Students as Lead Designers of Learning Analytics Dashboards: Lessons learned in a Northern Irish University

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ABSTRACT

There is an increasing scholarly and practitioner interest in developing user-centred, personalized learning analytics dashboards (LADs) in higher education institutions, to support student success and improve learning and teaching. In most implementation efforts, however, a teacher-centric, institutional view tends to drive dashboard designs, while using students only as data providers. We stretched our engagement approach by empowering them to be the lead-designers of LADs to learn what data they would like presented in a dashboard, and how. Using a novel cord sorting technique, we asked 42 Northern Irish university students to construct dashboards that reflect their priorities. Using observation, photography and semi-structured interviews, we collected data on student-constructed dashboards. Content analysis of students' constructions revealed a strong preference for the inclusion of personal financial data (money spent so far vs resources utilized), among others, and exclusion of social media data. Thematic analysis of qualitative data uncovered within-group variations in students' LAD-related assumptions, particularly between undergraduates and postgraduates, and between international and home students. Participants challenged institutional overreliance on measurable digital footprints as proxies for academic success and emphasised the need for including success stories of their peers and seniors, in future dashboards. In advocating story-integrated LADs, we call for designs that better reflect learners' everyday needs and priorities. We provide a caution that offering genuine control and oversight to students for designing LADs, despite being useful, might be more complex than currently assumed in the literature. We discuss pedagogical implications for teachers and LA designers in advancing student-led LA designs.

Keywords: Personalization; student-led design; learner engagement; customised design, learning analytics dashboards.

1. Introduction

The visual representation of learners' data, in dashboard formats, in educational settings has gained considerable attention in the field of learning analytics (Bodily et al. 2018; Viberg et al. 2018). A learning analytics dashboard (LAD) provides visual information on students' learning behaviours so that teachers and learners make sense of data at a glance (Few, 2013) and reflect on their practices so that they can become better in their respective roles (Verbert et al. 2013; Verbert et al. 2014). In general, the LADs collect student data unobtrusively and provide rich reports to inform the end-users of the students' behaviours in a course. Reviewers (Schwendimann et al, 2016) conclude that most of the LADs are currently teacher-facing, and these dashboards tend to overlook students' need for self-improvement and strategic learning. Hence, in order to keep students' priorities at the core, we took a different approach and asked them to design LADs, and this empirical study presents the lessons learned in the process of exploring these questions.

2. Literature review

Many HE institutions are implementing learning analytics systems to better understand and support student learning (Schumacher et al. 2018; Newland & Trueman, 2017). Due to the proliferation of LA studies, our knowledge about learning analytics dashboards, in general, is steadily increasing. Scholars have proposed frameworks and guidelines for implementing LADs (Aljohani et al. 2019; Corrin & Barba, 2015) while also sharing their experience of designing, developing and implementing student-facing LADs (Chen et al, 2018; Kim, Jo & Park, 2016) in a variety of learning environments. For example, in a post-secondary setting, Chen et al. (2016) reported that students found their social learning analytics toolkit neither useful nor user-friendly, and the authors called for simplifying the LAD designs, the need to educate students in data literacy, and a closer integration of analytics and pedagogical intentions. In an experimental study of LADs (Kim, Jo & Park, 2016) designing dashboards in ways that motivate students consistently, and the need to support those who have different academic achievement levels were highlighted.

