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Data Literacy and Data Usage Amongst Teaching Staff in UK Higher Education Institutions: Current Practices, Challenges, and Aspirations

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Abstract. While research on Learning Analytics (LA) is plentiful, it often prioritises perspectives on LA systems over the practical ways instructors use data to analyse and refine the learning process per se. The present study addresses this inadequacy by investigating how student data is employed by educators in UK Higher Education Institutions (HEIs) and how it could be optimised. Specifically, a mixed-methods approach was employed combining survey data, mainly from one institution (N = 85) with insights gleaned from interviews with academics (N = 11). The findings reveal a real desire for better data capabilities and access, underscoring the need for HEIs to enhance data capture, better integrate systems and invest in professional development to enhance data literacy and foster a culture of data-driven decision-making. Importantly, a similar emphasis to that given to assessment and attendance needs to be given to data for the differentiation and personalisation of learning.

Keywords: data-driven decision making, higher education, pedagogical data use, educational data literacy, educators.

1. Introduction

1.1. *Problem Statement*

The adoption of educational technologies in teaching and learning has led to the development of large sets of learning- related data (Ley *et al.*, 2022). Naturally, this abundance of data has led universities to develop an interest in exploiting the digital traces left by students when interacting with institutional systems, in order to understand how their educational experience is shaped (West *et al.*, 2020). However, the growth of data availability does not automatically translate to an increase in educators' ability and capability to make use of such data to inform their instructional strategies as they need to possess the requisite data literacy skills (Henderson and Corry, 2021).

A broad definition of data literacy refers to the ability to understand and use data to inform decisions (Matthews, 2016). This encompasses specific skill sets and knowledge required to enable individuals to transform data into information and then into knowledge (Papamitsiou *et al.*, 2021). Generally, such skills comprise the ability to identify, collect, analyse, and interpret data through extraction, analysis, visualisation, and interpretation procedures (Raffaghelli and Stewart, 2020). However, when it comes to instructional practice and decision-making, educators are also required to have pedagogical content knowledge know how to apply the educational data (Cui & Zhang, 2022).

Alongside literacy, self-efficacy is also one of the most important determinants in data use for individuals to feel competent and confident in using certain skills and employ them effectively (Kurbanoglu, 2003). Bandura (1982) defined self-efficacy as a personal belief that one possesses the skills and capabilities to perform tasks successfully. However, in the case of data driven decision making, educators may lack the skills and confidence to work with data and the anxiety they feel related to their ability to engage in DDDM (Dunn *et al.*, 2013).

Although universities do offer opportunities for professional development and training, these resources are often limited and inconsistently available (Ndukwe and Daniel, 2020). Moreover, the lack of standardised training exacerbates the existing ambiguity surrounding the specific competencies required for data literacy development (Lin *et al.*, 2023). This lack of clarity manifests in the available training programs which often prioritise technical skills over the personalised approach to data usage that educators need (Raffaghelli and Stewart, 2020). Additionally, the conflation of data literacy with assessment literacy further complicates this issue as the latter encompasses dimensions beyond data-related skills (Siemens, 2013).

1.2. *Contribution of the Study*

Despite data's critical role in enhancing teaching and learning practices within Higher Education (HE), a significant disconnect persists between data availability and educators' capacity to effectively use it. Current data literacy initiatives and training programs often fall short in equipping academics with the necessary skills and understanding to meaningfully integrate data into their pedagogical practices. Consequently, this creates the need to investigate the specific barriers hindering data use among academics.

The present study sheds light to the current landscape of data utilisation within UK Higher Education Institutions (UKHEIs) with the aim of identifying current practices, challenges, and aspirations regarding data use. By developing a deeper understanding of these factors, we can inform the development of tailored tools, training programs, and resources that directly support and empower educators to harness the full potential of data.

In this study the term data refers specifically to student data related to teaching and learning generated by institutional digital platforms and educational technologies. This includes data collected from learning management systems (LMS), virtual learning environments (VLEs), learning analytics dashboards, assessment platforms, and other AI or data powered educational tools. Such data may encompass metrics on student engagement (e.g., logins, clicks, resource views), academic performance and attendance. Our focus is on how instructors interpret and apply this type of data to inform teaching and learning strategies. With this aim, the present study explores and responds to the following research questions (RQs):

RQ1: *How do instructors from UKHEIs use teaching and learning student data in their practices and what are the challenges they face in doing so?*

RQ2: *What is the relationship between data use and instructor characteristics and confidence / self-efficacy?*

RQ3: *In addition to data that instructors actually use, what additional data would they ideally like to have to address their personal pedagogical goals, and what training is needed to achieve this?*

2. Materials & methods

2.1. *Research Design*

We employed a sequential mixed-methods design (Creswell & Plano Clark, 2023) to investigate how academics make use of student data in their practice. This approach allowed for the quantitative data to inform the development of the interview questions and guide the selection of participants for the qualitative phase. The design involved two distinct phases:

- **Phase 1**: A survey to collect data on the prevalence of student data use, identify patterns and trends, and explore potential relationships between data utilisation and various demographic and contextual factors.
- **Phase 2**: Semi-structured interviews to gain deeper insights into the motivations, challenges, and perceptions associated with student data use, as well as to explore desired data needs that are not currently being met.

