongly highlight its usefulness
Material recommendations			
Comparisons			
Comparison data		X	No agreement in student opinions as to which type of data should be shown in a comparative format

4. Discussion

In this study, we described a participatory process that engaged 20 online and distance learning students in the design of a student-facing dashboard. The process involved a screening questionnaire that captured the learning needs of online students, the data from which informed the design of the focus group discussions. In focus groups, students reflected on the usefulness of various data points and visualizations. Student responses influenced the selection of data points regarding the usefulness of a feature, a high frequency of agreement, and in one instance, the feasibility of retrieving relevant data from the university's systems. The analysis of the screening questionnaire revealed that the learning needs of online students relate to two main aspects: 1) course content and study expectations: the provision of course support including understanding the content and any relevant prior knowledge, guidance as to how to study and stay motivated, and planning information as to what is needed and by when; and 2) communication with tutors and other students as a means of keeping in touch and discussing study issues. In response to these needs, students would like to have access to information related to their assignments, time studying, and tutorials. This information would address specific learning needs. For instance, comparisons with other students could provide social context and alleviate feelings of isolation, while forecasts of next assignment scores and study time could enhance study skills and planning.

Considering the reasons why online students found certain information useful, it could be argued that their learning needs focus on improving study skills, maintaining progress, staying motivated, and boosting self-confidence. These findings align with existing studies emphasizing that dashboards can enable students to monitor and adjust their behaviour to meet personal goals, thus facilitating the development of self-regulation skills (Sedrakyan et al., 2020). The focus group analysis provided detailed insights into the data points students wanted to access and their reasons for these choices. The data points related to the following aspects:

1. **Assessment:** Students endorsed scores of assignments citing reasons such as understanding progress so far.
2. **Progression:** The number of credits passed was seen as particularly useful for indicating progress, motivating students, and building confidence.
3. **VLE:** The type of material interacted with the most or the least elicited mixed responses, with some students seeing it as a way to become more aware of their study habits, while others deemed it unnecessary due to their personal study methods.
4. **Tutorials:** Attended tutorials were seen as a way to raise awareness of a student's level of activity, whereas some students felt this was unnecessary as they already knew which tutorials they had attended, or they could watch a recorded tutorial on their own time.
5. **Forecast:** Some students saw this as an indication of progress and a trigger to study; for others, forecast data were perceived as not accurate since unexpected life events could change a prediction.
6. **Recommenders:** Most students endorsed having material recommendations and easy ways to contact student support teams and tutors when needed. Adaptive recommendations were also endorsed by university students in other studies (Rets et al., 2021), along with features that support planning and organization of learning (Schumacher & Ifenthaler, 2018).
7. **Comparisons with other students:** There were varied opinions on what type of data students would like to compare, such as material accessed, tutorial attendance, and performance comparisons with students from the previous year. Overall, comparative features found less support with students, aligning with existing studies (Divjak et al., 2023; Herodotou, Boroowa, et al., 2020).

Overall, it could be argued that student choices of data points were related to gaining a better understanding or awareness of their own study progress and acting accordingly, including planning for study and studying specific material. This information would motivate students and help them to build confidence in their studies. These insights align well with proposed principles for designing dashboards (Bennett & Folley, 2020), in particular the need to enable students to act following understanding of the dashboard data. Certain data points were not endorsed due to reasons such as increased stress originating

from a greater awareness of study processes and outcomes, a belief that students already knew specific information (e.g., number of tutorials attended, number of extensions requested), and technological limitations, such as tracking offline studying and personal situations that may hinder studying.

Student reflections on a set of hypothetical dashboard images provided insights into the usefulness of specific data visualizations. There were mixed opinions about the metaphors used to visualize predictions of the next assignment score. Some students suggested a tree growth metaphor would be appropriate as it communicates messages of development and a learning trajectory. Students would like to be able to choose the metaphor used to preview assignment forecasts, pointing to the need for designing customizable dashboards (Bennett & Folley, 2020). Students found suggestions of study material and easy access to contact tutors and student support services particularly helpful, as these resources could be easily accessed within a single place. Prescriptive data, such as study material recommendations and proposed sources of help, is of special significance to online students since it moves beyond describing their data to offering actions they should undertake to improve performance (Herodotou et al., 2025). In terms of activity progression, students favoured elements that indicate progress, such as green ticks, a progress bar, and a badge. Gamified elements were shown to have a positive impact on student performance (Alam et al., 2023). Students proposed "time per activity" as an additional feature. This feature could be further enhanced by comparing it with the time other students spend on an activity. Aligning with perceptions of useful data points, students endorsed data visualizations that can provide study support (through recommendations and contacts), visualize progress, recognize achievements, and indicate how a student's study patterns relate to those of other students (time spent on each activity, etc.). These findings are consistent with existing studies that have observed actual dashboard usage and noted its benefits in helping students find study material, plan for the next assignment, and reflect on changes needed in their study behaviour to succeed (Teasley et al., 2021). In this study, although participants did not have a clear opinion on comparative data, they supported social comparisons related to study patterns and activities, which could inform their own study methods.