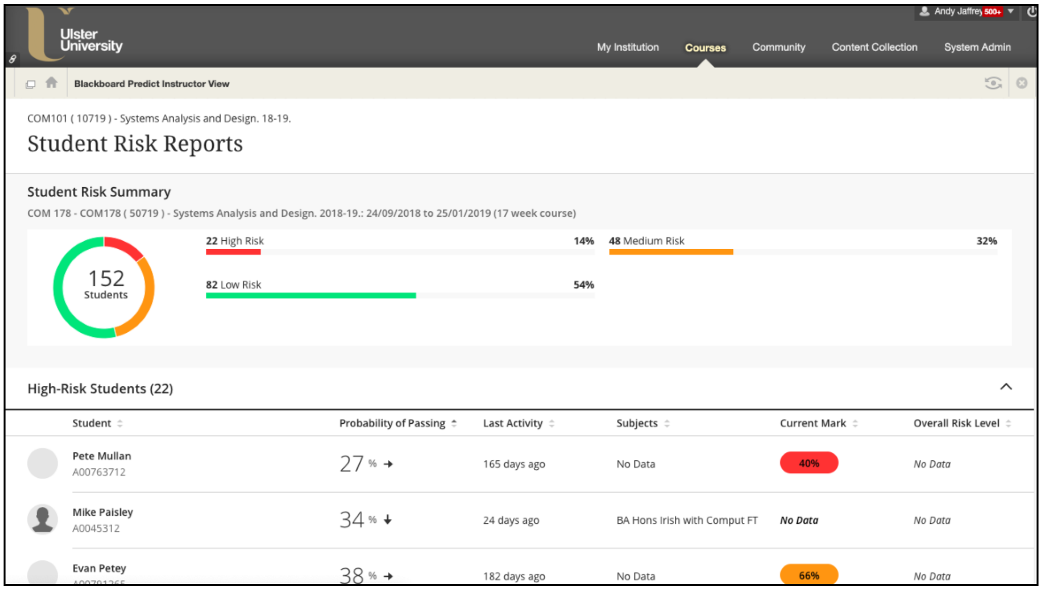
In a similar vein, a review (Viberg et al. 2018) confirms that there is *a shift towards a deeper understanding of students' learning experiences* in Learning Analytics. Nation-specific exploratory studies that analyse students' expectations of features of LA systems are evidence of this shift (Schumacher et al. 2018). Nigerian undergraduates were found to have used lecture resources in various ways, and the variations were mediated by age, subject major, prior academic performance, gender, age, distance from campus and their resident status (O'Brien & Verma, 2019). In an English University, students' academic performance in a lab-based design course were seen to be positively influenced by their social stability in terms of peer grouping, time spent on task, and attendance, negatively by students' seating distance relative to the lecturer's position (Akhtar, Warburton & Xu, 2017). Taken together, the relationship between students' achievement and LA data appears to be complex. A complex of students' characteristics or the alignment with their specific needs might determine the value of student LADs (Teasley, 2017). As a consequence, studies that investigate learners' behaviours and experiences in different national and institutional contexts are on the rise. They call for personalising the dashboards (Lim et al. 2019; Roberts, Howell & Seaman, 2017) and making them as interfaces that explain to the users what is useful to them, at a time when they need it, while also highlighting the necessary actions is also recommended (Echeverria et al. 2018). However, how that personalised, explanatory dashboard might look like is yet to be fully known.

In addition, researchers caution us about poor interface designs and the lack of usability testing found in commercial dashboard products (Tesley, 2017; Reimers et al. 2015). It is also reported that such products tend to visualise items that students may not really want or need, as large samples of key stakeholders such as students and teachers are not regularly consulted as part of the design process (Holstein et al. 2017). It is also important that we understand students' perceptions on what additional data sources could be used in PLA dashboards so that we make cost-effective, more accurate, more meaningful predictions that help motivating our students. Our study is intended to address this gap. The remainder of the paper is structured as follows. Section 3 discusses the institutional context. Section 4 describes an exploratory study with students, to illustrate our approach to student-led design of LADs. Section 5 presents analysis and results from the study. The paper concludes with implications of our findings to future LAD designs.

3. Institutional context & The PLA dashboard in *Blackboard Predict*

Ulster University, Northern Ireland's civic university, has approximately 27,000 students distributed across four locations in the region and within partnership campuses in London and Birmingham. The university has implemented a pilot project on predictive learning analytics in less than a year of its introduction in 2017. Through the application of a predictive model, this initiative allowed professors, instructors, and student advisors to make early interventions when a student triggers an early warning system. The project aims to enhance intervention strategies with real-time, just-in-time data and to encourage data-informed decision making.
The dashboards, in *Blackboard Predict*, use a percentage score which relates to the likelihood of a student achieving a grade of 50% or above. It is recognised that this is above the pass threshold for undergraduate modules, of 40%, however historical analysis shows that less than 3.1% of students scored 40 or below, rising to 14.7% for 50% or below. Therefore, the university decided a 50% grade cut off as more significant as an *at-risk* indicator for its students. Accordingly, in Ulster University's case, the outcome question being answered for the pilot is: What students are likely to pass/fail a course with a 50% grade or higher? The result of the prediction is a probability that the student will not score greater than 50%. The higher the probability the more likely the student is to fail. This value might be a 75% probability indicating the student is predicted to fail with 75% confidence. What is displayed is the inverse of the prediction (or the probability the student will succeed). In the example above, the indicator will show 25%, underlining the prediction that it is only 25% probability that the student will succeed with a 50% grade or higher. The system also helps us identify those students, through available engagement indicators, who show similarities with students who have previously dropped out or failed to achieve 50% or above. As seen in Figure 1 below, the system identifies the total number of students at risk in a cohort (n=152), using Red, Amber, Green status indicators. Among the high-risk students, the student Peter Mullan (a pseudo name) has only 27% probability of passing a module and hence requires an intervention. Although *Predict* may appear to facilitate reactionary intervention strategies, staff are encouraged to utilise PLA dashboards as a data source for undertaking proactive support and retention strategies in person.