All participants provided informed consent before participating in the study.

2.2. *Participants*

Academics across all the UK HEIs were invited to participate in the study via the contact details that are publicly available on their institution's website. A total of 108 academics initially expressed interest in the study and eighty-five (85) of them completed the questionnaire. Of these, twenty-three (23) respondents expressed interest in follow-up interviews, and a purposive sample of eleven (11) was selected. The interview sample was diverse, representing different UK universities and subject areas.

2.3. *Data Collection*

In line with the research plan, the data collection process consisted of two distinct phases:

Phase 1: Quantitative Data Collection

A cross-sectional questionnaire survey (Appendix A) was distributed to academics via email. The survey instrument, comprised four sections, was developed based on existing literature from which the question sets on data usage and self-efficacy were taken (Reeves *et al.*, 2016) and refined through pilot testing with a small group of academics (N = 5). This surfaced one query about what was meant by "data" and "data use", and so our definitions were added to the questionnaire[1]:

- **Section 1 (RQ1)**: Demographic data (gender, age, academic role, years of experience) were collected to understand participant characteristics and their potential influence on skills and perceptions.
- **Section 2 (RQ1)**: Assessed participants' use of student data in relation to their teaching areas, the frequency of use, and the specific types of data used (e.g., assessment results, attendance records, application of LA practices).
- **Section 3 (RQ2)**: Explored participants' views regarding data collection and analysis processes, focusing on their skills and confidence levels in areas such as data cleansing, statistical analysis, and interpretation of results.
- **Section 4 (RQ3)**: Gathered participants' written responses regarding the training they had received on student data use, as well as the types of training available at their institutions. This section also included open-ended questions to capture additional thoughts and experiences.

Phase 2: Qualitative Data Collection

Semi-structured interviews were conducted online via MS Teams with. Interviews averaged thirty (30) minutes in length, were audio-recorded with participant consent, and transcribed verbatim. The interview guide (Appendix B) focused on participants' data use practices, skills, and perceptions regarding student data. Specific questions explored:

- The sources of their knowledge about student data and how this knowledge has evolved (*RQ1*).

[1] "**Data** are pieces of information and include assessment data (e.g., test scores, student performance on formative and summative assessments and student work) as well as other types of information such as attendance and demographics.
Data use is the process in which an actor accesses or collects data, filters, organises, or analyses data into information, combines information with expertise and understanding to build knowledge."

- The types of student data they use most frequently and find most valuable (*RQ1*).
- The challenges they face in accessing, analysing, and interpreting student data (*RQ1*).
- Their confidence levels in using student data and the factors that have influenced their confidence (*RQ2*).
- The types of data they would like to have access to but currently do not (*RQ3*).

2.4. *Data Analysis*

2.4.1. *Quantitative Data*

Descriptive statistics (frequencies, percentages, means, standard deviations) were used to characterise the demographic information of survey respondents and their responses to closed-ended questions. Chi-square tests were employed to examine potential relationships between categorical variables, such as the relationship between subject area and confidence in data use (Cohen, 2013). Correlation analysis was used to explore the strength and direction of relationships between continuous variables, such as the correlation between years of experience and frequency of data use (Cohen, 2013). Finally, an analysis of variance (ANOVA) was conducted to examine the potential influence of Data-Driven Decision Making (DDDM) self-efficacy on overall data usage. All statistical analyses were conducted using *R* v4.3. Responses with missing values were excluded.

2.4.2. *Qualitative Data*

Following the transcription of interview data, the transcripts were uploaded to NVivo 14 for further examination. Thematic analysis was employed to identify and interpret patterns of meaning within the data (Braun and Clarke, 2022). An inductive approach was adopted, allowing themes to emerge organically from the participants' responses (Thomas, 2006). Codes were developed based on both the explicit (semantic) and implicit (latent) meanings conveyed in the participants' words (Miles *et al.*, 2014).

3. Results

3.1. *Surveys*

3.1.1. *Background Information*

Respondents (N = 85) were primarily male (64%) and represented diverse experience levels, with a relatively even distribution across years of service (Table 1). The most common subject area was computing (37%), followed by business (12%) and education (11%). The majority of respondents were affiliated with University of West of England (UWE, 76%).

Table 1
Breakdown of survey respondents (N = 85)

Characteristic	Categories
Gender	Male: 54 (64%), Female: 25 (29%), Self-describe: 2 (2.4%), non-disclosed: 4 (4.7%)
Years of Experience	0–4: 19 (23%), 5–9: 24 (29%), 10–14: 13 (15%), 15–19: 8 (9.5%), 20+: 20 (24%), Unknown: 1
Subject Area	Computing: 30 (37%), Business: 10 (12%), Education: 9 (11%), Architecture: 7 (8.5%), Health: 8 (9.8%), Mathematics: 3 (3.7%), Transport: 2 (2.4%), Construction: 3 (3.7%), Engineering: 5 (6.1%), Geography: 3 (3.7%), Media Communications: 2 (2.4%), Unknown: 3
Institution	UWE Bristol: 64 (76%), De Montfort University: 2 (2.4%), LJMU: 1 (1.2%), Bedfordshire: 3 (3.6%), Coventry University: 1 (1.2%), Cardiff Metropolitan University: 1 (1.2%), Warwick: 1 (1.2%), Newcastle University: 1 (1.2%), Aston University: 1 (1.2%), University of Glasgow: 2 (2.4%), Loughborough University: 1 (1.2%), University of Birmingham: 1 (1.2%), University of Sheffield: 2 (2.4%), University of Leicester: 2 (2.4%), Edinburgh Napier University: 1 (1.2%), Unknown: 1

