Charting Design Needs and Strategic Approaches for Academic Analytics Systems through Co-Design

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Academic analytics focuses on collecting, analysing and visualising educational data to generate institutional insights and improve decision-making for academic purposes. However, challenges that arise from navigating a complex organisational structure when introducing analytics systems have called for the need to engage key stakeholders widely to cultivate a shared vision and ensure that implemented systems create desired value. This paper presents a study that takes co-design steps to identify design needs and strategic approaches for the adoption of academic analytics, which serves the purpose of enhancing the measurement of educational quality utilising institutional data. Through semi-structured interviews with 54 educational stakeholders at a large research university, we identified particular interest in measuring student engagement and the performance of courses and programmes. Based on the observed perceptions and concerns regarding data use to measure or evaluate these areas, implications for adoption strategy of academic analytics, such as leadership involvement, communication, and training, are discussed.

CCS Concepts: • **Human-centered computing → HCI design and evaluation methods**; **Interface design prototyping**; **User centered design**; • **Applied computing** → *Computer-managed instruction.*

Additional Key Words and Phrases: academic analytics, educational quality, co-design, implementation strategy, higher education

ACM Reference Format:
Yi-Shan Tsai, Shaveen Singh, Mladen Rakovic, Lisa-Angelique Lim, Anushka Roychoudhury, and Dragan Gašević. 2022. Charting Design Needs and Strategic Approaches for Academic Analytics Systems through Co-Design. In *LAK22: 12th International Learning Analytics and Knowledge Conference (LAK22), March 21–25, 2022, Online, USA.* ACM, New York, NY, USA, 16 pages. https://doi.org/10.1145/3506860.3506939

1 INTRODUCTION

The extensive amount of student data generated at higher educational institutions have opened up opportunities for educational stakeholders at different administrative levels (e.g., institutional leaders and academic leads) to gain insights into student experience and the effectiveness of teaching [50]. This, in turn, can inform future decision-making processes related to the overall design of academic curricula and educational environment, thereby enhancing student success and experience [2, 19]. The process of collecting, analysing and visualising educational data to generate institutional insights for the purpose of improving institutional decisions in academic matters is generally understood as academic analytics [30], which is inseparable from learning analytics, a field that leverages data generated by learners in a learning context (e.g., patterns of access to learning materials) to understand and optimise learning processes [43].

To date, different academic analytics solutions have been developed to support administrators in higher education, including systems that timely detect students at risk of failing across courses and academic programmes [23, 29] and systems that optimise the curricular structure and learning outcomes [18]. In this way, academic analytics can contribute to long-term improvements of organisational processes (e.g., personnel management and resource allocation) and overall educational efficiency. Equally important, academic analytics can aid learning analytics. For instance, rich institutional data collected from multiple data channels (e.g., student enrollment, grades, log data, and programme accreditation reports) can be analysed to identify issues important to academic planning and strategic formation at institution-level as well as support for students and teachers at the ground level. For example, upon identification of misalignment between the design of a programme and student outcomes (e.g., academic performance and employability), academic decisions can be taken to improve the structure of the overall programme or of particular courses within the programme [2]. At the same time, effectiveness of learning design at course or programme level may rely on evidence collected through learning analytics. On the other hand, insights obtained through academic analytics can inform the choice of suitable learning analytics tools to effectively support learners, or further inform the development of new or refinement of existing learning analytics solutions [22].

Despite the promises of academic analytics to benefit educational stakeholders and students, many obstacles have prevented academic analytic tools from being fully adopted at higher education institutions. Prominent challenges include the difficulty to navigate often complex organisational structure and privacy issues such as providing users with access to relevant data sources and reporting functions [37]. As well, adoption challenges are often related to different views that stakeholders may have towards possible benefits and outcomes of analytics in education [45]. For this reason, it is important to engage educational stakeholders in a co-design process, through facilitating a dialogue about existing challenges and institutional needs for academic analytics. Although co-design methods have been adopted increasingly to create learning analytics solutions [6, 49] and inform evidence-based policy/strategy frameworks for institutional adoption (e.g., [5]), using co-design approaches to identify user needs and concerns for the development of academic analytics tools and implementation strategy is relatively new.

To bridge this gap, we took co-design steps to identify design needs and strategic approaches for the design of academic analytics systems. The current study involved 54 educational stakeholders from different faculties at a large research university. The university's focused educational strategy is continuous improvement of student experience and academic analytics was identified as a means to support this strategic area. To this end, we first interviewed faculty leaders to learn about how institutional data can be used to enhance educational quality. This was followed by another phase of consultations with stakeholders who worked closely with institutional data. We demonstrate how co-design methods can be used to obtain deep insight into ways in which institutional data may be utilised to support the evaluation and enhancement of educational quality.

2 LITERATURE REVIEW

2.1 Creating value through co-design

Along with advances in digital learning technologies as well as increased implementations of online learning, a plethora of analytics tools and systems have been developed to provide insights into students' learning and performance [24]. However, despite the range of potential solutions, actual adoption of analytics systems in practice has continued to lag behind developmental work, as shown in the learning analytics literature [10, 34]. Reasons for the slower adoption rate have been described at two levels: the micro (classroom-level), and the macro (institutional level) [49]. At the micro-level, mismatch between tool design and the requirements of real users results in seemingly sophisticated tools being unfit for purpose [12, 34]. At the macro-level, more systemic challenges exist, for example, the lack of dialogue among stakeholders as well as the institution's strategic plans for, and level of experience with, learning analytics [8, 46].