Figure 1: Risk Report sample generated by Blackboard Predict system



At the end of the pilot period in 2018, as a preparation for making the dashboards available to students, the institution paused for an interim evaluation. We were keen to understand learners' perceptions on the use and value of LADs. In the context of students demonstrating an ever-increasing engagement with social media and cloud services, we also wanted to know what datasets they might want to see in LADs so that the predictions made by the system are usable. Thus, the transitional time presented us with the research opportunity to learn about students' emotional reactions to LADs [34]. The following research questions guided our study:

1. What do students perceive as important datasets to be included in a useful, student-facing learning analytics dashboard?
2. What are students' perceptions on the uses of predictive learning analytics?
3. What are students' perceptions on the value of predictive learning analytics?
4. How do students respond to viewing a machine-generated prediction of their likelihood of passing a module?

5. Methodology

In this interpretative, qualitative case study design, we used multi-qualitative methods, including sixteen semi-structured interviews, three paired interviews and two focus groups to capture students' (n=42) perceptions on different aspects of LADs. On gaining the necessary ethical approval from the university, we conducted a pilot study with four undergraduates. Unfortunately, our questions did not fetch the data we required, as these students had a limited knowledge of what LA is and even less so about what PLA is. This is not surprising as other researchers too have reported such experiences with students and called for dashboard literacy [33]. Based on the learnings, we decided that interviews alone would not be practical because our respondents would probably not know a lot about Learning Analytics and its predictive capabilities. Therefore, we opted to utilise a Card Sorting method [39] (explained in full later) to elicit students' perceptions of LADs. Students enrolled in undergraduate and postgraduate Human

Resource Management (HRM) degrees programmes, during the academic year (2018-2019) were recruited for this study. Among the respondents, 20 undergraduate and 20 postgraduate students were selected using a purposive sampling method to ensure maximum variation in terms of their age, gender, year of study, fee status, work experience and nationality. The sampled students received an information sheet detailing the study. Interviews took place during lunch breaks, and when students did not have scheduled lectures.

5.1 Data collection

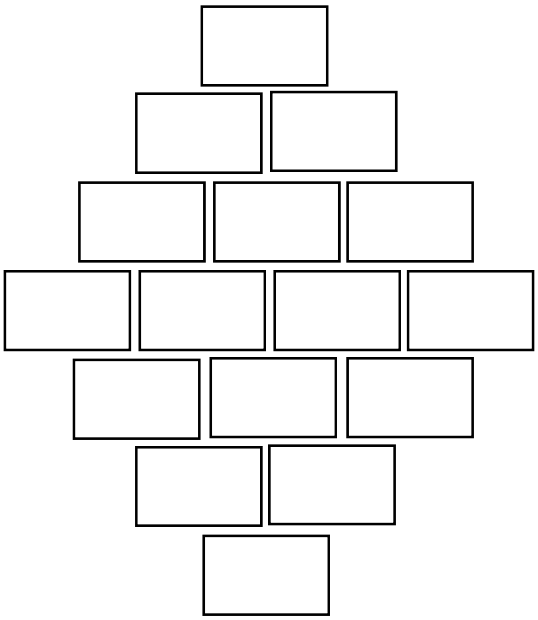
Card Sorting techniques (Rugg & McGeorge, 2005) are a useful way of eliciting variation and commonality in research participants' categorisations of features that they perceive in a set of entities, such as cards, pictures or objects. These are simple-to-use, user-centred techniques, which focus on participants' terminology (rather than that of researchers and experts) and are known to be able to elicit semi-tacit knowledge that traditional interviews and questionnaires fail to access (Fincher & Tenenberg, 2005) and hence deemed suitable for this study. Essentially, card sorting involves asking participants to sort labelled cards into a hierarchy, groups or categories, using a single criterion. Among the various sorting techniques, we used 'repeated single criterion sorts' method (Rugg & McGeorge, 2005), as it has been recommended for its flexibility and ease of implementation and has been demonstrated to be of value in eliciting user beliefs and perceptions on various aspects of their worlds (Upchurch et al. 2001; Nawaz, 2012).