3.1.2. *Confidence in Data Use*

Exploratory factor analysis was conducted on the DDDM self-efficacy scores, with minimum residual, as the factoring method. A four-factor solution was suggested by Eigen values and scree plot elbow, indicating that four underlying latent variables could explain 0.97 of the variable correlation. These factors are illustrated in Fig. 1 with their variable and co-factor correlations. These could be associated by our own interpretation as: 1) ratings related to data anxiety, 2) self-efficacy with university tools, 3) self-efficacy with data for assessment and 4) self-efficacy with data for other pedagogy (non-assessment purposes). This factoring differs from that of the original DDDM scale developers (Dunn *et al.*, 2013), who had the same factors for anxiety and tools, but divided the remainder into factors for data identification, interpretation and application, i.e. they did not distinguish assessment from other pedagogy as we have done. We suggest this is due to differences in the population studied – Dunn *et al.* (2013) basing their analysis on US K12 school teachers rather than UK academics.

This difference was confirmed by a *t*-test to compare assessment to other pedagogy ($t = 5.477$, $df = 80$, $p < 0.01$). The marked nature of our distinction between self-efficacy related to assessment data as opposed to other pedagogical information is illustrated by comparing the average scores on the three factors excluding anxiety (Fig. *2*). Respondents rated as themselves significantly more confident working with assessment data than with other pedagogy or tool use.

To understand our sample characteristics, we conducted a clustering on individuals based on the principle components of the DDDM self-efficacy scores. Three clusters were suggested, which we label in Fig. 3 as low, low-medium and high self-efficacy. The low-medium group straddled the middle ground in terms of self-efficacy, but tended to be higher on their data anxiety ratings.