The same challenges apply to academic analytics: at the micro-level, if data requirements for different stakeholders are not addressed, platforms may be perceived as having limited usability no matter how visually appealing reports might be. At the macro-level, wider policy such as data governance and access may present difficulties around data availability for reporting on programme quality, even if a tool is available for generating quick analyses and reports of the data [2].

Underpinning these micro- and macro-level challenges is the fact that educational analytics systems are born into a wider socio-technical structure, comprising "pedagogy, stakeholders, communities, current practices, context, technical components, and business models" [6, p. 5]. In view of the considerations of the wider socio-technical environment, there have been calls for human-centred design approach [6]. Human-centred design refers to an approach whereby "the natural focus of the questions, insights and activities lies with the people for whom the product, system or service is intended, rather than in the designer's personal creative process or within the material and technological substrates of the artefact" [17, p.610]. In relation to academic analytics specifically, this means that the design of tools for the collection, analysis and reporting of academic program activities cannot be driven purely by data availability or complex algorithms alone, but in consideration of potential users or key stakeholders in the specific contexts. The immediate teaching and learning context is of particular importance because this influences learning design: the 'pedagogical intent' of the course affects the way that learning activities and assessments, as well as the interactions among teachers, students, and their peers are orchestrated to help students meet learning objectives [25, 32]. The institutional context embodies organisational culture, leadership and management which can affect inter-departmental communication and conflicting agendas that may promote or hinder the way academic analytics is designed [10]. The geographical context includes policies and infrastructure, which can affect stakeholders' experiences with data and analytics and therefore their expectations of academic analytics. Thus, the involvement of stakeholders in the design process is key to successful implementation of academic analytics. In particular, academic analytics can benefit from human-centred approaches, such as co-design, which have shown promising results in human-centred learning analytics (HCLA) [6].

Co-design has been employed as a participatory approach to developing educational technology tools for a few decades now, and therefore is not new [21]. Although sometimes used interchangeably with co-creation, co-design is defined as a process that involves researchers and designers aiming to translate diverse stakeholder voices into design requirements [41]. It is only within the last 4 years that frameworks for learning analytics co-design have emerged, and these tend to be mainly targeted at teachers. For example, Holstein et al [21] describe a real-time classroom orchestration tool in a co-design of wearable learning analytics systems in a middle school setting. Martinez-Maldonado et al [34] proposed LAT-EP, or the Learning Analytics Translucence Elicitation Process, a five-step process to design effective multimodal learning analytics systems. Alvarez et al [1] propose a co-design toolkit called LA-DECK, which aims to facilitate diverse stakeholders' expressions of their requirements for new learning analytics systems. Chatti et al [7] present their Human-Centered Indicator Design (HCID) approach (including four steps: defining goal/question, ideate, prototype, and test) to guide the design of a teacher-facing dashboard. These case studies provided initial evidence showing how co-design can give stakeholders in different settings an active voice in the development of analytics systems. The research on HCLA in higher education institutions highlights the importance of including different groups of stakeholders who have different roles, as they will have different values, expectations or challenges [47]. Furthermore, the involvement of higher management stakeholders has been observed to influence learning analytics adoption by stakeholders in other roles, such as support [46] and teaching [20]. Overall, research in HCLA is still nascent. More work needs to be done to understand the different values, needs, and goals of different stakeholders, and how academic analytics can be well-embedded within institutions for sustained adoption [6]. To this end, we undertook a co-design approach to foreground user needs, In particular, this paper presents the *defining goal/question* and *ideation* stages that serve to identify design requirements before the *prototype* stage Chatti et al. [7].

2.2 Quality Measurements in Higher Education

For over a decade now, universities have been under increasing pressure to demonstrate greater accountability in terms of student outcomes[22, 35]. In this context, student engagement has been recognised as key to positive student outcomes [27, 39]. The extensive collection of big data from learning management systems (LMSs), student information systems (SIS), and interactions with institutional services such as libraries makes academic analytics an attractive solution to understand student engagement and how this affects student outcomes. Importantly, harnessing such rich data from multiple sources may place universities in a better position to make evidence-based decisions [42].

Student engagement can be defined broadly in terms of the time and effort invested by students in activities associated with positive learning outcomes [28]. These activities can take the form of interaction with learning materials, interaction with faculty, interaction with peers, as well as wider participation in co-curricular activities. Engagement as a concept has been viewed through different theoretical lenses [16, 26], but there is wide agreement that engagement is multi-faceted, comprising affective, behavioural, and cognitive dimensions [15, 39]. While the concept emerged in research within school settings, the work of Kahu [26] was instrumental in framing engagement within higher education. Her conceptual framework posits the three dimensions of engagement as mediating between structural and psychosocial antecedents, and proximal and distal outcomes. In situating engagement within the wider antecedents and outcomes, Kahu highlights the important role of socio-cultural influences in student engagement. In her framework, affective engagement refers to students' reactions to learning and the institution, namely, enthusiasm, interest and belonging. Behavioural engagement is demonstrated by students' attention and effort in learning activities, their interactions with peers and teachers, as well as their participation in wider institutional activities. Cognitive engagement describes the internal mental processes that students undertake in order to attain deep learning and self-regulation. More recently, Reeve and Shin [38] also proposed a fourth dimension - agentic engagement, described as students' constructive inputs contributing to the flow of an instructional event, with the intent to enrich both the learning as well as the immediate context within which it is taking place. Importantly, agentic engagement is uniquely characterised as being reciprocal, whereby the student interacts with the teacher in such a way as to enhance motivation, and foster teacher-student relationship, ultimately resulting in a personally-valued learning experience [38].