5.2 Card Sorting Procedure

Based on our review of literature, we created twenty-five A5-sized cards, (including four blank cards). Each of the 21 cards included a label of a dataset, such as attendance record, number of library visits (See Appendix 1). At the start of the session, students were asked to look at all the cards before sorting them out so that they were aware of the kinds of datasets they could consider for sorting. In line with our first research question, they were asked to assemble the chosen cards on a table, based on their perceived usefulness, as a criterion. It was also made clear that they use only those cards considered as important and can abandon those that are not perceived as useful for a LAD. To reduce the time involved in statistical analysis of a sematic distribution, drawing from [45], we suggested using a structure, representing an importance continuum that helped them rank the chosen cards. (See Figure 2). In this, the cards on the extremes are assumed to represent the strongest views and those in the middle are to contain moderate views on the chosen criterion, utility. Although not all participants used this structure strictly when assembling their sorts, supplying it at first, enabled us later not only count the number of times a card is perceived useful, but also to compare results across the participant population. We also provided them with four blank cards, so that participants could include additional datasets we might have omitted. We observed the participants in action, during the process. Once a construction was stabilized, we photographed the card sort. The recorded sorts formed the basis of the interview that followed and was archived for further analysis (See Figure 3).

Figure 2: The suggested structure of importance continuum for card sorting

Figure 3: Record of a final sort



We found the card sorting exercise unlocked students' tacit awareness of, and attitudes to, LADs as they felt more at ease to explain why they sorted the way they did. Then, students were asked to answer the perceived uses and the value of such dashboards should they be designed using their assembly (To answer research questions 2 and 3). Then, we asked them if they wanted to view their own machine-generated predictive score (to answer research question 4). All participants showed an interest and they were shown their Blackboard Predict dashboard - which contained predictions on their likelihood of passing a module, along with other data on their learning behaviour. On allowing them to take sufficient time to look at their scores, they were asked about their immediate emotional responses. When viewing the 'machine generated predictive score' their emotional responses were less complex. Their responses were neither overly enthusiastic and nor noticeably depressive. We noted down their reactions, for thematic analysis, and their simplistic expressions did not require sophisticated analytical tools and expert interpretations. This may be in part, the nature of prediction displayed (which only indicated the likelihood of a student passing the module with 50%) did not trigger any complex emotional responses in the viewers. A more nuanced prediction might have generated a different response. The interviews were recorded and were transcribed verbatim by a professional firm.

5.3 Data Analysis

In line with the guidelines provided in (Rugg & McGeorge, 2005), we analysed the participants' constructions, using the photographs and the interview transcripts. In our content analysis, we looked for commonality in the patterns created. We also investigated the 'discarded' datasets, along with the justifications provided. We searched for patterns in the discarded sets to reveal inner beliefs, attitudes and values, in light of the implications these may have for PLA dashboard designs. We also looked for datasets, introduced by the participants as they might contain important indicators of perceived utility. Interview transcripts were thematically analysed and findings are presented next.

6. Findings

6.1 What do students perceive as important datasets to be included in a useful, student-facing learning analytics dashboard?

At the outset, there is a clear desire for 'student-focused, customised predictive analytics dashboards' among all the participants of this study. No one preferred a pre-designed LAD and they expressed that allowing students to design their own LADs was the right thing to do. Although they demonstrated a desire to be the lead designers of LADs, there is less agreement among the participants on what to include/not to include in such personalised dashboards – indicating a preference for having a greater autonomy and agency for self-selecting the datasets, deemed significant to participants.

While confirming the earlier findings on the need of personalised dashboards [7, 47], our study goes further to identify the most preferred features in those dashboards (see Table 1). These datasets include, students' financial information, frequency of accessing online learning materials, grades, cohort comparison data and attendance. Similarly, our study also highlights students' perceptions on 'what not to include in dashboards.' These include building usage data, students' physical, mental, social media, health data, and sports centre access data. When discussing these features, our participants showed stronger emotional connections with these data and expressed value-laden arguments for their exclusion from such designs. It is important to note here is that participants overwhelmingly preferred individually focused, fully personalised dashboards that could help them sustain their motivation to succeed in the current programme of study.