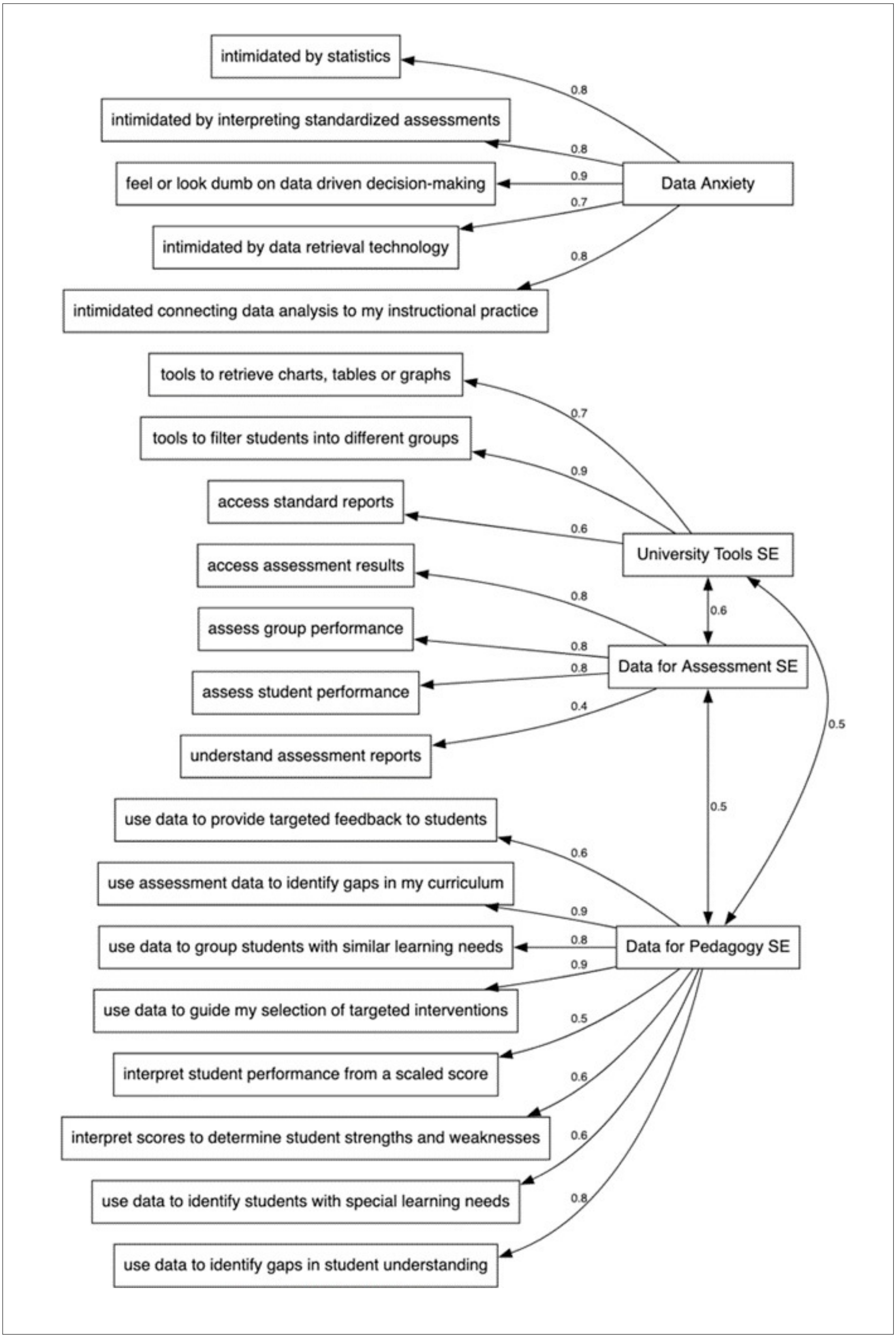

Fig. 1. Relative levels of self-efficacy factors (N = 85).

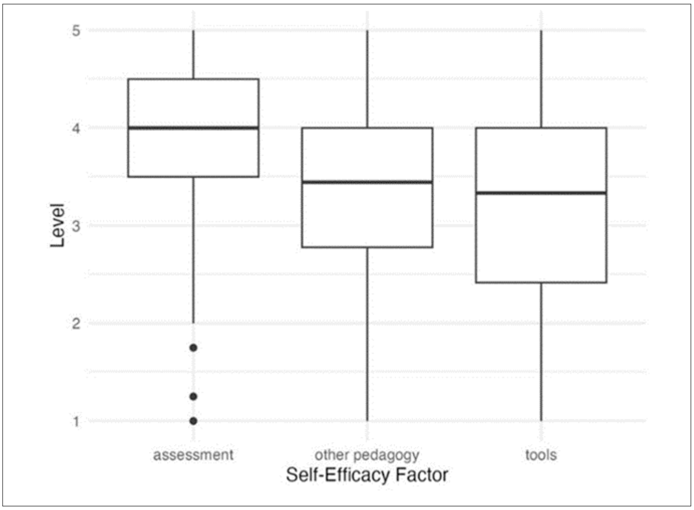

Fig. 2. Relative levels of self-efficacy factors (N = 85).

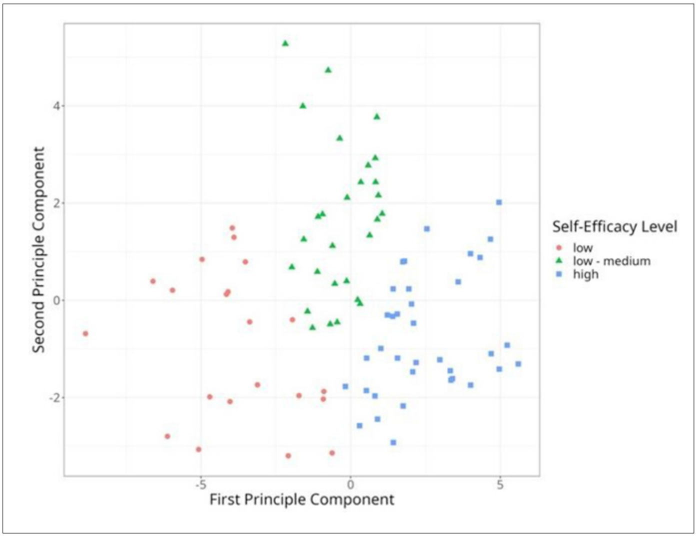

Fig. 3. Cluster analysis of self-efficacy levels.

The analysis of data usage frequency among educators reveals an interesting picture of their practices. Teachers frequently employ data for tasks directly tied to managing and evaluating student learning, as evidenced by the high ratings for giving feedback (M = 2.45), evaluating instruction (M = 2.34), communicating performance (M = 2.31), and lesson planning (M = 2.28). This emphasis on using data for immediate and aggregate feedback underscores the importance placed on monitoring overall classroom performance and making broader adjustments to instructional strategies.

However, a significant gap exists when it comes to using data for more individualised, student-centred practices. Differentiating instruction (M = 1.82), selecting appropriate scaffolds (M = 1.77), and identifying students who need individualised support (M = 1.68) are among the lowest-rated applications of data. While educators generally value data- driven decisions, they may not be fully utilising this approach to tailor instruction to each student's unique needs.

To understand the relation between DDDM self-efficacy and the 27 data usage scores, we conducted an ANOVA comparing the data usage of the three clusters. As hypothesised, it showed a significant effect of self-efficacy cluster on data usage ($F(1, 83) = 23.8$, $p < 0.001$). This result confirms significantly higher overall usage of data in the higher self-efficacy cluster.

Multiple regression of the extent and spread of data usage and literacy scores against the gender, experience and discipline of respondents did not reveal any significant relationships. For example, those teaching between 0 and 4 years reportedly made more use of data than those with 5–9 years of experience, but less than those with 10–14 years, so the relationship was non-linear. Respondents from STEM subjects were not recognisably more data literate than those from non-STEM. In our sample, women were marginally more likely to make use of learning data, but this finding was non-generalisable.