Early work on academic analytics [23, 30] focused on predicting at-risk students through exploratory algorithms, drawing largely on behavioural engagement data (LMS logs) and psychological antecedents, especially prior academic performance. As increasing digitisation enabled more data to be captured, other sources of engagement data were explored for academic analytics, such as participation in campus activities [4]. Less frequently, cognitive engagement data has been explored; for example, [4] gathered indicators of self-regulation from library records, as they provided some evidence of self-directed learning strategies. Even less frequently captured in academic analytics is affective engagement data. Freitas et al. [11] describe their attempt to capture affective engagement through student evaluation surveys. They found that students who were satisfied with their academic performance showed higher likelihood of retention. This example shows how it is possible to use fine-grained self-report data to understand engagement.

Engagement from the student perspective might look different from the institution's perspective. Millennial students hold pragmatic goals for university education, especially, to equip them with marketable skills to secure future work [14]. Overall, students in contemporary higher education today may be seen as prosumers who are aware of what institutions are promising to deliver. This means that, although there is a tangible link between student engagement and learning outcomes, it is also important to capture the students' perspectives of the learning contexts they find themselves in. For example, Silvola et al. [44] found that students in pre-service training expected that learning analytics should support student autonomy by allowing them more flexibility to make individual choices on their academic path. This is an aspect of agentic engagement. However, this desire for autonomy might conflict with the institution's mandate to ensure that students acquire requisite skills and knowledge through specific courses so that they can present themselves as viable candidates for future employment. Thus a tension exists in higher education trying to balance students' expectations of higher education and being accountable to quality and standards of a university degree. This tension further highlights the question of what should constitute quality measurements in higher education.

Given the mandate for universities to demonstrate quality especially in terms of engagement and outcomes, the challenge faced by institutions with regard to academic analytics is: how to leverage the vast amounts of data from learning platforms, student administration systems, and other sources, in order to provide quality measurements that will help higher education administrators, program coordinators, and instructors to make meaningful decisions for teaching and learning? While student engagement has been recognised as being multifaceted, research in the field still demonstrates a focus on behavioural engagement, drawing particularly on time and effort as key indicators [48]. As described above, fewer instances exist where cognitive and affective engagement is captured. While the field of learning analytics has matured to demonstrate how to leverage student activity data at the course level, for example by scaling personalised feedback, e.g., [31], comparatively lesser research has featured for academic analytics.

3 METHODOLOGY

3.1 Co-design Steps

This study focuses on two initial steps of co-design [7]: Phase 1 – *defining goal/question* and phase 2 – *ideation.* In Phase 1, we started with the following research question: *How can we use data to enhance educational quality?* We interviewed institutional leaders who were in charge of the educational portfolios in their faculties (one interview session per faculty). Excluding the data from faculties that did not wish to be part of a research study, there are nine interviews included for the analysis. Each interview[1] lasted approximately one hour and included questions about existing practices of data-based evaluations of educational quality, related challenges, and areas of improvement regarding using institutional data to inform educational planning, decision making, and evaluation of courses and programmes. We found the institutional leaders broadly agreed that, to be able to measure educational quality of courses and programmes, educational stakeholders (e.g., chief examiners, course/ programme coordinators[2]) need data that can reflect (1) student engagement and (2) overall performance of courses and academic programmes. These formed two user cases to be explored further in the next phase.

In Phase 2, we carried out a series of consultations with stakeholders who worked more closely with institutional data, e.g., educational designers [3] and course/ programme coordinators. Based on the two user cases identified in Phase 1, we refined our initial research question and asked: *How can institutional data be leveraged to support the measurement of student engagement and the performance of courses and programmes?* Guided by this question, Phase 2 interviews[4] was divided into two parts. In Part 1, we asked the interviewees which aspects of engagement (i.e., behavioral, cognitive, affective, and agentic [44]) were measured at their faculties, what data was used, whether there were additional data

[1]The complete Phase 1 interview protocol can be found at https://bit.ly/39IRX50.
[2]Chief examiners are responsible for the overall design and delivery of a course to a student cohort, whereas course/ programme coordinators coordinate multiple cohorts of students and teaching teams in addition to ensuring the coherence of the curriculum and alignment with accreditation requirement (a degree programme contains several courses and a course can be catered to multiple campuses of students).
[3]Educational designers are education professional who assist academics in the planning, development, and delivery of teaching.
[4]The complete Phase 2 interview protocol can be found at https://bit.ly/3kNOFUA.

sources needed or areas of data practices to be improved. In Part 2, we asked similar questions related to the monitoring of the quality of courses and academic programmes. Moreover, in order to gain a better understanding of the data channels and metrics academic leaders valued as a good proxy or measurement for the two use-cases identified in Phase 1, the interviewees were asked to rank data channels by importance in both parts of the interview. All the interviews lasted for about an hour. In total, six faculties participated in this phase. One of the faculties received three separate interviews due to the availability of the participants. In total, Phase 2 contains eight interviews from six faculties.

3.2 Study Context and Participants

The study was conducted at a large research university in Australia. The university provides a wide range of undergraduate, post-graduate and research-based academic programmes and degrees, primarily in the fields of Humanities and Social Sciences, STEM, and Medicine and Pharmacy. In Phase 1, 30 institutional leaders from nine faculties participated in the study. Of these stakeholders, 10 were associate deans of education (ADE), 4 were deputy deans of education (DDE), 12 were academic programme directors (APD) and 4 were involved in other roles that provide key support to their ADEs, DDEs and APDs (e.g., head of department and factotum). In Phase 2, we interviewed 27 stakeholders to deepen our understanding of the current practices of data-based evaluations of educational quality and identify ways to enhance these processes with an academic analytics tool and suitable implementation strategy. Of these stakeholders, 8 were educational designers (ED), 14 were academic programme directors (APD), 3 were chief examiners and lecturers (CE/L) and 2 were heads of departments (HoD). Of these stakeholders, 3 participated in the Phase 1 interview, too. Ethics approval (ID number: 25362) was received from the institution before the research activities took place. With participant permission, all the interviews included in this study were recorded and transcribed verbatim for analysis.