In terms of the characteristics of online students participating in this study, nearly half the participants declared a disability, half had less than A levels, and most were white and middle-aged. Seven of them had withdrawn from a course in the past. It could be argued that the perceptions presented in this study reflect a diverse set of student demographics and abilities. This could explain why, in some instances, there was no clear picture as to whether a data point or visualization was strongly endorsed or rejected by students. In future studies, it would be worth examining whether accepting or rejecting certain data points (e.g., due to causing stress, having their own ways of monitoring progress) may be explained by student prior performance and high/low confidence in studying, suggesting that a dashboard should be personalized to meet the needs of diverse groups of students. Prior studies suggest that the usage patterns of a dashboard relate to student prior performance (Chen et al., 2023; Broos et al., 2017) while satisfaction with it may be higher in students who are not performing well due to a lack of awareness of how they are progressing (Kim et al., 2016). This approach was not feasible in the present study since student demographics were received from the university systems after students took part in the research activities and were anonymized, making it impossible to distinguish which students are, for example, high performing as opposed to low performing. Existing studies point to perceived benefits specifically for online students with average performance, younger than 40 years old and those with low self-efficacy (Rets et al., 2021).

It could be argued that the choice of data points and visualizations for inclusion in the dashboard are likely to be inclusive as they emerged from a rather diverse sample of online students in terms of prior qualifications, prior performance, and disability, but less diverse in terms of ethnicity and age. Future studies should track student engagement patterns with the dashboard in an effort to understand which students are using it and thus are more likely to benefit from it. Student performance following use of the dashboard should be analyzed to identify whether such tools are beneficial for certain groups and not others, such as low income and minority students (Denley, 2014). Should participation by certain student groups be low and evidence of enhanced performance are in place, action should be taken to facilitate more diverse student participation.

The data points and visualizations selected for inclusion in the dashboard were informed by student preferences, considering also for technical limitations in accessing relevant data. These ten data points are as follows: 1) assignment scores, 2) number of credits passed, 3) number of credits studying, 4) last time one was active on VLE, 5) days visited VLE, 6) material most interacted with, 7) number of tutorials missed and number attended, 8) forecast of performance on next assignment, 9) contact tutors and student support teams, and 10) material recommendations. In terms of the proposed data visualizations, there was a variety of opinions regarding the metaphor to use to denote predictive data while badges were seen as acknowledging progress and achievement, thus motivating further study. Given these preferences, a first version of the dashboard has been produced (Figure 3) and will be piloted with students from one undergraduate course in the next few months. Information about credits has not been included in this first version since it is the only piece of information that does not refer to a specific course (but all courses a student is currently attending). We aim to incorporate credit-related information after we trial and improve the first version of the dashboard and before we share it with students.