3.2. *Interviews*

The participants represented a diverse range of academic disciplines, including Computer Science, Business, Geography, Media & Art, Applied Science Education, Architecture, and Engineering (Table *2*). This diversity ensured a broad range of perspectives on the use of student data in HE. The participants also held various academic roles, with lecturers and senior lecturers comprising the majority. Years of working experience

Table 2
Background information of the interview participants.

Participant	University	Role	Subject area	Years of working experience
1	UWE Bristol	Lecturer	Computer Science	8
2	UWE Bristol	Lecturer	Business	20
3	UWE Bristol	Senior Lecturer	Business	9
4	Loughborough	Lecturer	Business	7
5	Leicester	Associate Prof	Business	17
6	UWE Bristol	Senior Lecturer	Geography	3
7	Coventry	Lecturer	Media & Art	9
8	UWE Bristol	Senior Lecturer	Applied Science-Anatomy	12
9	UWE Bristol	Senior Lecturer	Education	22
10	UWE Bristol	Senior Lecturer	Architecture	6
11	UWE Bristol	Senior Lecturer	Engineering	8

ranged from 3 to 22 years, providing insights into the experiences of both newer and more established academics.

The identified codes were grouped into four overarching themes:

1. **Understanding and Context**: How academics learned about student data and their evolving knowledge.
2. **Practical Applications**: The specific types of student data used in teaching practice.
3. **Pedagogy and Data Preferences**: Desired data that is not currently accessible and its potential impact on teaching.
4. **Confidence and Skills**: Building confidence in accessing and interpreting student data.

Theme 1: Understanding and Context: (exposure to data, motivation, training)

Motivation served as a powerful driving force for participants' interest in and learning about student data as, the desire to understand student performance, progress, and engagement to inform and improve teaching was a recurring theme. P1 noted that data helps to "keep track of what I'm doing so far, and what I need to do next," while P7 expressed a "fascination of data analysis" to enhance teaching and engagement.

Initial exposure to student data varied among participants; some were driven by personal interest and curiosity, leading them to independently explore available data (P2) whereas senior participants often gained initial knowledge through institution-provided training related to their leadership roles. However, this training was not perceived as helpful for data analysis and interpretation as most participants acknowledged a lack of clear instruction and opportunities to develop data literacy and analytical skills. P7 confirmed, "So we do get training on Blackboard mainly on how to use it, how to create content on Blackboard, but as far as I know we have not had any training … about the analytics".

Guidance and collaboration with colleagues emerged as an important avenue for learning, supplementing inadequate training and fostering confidence in data use. P4's advice to "ask colleagues to find out things as training is not enough to understand how to find the information you need" highlights the value of peer support in navigating the complexities of student data analysis.

Theme 2: Practical Applications (identify patterns, adjust teaching, tools, platforms and how they prioritise data)

Participants consistently emphasised the importance of engagement and student background data in their teaching practice. Engagement data, primarily gathered from Learning Management Systems (LMS), encompassed metrics such as content access, resource downloads, and material selections. Academics sought insights into content preferences and usage patterns, with P3 noting, "I'm just trying to see what perhaps they didn't select the most and what content they're using the most".

Frequency data, including time spent on activities and frequency of accessing materials, provided insights into student understanding, teaching clarity, and topic difficulty.

Lower engagement often indicated a need for additional support, as P7 remarked, “At the moment it’s basically just how often do they access [LMS] materials and also, how often they access the same type of materials so often? Do they have to repeat a certain topic which was taught?”.

Engagement and student background data were prioritised across various data sources. Student background data, such as ethnicity, prior degrees, and commitments, aided in understanding support needs and tailoring instruction. P4 explained, “Especially towards the beginning of the semester when I have a new cohort of students to teach. I take a look at their previews, the history, especially if they are students who studied at the university before...in order for me to know where my students stand and whether I need to make any changes in my lecture”.

Attendance data, often used in conjunction with grades, offered insights into student behaviour and performance. Low attendance could trigger interventions, such as encouraging peer engagement (P1). Likewise, assessment and performance data were highly valued for comparison with attendance data, providing a deeper understanding of student performance (P11).

Academics also valued student feedback as crucial data for understanding teaching and improving learning. Addressing and responding to feedback, especially collaboratively with students, was considered vital. P1 described a cyclical process: “I use student feedback during the term to inform my next steps and plans for improvement. I then share these plans with the students”.

Engagement and attendance data were primarily used to identify patterns in student performance and adjust teaching strategies. High engagement with course materials was seen as an indicator of both understanding and enjoyment of learning. P10 noted, “We use regular assessments to identify students who might be struggling or not engaging. We analyse submission patterns to offer extra support,” underscoring the role of data in tailoring interventions.

Both the data collection and analysis processes were primarily conducted through the university’s LMS and built-in visualisation tools. However, many participants preferred Excel for record-keeping, analysis, and visualisation. Interestingly, some participants reported using data visualisation tools like Tableau, Power BI, and Co-tutor for clearer summaries of student performance and engagement. For instance, as P4 stated, “Tableau provides an aggregated summary of student performance...allowing for changes to the program or discussions with module leaders on engagement strategies”. Such claim highlights the use and, perhaps, the necessity of advanced tools to inform both programmatic and instructional decisions.