Table 1. Number of participants in each phase, per faculty

Faculty	Phase 1					Phase 2				
	ADE	DDE	APD	Other	Total	ED	APD	CE/L	HoD	Total
Business	1	1	0	0	2	0	2	1	2	5
Arts	1	1	1	0	3	2	3	1	0	6
Design and Architecture	1	0	0	2	3	-	-	-	-	-
Law	1	0	0	0	1	2	2	0	0	4
Education	1	0	3	1	5	-	-	-	-	-
Information Technology	1	1	0	0	2	1	2	0	0	3
Science	2	0	1	1	4	-	-	-	-	-
Medicine	1	1	3	0	5	1	2	1	0	4
Pharmacy	1	0	4	0	5	2	3	0	0	5
TOTAL	10	4	12	4	30	8	14	3	2	27

Note. **ADE**: Associate Dean of Education, **DDE**: Deputy Dean of Education, **APD**: Academic Programme Director, **ED**: Educational Designer, **CE/L**: Chief Examiner/Lecturer, **HoD**: Head of Department; **Phase 1, Other**: Design and Architecture (two department heads), Education (factotum), Science (committee chair)

3.3 Data Analysis

3.3.1 Phase 1 – Interviews with institutional leaders. In this step, institutional leaders were asked about their current practice of using data for planning and decision making related to educational delivery and quality enhancement within their faculties, e.g., how different types of data help them form, implement and monitor relevant educational strategies. Based on the responses, an inductive analysis [40] was performed to map critical data needs with the data channels that can be used to address them. Codes emerging during this process were thematically grouped to identify *use-cases* (i.e., usage scenarios of an academic analytics tool). The analysis resulted in 14 different themes or requirements. These themes were ranked based on the frequency of appearance. Next, the codes were further refined into 16 use-cases to better capture desirable functionality that the analytics system should support[5].

Following the coding for user case identification, we explored the interview data further by analysing segments that were previously identified as concerns or challenges. In this process, 13 different themes related to *institutional process* and *stakeholders* emerged. The former contains nine themes (codes) and the latter contains four[6]. This process involved two coders co-coding two different transcripts and resolving disagreement based on the coding results. The inter-rater reliability test result (using Cohen's Kappa) increased from 0.64 to 0.76 (0.61 − 0.80 was considered 'good' agreement [33]) after two rounds of co-coding practice. Following that, the coding scheme was finalised and one of the coders completed interview coding using NVivo software.

3.3.2 Phase 2 – Interviews with academic leaders and educational designers. As described earlier (Section 3.1), participants were invited to share their current data usage practises and rank the importance of the different data channels they have been using in relation to the two use cases we identified earlier in Phase 1 (*UC1: Ability to monitor student engagement in courses and academic programmes* and *UC2: View performance of courses and academic programmes*). We noted that the rankings for the data channels varied among participants, even for those responsible for similar academic programmes and courses within the same faculty. To reconcile the rankings of the participants to get an agreement, we employed the modified Borda Count method [13], which is a consensus-based voting system and considers a more broadly acceptable option (data channel) while performing the ranking. Similarly, we used the same approach to reconcile the faculty rankings to achieve a combined consensus to guide the design of academic analytics.

In addition to the analysis of preferred data based on the ranking tasks, we used a thematic coding approach to analyse all the transcripts, following a similar approach taken in Phase 1, except that our approach at this phase was not limited to identifying challenge/concern themes. A preliminary coding scheme was first developed based on key themes covered in the interview protocol. The coding scheme was subsequently revised multiple times in a 'spiral process' [9] where researchers read and re-read the transcripts to identify emerging themes and discussed disagreement based on the inter-rater reliability test results. The process of running inter-rater reliability tests in this phase also involved two coders and two rounds of co-coding two different interviews. In this process, the inter-rater reliability increased from 0.55 (moderate agreement) to 0.67 (good agreement), and the coding scheme was finalised. The coding scheme contains three groups of thematic codes: *data practice*, *challenges and concerns*, and *improvement and suggestions*, and a total of 41 sub-codes in these groups[7]. One of the coders completed interview coding using NVivo software.

In order to protect the identity of interviewees, the numbering of faculties in the two phases does not follow any particular order. In the remaining of this paper, we use P to denote phase, F to denote faculty, and R to denote respondent. For example, P1F2-R3 means Respondent 3 from Faculty 2 in Phase 1. P2F5-1-R1 means Respondent 1 from the first interview with Faculty 5 in Phase 2 (there were three interviews with Faculty 5 as described earlier). Whenever a participant was mentioned, we also include a bracket indicating their role using the acronyms described in Table 1.

3.4 Limitations

This study is limited to a particular context (the university where the study took place) and a small sample of participants. Although the interviews served to understand existing practice of and needs for data-based evaluations of educational

[5] A full list of the use cases and associated codes is available at https://bit.ly/3moCxsu.
[6] The coding scheme is available at https://bit.ly/3zSSEU4
[7] The coding scheme is available at https://bit.ly/3okogQ9.

quality based on the experience of participants, it is important to acknowledge that the personal views and experience of the participants cannot represent those of everyone in the same faculty or in the overall institution.