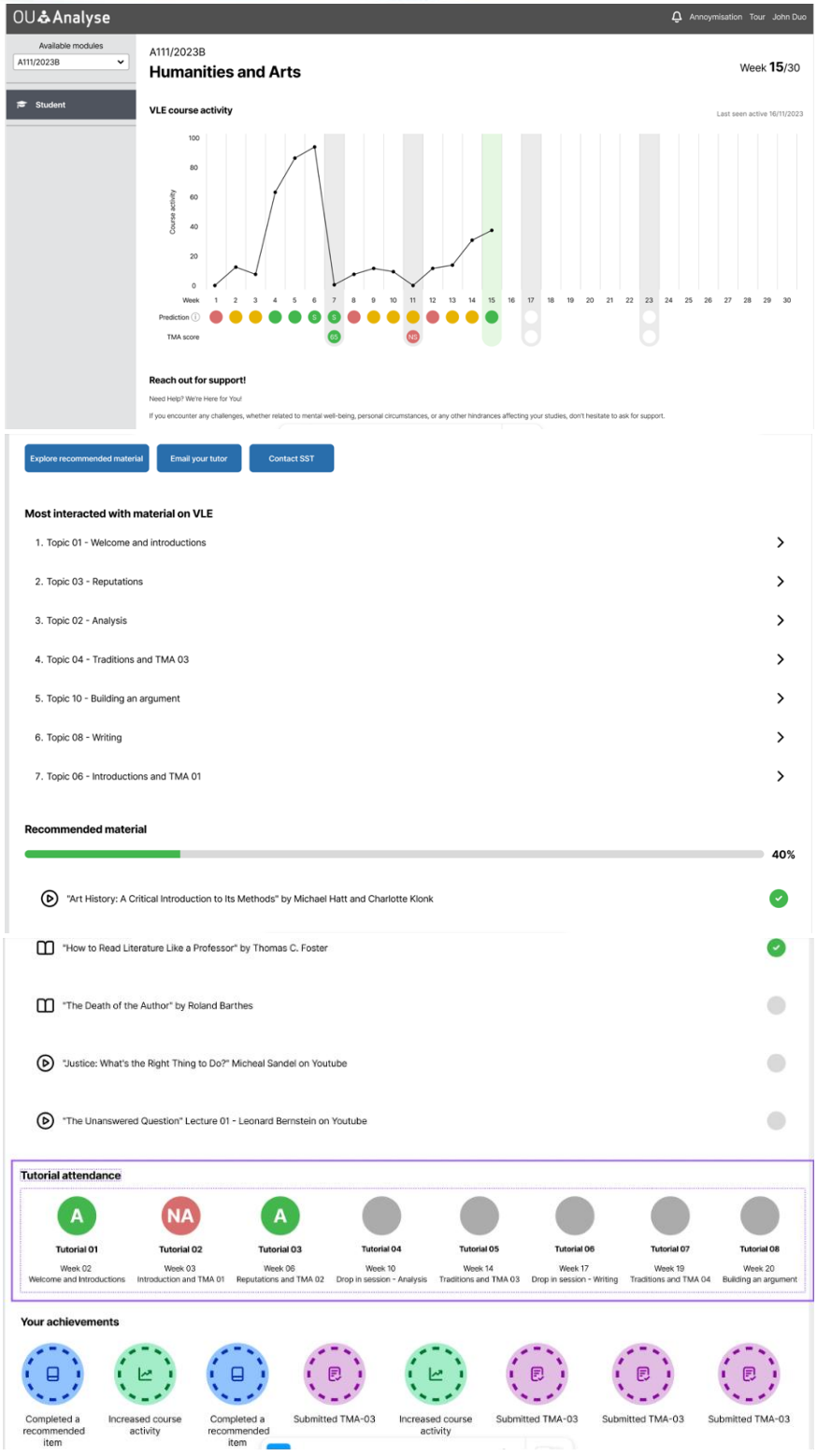

Figure 3. A student-facing dashboard following consultation with online students.

In terms of the use of participatory research, this paper provides a detailed account of how students became involved in the process of conceiving a learning analytics dashboard for their studies, including how student perceptions have been translated into design considerations. This account contributes to the existing body of studies that use participatory methods when designing LADs and specifically stresses the significance of understanding the needs and expectations of end users prior to designing a LAD by using a combination of qualitative and quantitative data (Hilliger et al., 2024). While it could be argued that students in this study had more of a consulting role than a decision-making one (Buckingham Shum et al., 2024), the process

of decision-making regarding which features to include in the first version of the dashboard (implemented by the research team and documented in this paper) was mainly based on student data, including the reasons why certain features were considered useful by students (alongside pragmatic reasons i.e., feasibility of retrieving relevant data from the university's systems). What could be seen as a challenge in the process of decision-making is the conflicting preferences regarding certain features and how these could be accommodated when designing a LAD. The use of design-based research (DBR; Wiley et al., 2024) that engages students in assessing different prototypes of a dashboard and iterating the design accordingly could accommodate diverse student needs and result in an inclusive LAD design.

In terms of ensuring inter-rater reliability, this was conducted by two of the authors, yet the process was not formally recorded, and example cases of disagreement could not be reported in this paper. Also, the process could be improved by measuring statistically the degree of agreement between the two coders using the Cohen's Kappa coefficient.

5. Conclusions

In this paper, we examined the perspectives of 20 students from an online and distance learning university about design features and data information to be included in a student-facing dashboard. A participatory, co-design approach, based on focus group discussions and a screening questionnaire, was deployed to ensure student voices and perspectives were captured and used to inform the dashboard design (Viberg et al., 2018; Rets et al., 2023). To ensure diversity of perspectives, special emphasis was placed on engaging with students from varied demographic backgrounds and prior performance. This diversity may explain why, in several instances of data analysis, mixed opinions were captured.

The data points and visualizations endorsed by students related to the inclusion of specific types of learning analytics data, in particular, descriptive data — what has happened in relation to a student's study journey (for example, assignment scores, engagement with VLE, material accessed); predictive data — what the likely outcome of a next assignment is (score prediction); and prescriptive analytics — what students need to do to change a negative prediction or increase their chances of achieving a higher grade (material recommendations for studying, contact information for tutors and student support teams).

Amongst the different data types, prescriptive analytics were highly endorsed by students, emphasizing the need to design student-facing dashboards in ways that do not simply highlight performance issues, but foremost provide students with potential solutions to overcome any performance challenges, such as which material to study to successfully submit an assessment and how to reach out for further help.

Declaration of Conflict of Interest

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Appendix 1

Screening Questionnaire

Scenario question: The university you are studying with is using different sources of student data to proactively support you and other students in achieving their study goals. Thinking of your learning experience so far:

- What information (data) about your studies would you like to have access to in order to help you progress and complete your studies?
- List the type/s of information you would like to see. Information may relate to the design and content of your modules, assessment requirements, interactions with others, support given etc. [list provided: e.g. usage of VLE, attendance of tutorials, extensions].
- How would this information help you with your studies? Explain how you would use the above information to meet your learning goals?
- What would you say your main learning needs are when you are studying a new course? This would help us to understand what student data should be collected to inform your needs.
- Any other thoughts.