Theme 3: Pedagogy and Data Preferences (data they wish to have, misleading data and challenges they face related to data)

Participants expressed a strong desire for access to data that could enhance their understanding of students and refine pedagogical strategies. This included deeper insights into student background information, such as commitments, psychological well-being, and overall satisfaction, as well as more comprehensive and accessible engagement, performance, attendance, and assessment metrics. Below we summarise the key categories as they emerged:

1. **Challenges with available data**
   In their initial remarks, participants mentioned concerns about the challenges they face regarding the available data. Many expressed a need for faster feedback about student satisfaction. For instance, P3 envisioned a system capable of "rapidly gathering feedback from all seminars" whereas P7 mentioned other online platforms that use simple "thumbs up/thumbs down" buttons to quickly assess comprehension and content preferences. Furthermore, faculty members highlighted the need for data that could shed light on students' psychological states and learning approaches. For instance, P7 noted the challenge of differentiating genuine engagement from superficial interaction on online platforms by stating that "I would appreciate...a way to analyse how students are studying psychologically... so I can truly judge if someone is truly engaging...not just clicking around on Blackboard". Such desire for deeper insights into student behaviour and motivation emphasises the need for data that goes beyond basic engagement and attendance measurements.
2. **Limitations of available data**
   Instructors also found the available data to present several difficulties in their processing and interpretation. For instance, P3 desired more engagement-related metrics, noting that simple metrics like "views" or "clicks" do not adequately reflect student understanding ("I'd prefer metrics that go beyond simply opening a document to assess actual understanding"). Others emphasised the importance of having access to more comprehensive performance data particularly across different modules. To this end, P3 suggested that access to students' grades in other courses could help instructors identify areas where their own courses might need improvements or adjustments. Another, system-related limitation concerns the tracking of attendance as, some participants (P10, P7), found it disconnected from grade information thus, making it difficult to get a complete picture of student engagement-performance. Besides, P10 wished for a more streamlined way to view attendance across all courses, especially when responding to student inquiries, while P7 further shared these concerns and criticised the university's systems for focusing more on student access to materials rather than demonstrated understanding of the material. These collective experiences reveal a common thread; instructors believe that the current limitations of available data make it difficult to fully grasp student engagement, adapt their teaching methods effectively, and ultimately enhance student success.
3. **Data Overload and Fragmentation**
   Respondents frequently expressed feeling overwhelmed by the rapid expansion of the educational data resources. More precisely, they seemed worried about missing out on valuable information with one participant (P9) noting, "The fear of overlooking a dataset that could truly transform my teaching is always there". This lack of awareness prevents educators from fully leveraging data to inform and enhance their practice. Likewise, the fragmented nature of student data also

poses significant obstacles. The absence of a centralised system to aggregate and consolidate student-generated data limits educators' capacity to identify broader trends. As a result, participants expressed a strong need for a unified platform under the belief that it would streamline their workflow and provide program leaders with more comprehensive insights. This was simply expressed by P9, who underlined the importance of having "everything in one place", and further echoed by P10, who described the existence of a central repository as a "game-changer".

4. **Interpretation and application of data**
   Instructors encounter several challenges when utilising student data that hinder their ability to support and understand individual student needs. As one instructor (P9) put it, "It's not just about having data; it's about understanding the 'why' behind it". Indeed, simply having data without context is insufficient for providing tailored support to students. As a result, the method of data collection and the questions it seeks to answer were also highlighted as critical factors. Another instructor (P7) noted, "If we ask the wrong questions, we'll get the wrong data–not necessarily misleading–but simply not what we need". Indeed, the importance of providing educators with robust support systems, capable of guiding them in interpreting and applying the insights into their practice, cannot be stressed enough. Likewise, the general and aggregated nature of the available data was also raised as a concern. Instructors found it difficult to apply generalised data to individuals' needs. As P8 argued, "the lack of context behind the data limits its effectiveness in addressing specific student challenges". Furthermore, participants expressed a need for direct and timely access to National Student Survey data as the current practice that the universities follow – i.e., to provide them with report that encloses the key insights summarised – usually comes with delay and thus, prevents them from addressing their students' concerns promptly.
5. **Desired data**
   Instructors also expressed a strong need for additional data to better understand and support their students. For example, P1 highlighted the difficulty of accessing information on students who need learning accommodations whereas, P8 echoed this concern and emphasised the limited information available to instructors regarding students' personal matters such as part-time jobs, commuting situations, access to university resources, and family circumstances. This lack of a holistic view, what P8 referred to as a "silo mentality", prevents effective information sharing between student support services and academic staff.

Academics seemed also concerned about the difficulty in accessing even the "limited available information" on student learning challenges. P6 stressed the importance of understanding learning difficulties in order to provide inclusive teaching practices. However, the restrictions applied in the current system prevent academics from accessing such data. Others pointed out to the potential value of knowing about student commitments – such as long commutes or family-related responsibilities – as this information could help address issues like persistent lateness.

Instructors also expressed a desire for more detailed engagement data, specifically the frequency and timing of student interactions with the course materials. The current system's limitation of registering only a single access point per material, regardless of revisits, prevents accurate assessment of student engagement. Furthermore, delays in updating student records – especially regarding assessments – cause frustration and create discrepancies between real-time student performance and data availability with one instructor (P9) citing instances where "data lag resulted in discrepancies between student self-reports and official records". To address these challenges, instructors suggested integrating quizzes into the Virtual Learning Environment (VLE) to better understand student comprehension. They also reiterated their desire for more granular engagement data, such as frequency and timing of access with specific resources.