4 RESULTS

In this section, we present the results according to phases. In each phase, we have dual focuses:

- to understand user perceptions and encountered challenges regarding using data for quality measurement, and;
- to identify use cases for the design of an academic analytics system

4.1 Phase 1

In this phase, we engage with senior leadership in order to identify interest in and needs for academic analytics in each faculty. In particular, we seek to answer: *How can we use data to enhance educational quality?*

4.1.1 Perceptions and Challenges. In general, faculties used both university-provided and locally-collected data for purposes related to the evaluation and improvement of educational quality. Main data sources include course enrolment, student survey (university-wide course evaluation), log data from the university's online learning management system (LMS), grade distribution, retention, student background, graduate data, market analysis, faculty-initiated surveys and focus groups with students, and reports by external reviewers (e.g., accreditation and placements). At course and programme levels, the main interest was in using data to ensure alignment with standards of professional accreditation, coherence between courses and the degree programme, and constructive alignment of learning activities and assessment with learning outcomes, in addition to enhancing student experience, satisfaction, and overall learning performance.

Challenges and concerns raised by participants were categorised into two groups related to 'institutional processes' and 'stakeholders' respectively. In terms of challenges related to the former (Table 2a), all the faculties indicated issues with *data availability*; that is, participants desired for certain types of data, data in certain forms, or data-driven reports that were not available to them. Common issues are the lack of background information about students enrolled in a course (e.g., which year a particular student was in, which courses the student already took, and how the students performed in other courses), the lack of an overall picture of students at the programme level (e.g., patterns of course enrolment and access to learning materials), and the difficulty to track activities outside the LMS environment. Another challenge, also indicated by all faculties, is closely related to data availability; that is, *data integration*. The most common issue is regarding a laborious process of extracting data from different places about individual students, individual staff in charge of a course, or individual courses in order to map the information to a higher level.

Although not mentioned by all faculties, challenges related to indicators of educational quality had the highest reference, namely, highest counts of coded segments. Main issues related to this theme appeared to derive from the ambiguity in the definition of 'student engagement', how it was measured centrally (mainly based on the log data available on the university LMS), and hence disagreement in its implications for the quality of a course or programme. Several interviewees indicated the issue with missing the picture of engagement with activities outside the LMS environment, e.g., placement, and some questioned the meaning of engagement based on click data. The perceived misalignment between what was being measured and what was believed to need measuring has led to perceptions of university-provided data as being irrelevant or distracting instead of helpful. For example, one participant indicated,

> Often there's all this focus on providing information without any sense of understanding whether this is impactful or enabling action. Okay, so impactful would be.... the data that you provide is directly aligned with the questions that the people are wanting to ask. Not, obviously, superimposing questions. – *P1F2-R4 (Other)*

Table 2. Frequency of challenges (number of coded faculty interviews & number of references per topic)

Institutional processes	Faculty N = 9	Reference N = 128
Data availability	**9**	25
Data integration	**9**	22
Indicators of educational quality	7	**36**
Data presentation	7	18
Precision & Accuracy	5	10
Ethics & Privacy	2	6
Timing	2	5
Communication	3	5
Funding	1	1

(a) Challenges related to institutional processes

stakeholders	Faculty N = 9	Reference N = 47
Workload	**8**	15
Awareness & Capability	5	**22**
Distrust	5	9
Autonomy	1	1

(b) Challenges related to stakeholders

In terms of challenges related to stakeholders, all faculties but one indicated issues of workload (Table 2b). When comparing these issues with challenges related to institutional processes (Table 2a), we found that issues around *data availability*, *data integration*, and *data presentation* tended to attract concerns about workload, e.g., spending significant amount of time manually collecting information from different places about individual students or interpreting data in certain formats. A case in point is the difficulty to make sense of qualitative data and data in the form of spreadsheet, which was described as 'data dump' by some participants. For example,

> I find the sort of data we get really, really challenging to read. And to me, it's just like a data dump. And I just get piles and piles of Excel spreadsheets that don't even fit on my screen. And I find them almost unfathomable in terms of the density of what we get. – *P1F2-R5 (ADE)*

Although not mentioned by as many faculties as the challenge of *workload*, *awareness and capability* had the highest count of reference, namely, the most discussed stakeholder challenge. From the responses, we identified associations with two institutional process challenges: *data presentation* and *communication*. In line with the issues indicated by participant P1F2-R5 above, effective presentation of data is crucial to data interpretability, which also affects the extent to which participants felt capable of making sense of data. Similarly, the participants struggled to comprehend the data provided by the university when gaps seemingly existed in the communication with key stakeholders (e.g., meanings of engagement with the chosen indicators). Another interesting theme emerging from the conversation on *awareness and capability* challenges is the data literacy of key stakeholders, which has a direct impact on their 'data imagination'; that is, being able to think creatively and explore new ideas regarding leveraging data to support routine work:

> I don't know if there's something that exists totally outside of all of those things that could tell me something new about my students, and I just don't know what it is. So I can't ask for it, because I don't know that it exists. And I know that maybe I'm also possibly asking for something that doesn't exist. – *P1F3-R1 (DDE)*

Finally, although stakeholder *distrust* was not as prevalent as the two challenges discussed above, it was found to associate with the issue of *indicators of educational quality* particularly. In other words, when there was disagreement between the university and the faculties in the choice of indicators, this experience could lead to resistance and distrust in data-related practices or decisions initiated by the university:

> Fetishizing of data is not healthy. I know university higher-up bureaucrats love it, you know, they've got numbers, but numbers are flawed, it depends on what you're measuring.... And some of that require professional and expert understanding of the communities that your faculty serve.... University generated data has no relevance to that, really. – *P1F5-R1 (ADE)*

4.1.2 Use Cases. Based on the descriptions of functionality by the participants, we extracted higher level codes, which in turn translated into 16 use cases[8]. Each use case linked to a specific code. Based on the frequency of the codes, we identified UC1 *Student Engagement* and UC2 *Performance of courses and academic programmes* as the most desirable functions by institutional leaders for maintaining high standards of education and quality experience for learners.