Table 1: Students' choice of datasets for LA dashboards

Top five datasets of high importance		
1	Grades	71%
2	Library History	61%
3	Blackboard (online materials) usage data	57%
4	Financial Data	42%
5	Historical data sets of similar/senior students	38%
Bottom five datasets of least importance		
1	Social Media data	80%
2	Building usage data	66%
3	Prior educational data	51%
4	Societies & Clubs participation data	33%
5	Health data	29%
Rejected datasets (very often discarded in final sorts)		
1	Health data	80%
2	Demographics	72%
3	Sports centre usage	61%

Surprisingly, 30% of our participants expressed a need for the inclusion of personal stories and narratives as part of a futuristic dashboard design. They preferred vignettes of student stories (e.g. narratives describing the job roles that students currently have who had similar traces of data) instead of anonymous quantitative data. Are qualitative stories-integrated dashboards the future of LADs? More research is clearly needed.

6.2 What are students' perceptions on the uses of LADs?

Our participants' views on the uses of predictive analytics dashboards are mixed. 70% perceived that the information might 'motivate' them to do even better and the dashboards can help them *"say confidently to a potential employer that I am on course to get 2:1."* However, among them, 22% of students said that they would *'become complacent.'* Across the sample, 20% of them explicitly said, or implied in their narratives, that they will be 'devastated' 'discouraged' if they happen to see a prediction of them failing a module.

6.3 What are students' perceptions on the value of LADs?

In general, 80% participants agreed that a personalised LAD would be valuable in terms of understanding the bigger picture of their own personal learning behaviours, and that of others in their cohorts. 25% of the sample said that a positive prediction on their performance might help them pitch well to a potential employer so that the prospects of employability could be increased.

6.4 How do students perceive a machine-generated prediction of their likelihood of passing a module?

All undergraduate students showed high levels of enthusiasm to view their predictions. When students viewed their predictive scores, the researcher in the room, noted their immediate responses in words and their emotional outbursts revealed several important dimensions of LAD design issues:

> *'I am delighted to see that I am doing well' (T8)*
>
> *'The data is not correct; I have been regularly logging in to Blackboard but the footprint showing here is not accurate' (T11)*
>
> *'the prediction could be sharper and more focused – for example, if I am on course to get a 2:1 this year' -let the LAD tell me this. Just showing that you are on green, and this means, 'the likelihood of passing the module with 50% or more is high' is not that helpful (T16)*

A majority of students (65%) asked for finer, more nuanced, highly personalised predictions for individuals, and critiqued the way the university satisfies itself with a generic prediction, created with a sole purpose of identifying at-risk students. Although undergraduate students demanded more and more customised predictive visualisations, postgraduate students, in our sample, however, showed less interest in viewing their predictions. This may be due to the perceived strength of their knowledge of their own academic performance or to the questions of reliability of datasets used by the university. Further studies might reveal important aspects of the variation experienced by undergraduates and postgraduates, if they have access to larger samples, across levels of degree programmes.

7. Discussion

Our study presents a complex picture of students' learning journeys that further complicate the designing of student-focused dashboards. This study surfaces at least three important dimensions that affect future dashboard designs: within group variation and resulting design preferences, the need for the inclusion of financial data and qualitative stories in future designs and an over-reliance on a narrow set of datapoints.
First, while our study confirms earlier studies (Kim, Jo, Park, 2016; Bennett, 2018) in relation to the need for dashboard literacy, it surfaces a series of variations between Postgraduates and Undergraduates on the one hand, and international and home students on the other, in how these students perceive design attributes that contribute to predictions. Postgraduate participants were concerned about the time commitments they had, and the family and work pressures that reduce their ability to contribute fully to University life. There was a perception that attributes such as fitness or student leadership were important for undergraduates but were less so for the postgraduates. Among the international and home students, we observed significant variation in attitudes about the use of personal data. For example, some international students were more relaxed about the use of personal and medical records in predicting success, when compared with the home students, who showed extreme resistance to use such data. This study also highlights students' perceptions on what not to include in dashboards, such as building usage data, or health data and sports centre access. In addition to the privacy concerns, students said that they did not see the utility to them of tracking this information. They tend to overlook the possible benefits of combining this information with other data sets. For example, combining 'sports centre visits and health statistics' with 'classroom engagement metrics and time spent on additional reading and research' could show interesting patterns that may motivate people to develop more meaningful learning behaviours. Future efforts must focus on building up data literacy skills across student populations.
Second, to our surprise, inclusion of personal finance data was among the top five most-preferred feature in LADs. Participants often described feeling financially stable as the most important factor in their academic success. Displaying data on how much money was spent on fees on a given day, in comparison with, for example, how little library sources were used or how many times a student made use of the lectures appear to motivate 22% of our participants. This information when presented with data about other students' economic behaviours appear to be a powerful motivator of success. This means, scholars need to use insights from behavioural economics and neuroscience of learning for designing LADs of the future. Similarly, participants asked for the inclusion of qualitative narrative stories of success achieved by their predecessors who undertake a degree programme. They believe that, for example, viewing the stories of other successful students who studied a degree programme, along with their societal and economic background, might inspire them to recognise if someone with that background could achieve that success, they too might. Addressing these complex student expectations will contribute to advancing theory, practice and policy.
Finally, this study shows that many participants have concerns that the complexity of their lives cannot easily be measured by institutional systems. Although our focus was empowering students to sort and prioritise individual datasets, what was revealed by combining datasets as found across the multiple sorts was powerful. The card sorts and the subsequent interviews revealed that our participants had complex life arrangements that resulted in less time spent in the campus or in leaving limited 'digital footprints' in institutional systems. For example, one participant made use of a blank card to include a category called 'hours of work in employment, which was not included in our cards previously. Some participants had