Theme 4: Confidence and Skills (instructional support to improve data literacy, collaborative efforts, suggestions and advice)

Participants consistently reported that confidence in data literacy is a journey, cultivated through experience, practice, and increased familiarity with data. As P4 noted, "Year by year, confidence is improved in terms of accessing, interpreting and utilising student data...training helps and advice from colleagues...year after year you get experience."

Initial apprehension surrounding new systems like Blackboard was common, but hands-on experience proved to be a powerful antidote. P2 recounted, "Everyone is afraid of doing something that would break the system...I do remember investing quite a lot of time in understanding the feature...how to set up assessments in Blackboard." To this end, institutional support, primarily focused on data privacy training, seems to have left participants with a perceived need for further instruction in data management, analysis, and supplementary tools like Tableau and Power BI.

Collaboration also emerged as a key confidence booster, with P10 sharing, "When I didn't understand things to start with, I just asked colleagues to show me...the more you do it, the easier it becomes." While senior staff frequently engaged in collaborative data-driven problem-solving, junior colleagues reported limited involvement in such efforts. To this end, some participants offered the following advice to colleagues hesitant about data utilization:

- "Utilise data to gain a deeper understanding of your students".
- "Leverage data to identify areas for improvement in your teaching practices".
- "Seek guidance and support from colleagues and mentors".

The above are in line with participants' universal acknowledgement concerning the importance of developing their understanding on data and its applications. Indeed, such processes require continuous learning combined with practical experience as well as targeted training and support to apply the theoretical knowledge into their daily routine. To this end, P3 summarised this sentiment, perhaps, in the best possible way: "Data has become increasingly crucial as my experience grows. It's the only reliable way for me to gauge the effectiveness of my work".

4. Discussion

Responding to the call for further research in data utilisation within HE (e.g., Banihashem *et al.*, 2022; Márquez *et al.*, 2024), our study contributes to the evolving discourse by investigating the motivations, practices, and hurdles that educators face. Both the quantitative and the qualitative data revealed a complex interplay between data availability, skill levels, and the perceived value of student data in shaping teaching strategies.

A key finding is that, even with limited resources or knowledge, educators are willing to harness the power of student data in order to enhance their practices. This applies to educators of all levels, irrespective of their (self-assessed) skill level or the comprehensiveness of the information available. However, we did observe a disparity in data use between junior and senior academics, with junior staff reporting more restricted access to data thus, leading us to suggest that institutions should revise their policies in order to ensure that there is equitable access to data across all levels of seniority within academia. In addition, it underscores the necessity for institutions to invest in both data infrastructure and professional development to fully enable educators make data-driven decision-making, to provide feedback to students but also to gain insights into their own teaching effectiveness (Almasri *et al.*, 2022).

In response to the first research question concerning the educational data use in practice, the findings reveal that UKHEIs instructors primarily use data for feedback provision, instructional effectiveness assessment, performance communication, and lesson planning. This emphasises the critical role of data in shaping overall instructional approaches and monitoring classroom performance. However, a noticeable underutilisation of data exists in individualised, student-centred practices. Tasks like differentiating instruction, selecting appropriate supports, and identifying students needing individual assistance are less frequently data-driven. It is likely that stronger institutional policies on supporting differentiation would lead to stronger data exploitation in this area. Furthermore, the expressed desire for more comprehensive and accessible data, including deeper insights into student backgrounds and engagement patterns, suggests that enhancing data systems and tools could facilitate more effective exploitation of data.

Regarding the second research question, which examined the influence of instructors' characteristics in data use, a positive correlation between educators' self-efficacy and data use frequency is identified. In other words, teachers with greater confidence in their ability to effectively collect, analyse, and interpret data are more likely to integrate it into their teaching routines. The interview results validate this finding and further suggest that motivation and personal interest play a crucial role in driving educators' engagement with student data. Furthermore, the findings revealed that years of experience, gender, subject area and academic rank did not consistently correlate with higher data literacy or increased confidence in data use. Although senior academics often had initial exposure to student data through institutional training, this training was not always considered as practical in this regard. Therefore, it can be suggested that professional development efforts should not exclusively focus on new teachers but, instead, should address the needs of experienced educators who may also require specialised training in data analysis and interpretation techniques.

Another aspect of interest that emerged through the interviews concerns the importance of collaboration and peer support in fostering confidence and competence in data use. Specifically, participants who actively sought guidance from colleagues and mentors reported feeling more empowered to explore and make use of student data. This observation underscores the value of establishing collaborative environments where educators can share their experiences, knowledge, and challenges related to data use.

In addressing the final research question on data needs, the majority of the participants expressed a strong desire for a more comprehensive understanding of their students' profiles beyond academic performance. Indicative examples include insights into students' commitments, well-being, and overall satisfaction to better grasp individual needs and challenges. Instructors expressed a desire for a more centralised and integrated system for accessing and analysing student data. Such a system would enable them to identify broader trends, monitor student progress over time, and make more informed pedagogical decisions. Finally, the importance of timely and accessible student feedback to address concerns and improve teaching practices was highlighted as a key theme across respondent input.