UC1 *Student Engagement* was desired by all the nine faculties and was most frequently mentioned (21 times) during the interview session. The other use case that was considered almost equally important for strategic-decision making was UC2 *Performance of Academic Programmes and Courses*. The usefulness of this functionality was emphasised by eight out of the nine faculties, and it was brought about 20 times during the interview session, much higher that other next desirable use cases. Table 3 shows the top five use cases that was generated from our requirements elicitation process together with their description and desirability measures (i.e. how frequently it was mentioned in the discussion (*freq.*), and number of faculties considering it being useful (*fac.*)).

Table 3. Use cases extracted based on the coding of interviews with institutional leaders. *freq.* = number of instances that support the code. *fac.* = number of faculties that mentioned the use case as an important requirement.

Use Case	Description	Code	*freq.*	*fac.*
UC1: Ability to monitor student engagement in courses and academic programmes	This use case addresses the need to report on the behavioral, cognitive, emotional and agentic dimension of student engagement.	Student engagement	21	9
UC2: View performance of courses and academic programmes	This use case addresses the need to report on the 'health' of the academic programmes and course, e.g., student completion and attrition rates, SET scores, student performance in courses, etc.	Performance of courses & academic programmes	20	8
UC3: Ability to navigate data from macro level (aggregated) to micro level (fine-grained)	This use case acknowledges the request to see aggregated analytics but also allows the option to drill down and interrogate data at source level.	Non-Functional	15	5
UC4/5: Ability to custom tag items in LMS and reporting option	This use case acknowledges that *one-size-fits-all* may not work and thus, the need for customised reporting.	Custom features & reporting	11	6

Note. SET stands for Student Evaluation of Teaching. Use cases 4 and 5 are side-by-side functions (the former focuses on the ability to custom tag items, and the latter focus on reporting on the tagging results).

4.2 Phase 2

In this phase, we explored further the two user cases identified in Phase 1 by asking: *How can institutional data be leveraged to support the measurement of student engagement and the performance of courses and programmes?*

4.2.1 Perceptions and Challenges. From the responses, we identified three key areas of interests for measurement when faculties assessed the quality of courses and degree programmes. These are *student engagement*, *learning outcomes*, and *student experience*. The frequency of these codes being applied to the interviews is shown in Table 4.

[8] A full list of the use cases is available at https://bit.ly/3moCxsu.

In terms of *student engagement*, four codes were developed to capture interest in measuring engagement dimensions including *behavioural*, *cognitive*, *emotional*, and *agentic*. Based on the number of references (the frequency a code was applied), it is clear that the current measurement of engagement focuses on behavioural dimensions (N = 88), followed by cognitive (N = 31) and emotional dimension (N = 25), with agentic dimension attracting the least interest (N = 4). Based on the percentage distribution, Medicine seemed the most 'data-hungry' in the measurement of *student engagement*.

Table 4. Frequency of student engagement, learning outcome, and student experience codes (total number of references and percentage distribution among faculties)

	Student engagement				Learning outcomes			Student Experience
	Behavioural	Cognitive	Emotional	Agentic	Knowledge & Skill	Employability	Success or Failure	
	N = 88	N = 31	N = 25	N = 4	N = 30	N = 27	N = 18	N = 31
Arts	10.23%	3.23%	8.00%	0.00%	16.67%	11.11%	11.11%	11.63%
Business	9.09%	**29.03%**	**28.00%**	0.00%	0.00%	**29.63%**	11.11%	**22.58%**
IT	**21.59%**	**32.26%**	12.00%	0.00%	16.67%	11.11%	11.11%	6.45%
Law	**11.36%**	6.45%	**28.00%**	0.00%	3.33%	0.00%	11.11%	**22.58%**
Medicine	**29.55%**	**22.58%**	**24.00%**	**50.00**%	16.67%	22.22%	**27.78%**	**25.81%**
Pharmacy	18.18%	6.45%	0.00%	**50.00**%	**46.67%**	**25.93%**	**27.78%**	6.45%

In terms of measuring learning outcomes, three sub-areas were identified, including *knowledge and skill* development, *employability* after graduation, and the likelihood of *success or failure* in the context of a course or a degree programme. The first two areas, in particular, attracted the most interest (N = 30; N = 27). Overall, Pharmacy appeared to be most 'data-hungry' in the measurement of *learning outcomes*. As to measuring student overall experience of a course or degree programmes, usually through focus groups and surveys, Business, Law, and Medicine appeared to place a higher emphasis on this area than other faculties when evaluating educational quality.

It is worth noting that among the three key areas of measurement, there was a strong interest in identifying relationships between learning outcomes and student engagement, particularly behavioural and cognitive engagement. In terms of behavioural engagement, special interest was shown in understanding how this may relate to knowledge and skill development or the likelihood of success or failure. For example:

> Maybe the students who score better accessing (*sic*) the material at some time before a related assessment, and then again, before the related assessment, and maybe there's some way that the students who perform well used... that could then drive the faculty strategies. – *P2F6-R1 (APD)*

In terms of cognitive engagement, equal interest was shown in its relation with all the three areas of outcome measurement. For example, in relation to employability, a participant commented on the need to understand the development of teamwork skills as these are important graduate attributes demanded by the job market:

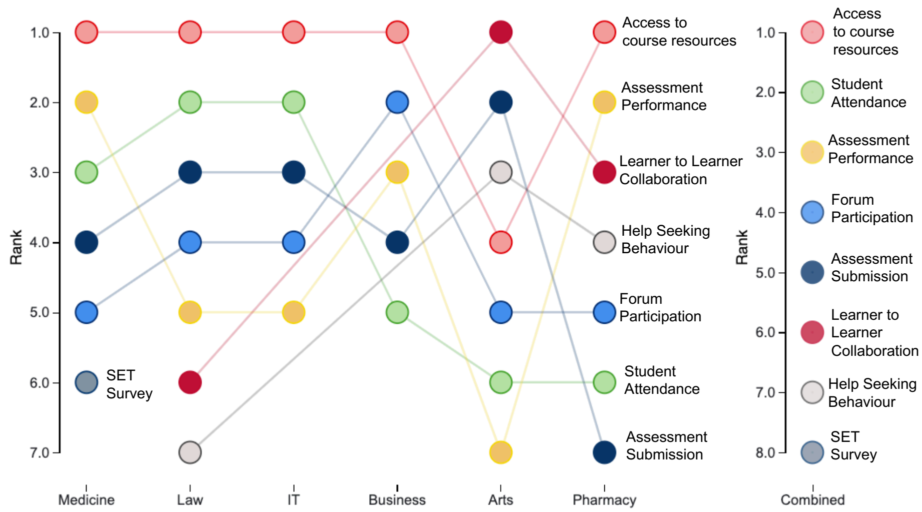
> This whole idea of them being work ready. It's not just understanding the knowledge, it's also being able to communicate, work in a team, looking at your assignment submissions. I mean, group assessment, so you want to know how they worked in the group? If someone take the lead, you know, who managed it? All that kind of stuff will be fabulous. – *P2F2-R3 (APD)*

All faculties indicated challenges or expressed concerns in areas including *data availability*, *time shortage*, and *tool/technology usage*, and issues related to *data quality* were mentioned by all faculties but one. When comparing these prominent challenges with different areas of measurement, we found that the lack of data was particularly an issue for participants when measuring employability and emotional engagement. As for the other commonly mentioned challenges, the participants tended to associate those with the measurement of behavioural engagement, perhaps due to the current focus of data practice in the institution (see Table 4). For example, when it came to challenges related to *data quality*, the participants indicated issues such as data being 'messy', 'not granular', or decontextualised (e.g., attendance may be measured in different ways). Related to these, several participants indicated that existing *tool/technology usage* was not effective, and that it was *time consuming* to extract or interpret data.

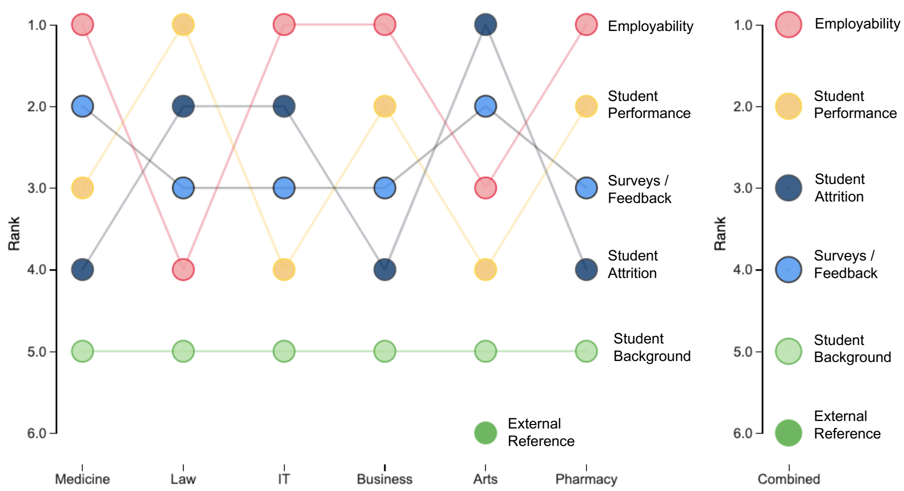
4.2.2 Use Cases. In order to prioritise what the participants would like to see in the early iterations of our academic analytics tool, we analysed their own rankings of preferred data channels and metrics for each of the two use cases previously identified in Phase 1. Figure 1 shows the outcome of how the ranking varied for the different faculties, and the reconciled (*'combined'*) ranking derived to direct the academic analytics implementation. From Figure 1a, it is evident that *access to course resources* (such as viewing lecture videos and accessing content-related sources) is perceived as a more widely acceptable proxy of student engagement across faculties (ranked as #1 in the *combined* ranking) followed by *Student Attendance*. For use case 2, it is evident that the faculties had far more differences on how they ranked the various data channels to report on performance measurement of courses and academic programmes (Figure 1b). *Employability of Graduates* was generally ranked higher for this use case, while there was agreement of *student background* as the lowest priority compared to the other four indicators. Overall, we can conclude that there is perceivable variation in ranking among the faculties for both the use cases, which suggests that flexibility, such as filtering options, needs to be a key element of the design for academic analytics in order to cater the varied contextual and teaching needs of the faculties.