regular practices of downloading the online course materials all at once onto their mobile devices, and use them at leisure, at a convenient place, thus leaving limited digital traces of their learning. Three participants receive help from support workers and their digital activity was often by proxy. For example, we encountered two cases of a translator and a scribe accessing online materials legitimately for two different students and their digital footprints had not been visible in the dashboard. Many of our participants expressed that the learning analytics systems, while in the process of becoming a watchful Big Brother, tend to overlook their off-campus lifestyles and the ongoing learnings they have from everyday experiences, and ending up 'taking a paternalistic approach'[48] and making insensitive and inaccurate predictions of success. Taken together, all these complexities challenge the idea of conceptualising learning as the one that leaves always observable traces, in a formal virtual learning environment, within specified time periods, during the academic year. We provide a caution that scholars will be challenged even further as learning, through Personal Learning Cloud is increasingly becoming 'personalised, socialised, contextualised.' (Moldoveanu & Narayanadas, 2019).

Overall, this study, by indicating the priorities of students - the main beneficiaries of LADs, helped sharpen our focus on designing student-focused predictive dashboards in the future, despite the complexities implied in their expectations. Since many learning analytics systems opportunistically use data just because it is there, we believe that a more strategic approach that understands what insights are needed and how data can support this can lead to improved learning analytics services. Furthermore, understanding students' views, particularly in the context of an increased awareness on protection, privacy and ethical use of data, helped us to better inform the next stage of system development. We acknowledge that it is a single institution based, small-scale exploratory study and clearly, our findings would benefit from a wider investigation in multi-university to test their veracity.

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APPENDIX 1: Cards used in this study

Card 1	Attendance monitoring	Physical presence in class
Card 2	Blackboard Activity	Logins, time spent on course, frequency
Card 3-6	Blank cards	
Card 7	Building usage data	Time spent on campus; times visited a campus.
Card 8	In-group comparison	Benchmarking data against your classmates; grades
Card 9	Demographic info	Age, gender, ethnicity, first in family to attend Uni.
Card 10	Fee status / domicile / nationality	More specific demographic info – Home student, International student, Visa expiry information etc.
Card 11	Financial data	How much money is spent so far
Card 12	Grades	Grades achieved in modules and courses
Card 13	Health & Fitness Data	Feeds from health and fitness apps you have
Card 14	Historical datasets of similar students	Students with similar profile – how they performed in the past academically
Card 15	Library history	eBook access, borrowing history, Journal access,
Card 16	Membership of societies or sports clubs	Participation in student groups, other achievements, contributions and engagement data
Card 17	Module selection history	Performance of alumni who studied the module
Card 18	Module-level marks	corresponding to each year completed
Card 19	Prior educational data	Previous school, exam results, grades
Card 20	Social background data	Home address, accommodation, family background,
Card 21	Social Media data	Analysis of social media accounts
Card 22	Sports Centre visits	Physical training data, group lessons, mindfulness sessions data
Card 23	Student leadership	Student union rep, course rep roles
Card 24	Students' voice	Engagement in NSS survey, student evaluation
Card 25	Within course comparison	Course-level, programme-level position.