5 DISCUSSION

In this study, we sought to identify design needs and strategic approaches for academic analytics system. To this end, we embarked on a co-design journey, focusing on two initial phases: *define goal/question* and *ideate* [7], with the objectives to 1) identify use cases, and 2) understand user perceptions and challenges encountered regarding the use of data for quality measurement. As suggested by Martinez-Maldonado et al. [34], our approach started by defining key stakeholders – faculty leaders in charge of educational portfolios, academic leads at course/ programme levels, and educational designers. In Phase 1, through interviews with faculty leaders, we aimed to answer the question: *How can we use data to enhance educational quality?* From the responses, we were able to identify two use cases (UC1 & UC2 in Table 3), which reflected the key areas of interests and allowed us to define the goals/questions [7] that concern faculties when using data for quality measurement. It became clear at this stage that the key challenges that faculties wrestled with as part of the institutional process, such as *data availability*, *data integration*, and *data presentation*, contributed to undue/unwanted *workload* (Table 2). This clarified a strategic need; that is, the design and adoption of an academic analytics system in the institution need to effectively reduce the efforts required for faculties to access required data and make sense of it. On the other hand, this finding suggests that effective implementation of academic analytics may require institution-wide transformation of the data systems to address the common issue of siloed data in higher education institutions due to the lack of strong data governance and management frameworks [2]. This also means the success of academic analytics can not be without key leadership that can mobilise resources and create an enabling environment for innovations [10]. In addition to leadership support and system-level transformation, the connections between *institutional process* challenges and *stakeholder* challenges (Table 2) also have important implications for



(a) UC1: Student Engagement



(b) UC2: Performance of courses & academic programmes

Fig. 1. Rankings for (a) UC1 and (b) UC2 by faculties and reconciled combined rankings

adoption strategy. As learning analytics adoption studies have shown [8], stakeholder awareness and capability are crucial to an institution's readiness for learning analytics and its scalability. Our study found that the effectiveness of *data presentation* and *communication* are closely related to *awareness and capability*. This suggests that having a sound and user-centred tool design that can enhance sense-making is not good enough. Equally important is transparent and two-way communication to scale stakeholder awareness of the purpose of academic analytics and the rationale behind selected metrics for measurement, so as to cultivate a sense of trust.

In Phase 2, we focused our investigation based on the two identified use cases by asking: *How can institutional data be leveraged to support the measurement of student engagement (UC1) and the performance of courses and programmes (UC2)?*

This was an *Ideate* phase of co-design, as suggested by Chatti et al. [7], in which the goal was to co-generate ideas with key stakeholders for indicators that may answer the defined question. We found that although there was no clear agreement in terms of preferred data channels for the measurement of course/ programme performance (UC2)(Figure 1), there was consensus that student background information was not as crucial as other types of data when it comes to quality measurement, even though this data was of particular interest to the participants in so far as providing insights for lecturers who have direct interactions with students. This exemplifies the benefit of a co-design approach in clarifying design requirements according to the targeted users, in our case, academic leads and faculty leaders. In addition, there was general agreement that being able to see patterns of access to course resources is important to the measurement of student engagement. Interestingly, while several faculty leaders that participated in Phase 1 expressed doubts in equating clicks with student engagement, responses from participants (who worked closely with data in each faculty) in Phase 2 revealed that the focused area of measurement of student engagement was the behavioural dimension, and their prioritised data type for this measurement suggested log data. This is understandable as such information is easier to collect in a passive and unobtrusive way [36]. However, the seemly discrepancy in views expressed by participants in the two phases has two important implications. Firstly, there is a perceivable gap in the understanding of technical constraints and pedagogical needs for different stakeholders. While the latter can be a demand driver to improve the former, this gap in understanding can also result in dissatisfaction or even distrust, as discussed earlier. On the other hand, the complexity of student engagement [26, 38] suggests that more work is needed to enable effective measurement. In other words, an important area of work, and potential for innovations, for academic analytics (and learning analytics) is to tackle technical constraint (e.g., commonly available data can only show information limited to, and as a proxy of, online engagement) and challenge the mentality of being content with data that is easily collectable. Secondly, not only did the rankings in Phase 2 reflect what participants desired, but also what they believed to be possible. As found in Phase 1, 'data imagination' could be an issue when there is limited exposure to different types of data. This is an important implication for adoption strategy in terms of stakeholder training.

Another important lesson learnt from our consultations is the need to cultivate a supportive culture as opposed to a judgemental culture for data. As evidenced by the results, each faculty had distinctly different learning activities and varying levels of interest in and experience using data to measure educational quality. When academic analytics was provided in a one-size-fits-all manner without effective communications regarding the rationale behind chosen metrics or flexibility for interpretations, a sense of being judged unfairly was noted among some faculties, resulting in distrust and resistance to 'centralised' data practices. This can be detrimental to the success of academic analytics even if leadership support is in place. Thus, we posit that context-based flexibility must be a key principle of tool design and institutional communication strategy should focus on negotiating intentions behind chosen metrics with the stakeholders involved in contributing to or interpreting data generated for the purpose of educational quality measurement. While the study was based in a particular higher educational context, our learnt lessons may provide adoption directions for institutions that face similar issues.

6 CONCLUSION AND FUTURE WORK

Our approach postulates that the value of co-design for academic analytics should not be limited to identifying user needs. Instead, the consultation with key stakeholders or key users should also seek to identify how people perceive the value of data in their focused practices and what might concern them about analytics, so as to ensure that a well-designed system can be implemented in a strategically sound manner to achieve institutional goals for quality measurement. We learnt from the experience that commitment of institutional leaders can be challenging during multiple phases of co-design for academic analytics, yet is critical to address challenges and complexities of academic analytics. Our work contrasts with many existing efforts in LA on co-design/co-creation and HCLA, where limited involvement 'across' the institutions (faculties) can easily lead to development of analytics solutions in silos [3]. Our next step is to introduce a low-fidelity prototype early into the hands of institutional leaders to further ascertain important insights into the requirements for tool design. Following that, we will seek to test the tool and have continuous engagement with key users to optimise value that may be created through a participatory process.

ACKNOWLEDGMENTS

We would like to thank colleagues who have provided generous support in arranging the interviews and throughout the study. We are also grateful for all the participants for their valuable inputs and time.

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