5. Implications

5.1. *Implications for Theory*

- The present study challenges the narrow view of educational data often focusing solely on performance metrics (e.g., scores, grades) (Nguyen *et al.*, 2020) or simple engagement patterns (e.g., clicks) (Fincham *et al.*, 2019) and advocates for a more expansive perspective, where data encompasses a rich variety of student background information, well- being, engagement patterns, and real-time feedback.
- The diverse range of data points desired by instructors suggests a shift towards a more personalised understanding of student needs by recognising the interplay of personal, social, and environmental factors that influence academic progression and outcomes.
- Instructors' preference for immediate feedback aligns with the principles of formative assessment, which emphasises the ongoing use of data to inform and adapt instructional practices (Kalaitzopoulou *et al.*, 2023; Lokkila *et al.*, 2022; Schildkamp *et al.*, 2020). Therefore, researchers should investigate how diverse data can be integrated into ongoing feedback loops to improve instruction.

5.2. *Implications for Practice*

- Shifting some emphasis from global assessment to individual progression would help to highlight the need to understand the learning journeys of individuals as much as overall cohorts.

- Comprehensive professional development programs are crucial to equip faculty with the skills necessary to effectively interpret and use diverse data from LMS's, student records systems and other sources. Such efforts should include training in data analysis, visualisation techniques, and the ethical use of student data (Christopoulos *et al.*, 2021).
- Fostering a data-informed culture within educational institutions is essential. However, in order for such an outcome to be achieved, university leaders should actively encourage collaboration and data sharing communities of practice among faculty.
- Given that student data is often scattered across different platforms and/or repositories, it is imperative to develop or adopt data integration layers that are available to academics of all levels.

5.3. *Implications for Policy*

- Institutional policy which places a greater focus on differentiation and a holistic understanding of learners' personal circumstances should be developed or strengthened. The focus on attendance and assessment has led to a notable one-dimensional and rather blunt approach to data collection and uptake, which only partially meets the needs of teachers.
- In view of the former, it is also imperative to involve all the stakeholders – administrators, faculty, students – in the development of such policies. This collaborative approach will help to ensure that data practices align both with the institution's values and mission and the specific needs / concerns of the community it serves.

6. Limitations and Future Work Recommendations

Like any empirical research, the present study also comes with its own limitations. Our reliance on self-reported data from academics introduces the possibility of social desirability bias (Larson, 2019) or recall errors (Eckman and Kreuter, 2018). Participants may have overstated their abilities or underreported their difficulties in using student data. Additionally, our sample, while diverse in disciplines and experience, is mostly drawn from a single institution. The purposive sampling approach (Campbell *et al.*, 2020), though valuable for this study, may have introduced some selection bias. We nevertheless feel that it surfaces challenges faced by institutions across the sector. Furthermore, our focus on individual academics' skills and perceptions limited our exploration of broader institutional factors that influence data use.

It is also important to acknowledge that this study offers a snapshot of current practices in a field that is rapidly evolving. Longitudinal studies would thus be valuable to track changes in data use practices over time and to evaluate the impact of interventions aimed at improving data literacy.

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Appendix A

Background Information

1. Please choose your gender
   - o Male
   - o Female
   - o Non-binary third gender
   - o Prefer to self-describe [Open-ended]
   - o Prefer not to say
2. Please choose your age group
   - o Below 25 years old
   - o 25–35 years old
   - o 36–45 years old
   - o 46–55 years old
   - o 56–64 years old
   - o 65 and over
3. In your current position, do you serve in an instructional role? [Yes / No]
4. In which University do you teach? [Open-ended]
5. In which department do you belong? [Open-ended]
6. Which subject(s) do you teach? [Open-ended]
7. What is your primary position?
   - o Lecturer
   - o Senior Lecturer
   - o Associate Professor
   - o Professor
   - o Other please specify
8. Including the current year, for how many years have you been teaching? [Open-ended]

A. Practices

Data use is the process in which an actor accesses or collects data, filters, organises, or analyses data into information, combines information with expertise and understanding to built knowledge.

Frequency of Data Use

Rating scale: Never (1)*, Once a month or less* (2)*, A few times per month* (3)*, Once a week* (4)

1. Use data to identity patterns in student thinking (e.g., errors, misconceptions).
2. Use data to determine students' level of achievement before instruction.
3. Use data to determine students' level of achievement after instruction.

4. Use data to monitor students' achievement growth/progress over time.
5. Use data to identify student strengths and weaknesses.
6. Use data to select appropriate instructional strategies.
7. Use data to select appropriate supplemental interventions.
8. Use data to plan/design lessons.
9. Use data to evaluate the effectiveness of your instruction (e.g., lessons, units).
10. Use data to group students (either homogeneously or heterogeneously).
11. Use data to identify reasons for poor student performance.
12. Use data to select assessments to administer.
13. Use data to identify students for more intensive intervention.
14. Use data to identify students for acceleration/enrichment.
15. Use data to identify students for individualized instruction.
16. Use data to identify next steps for instruction (e.g., move on, reteach).
17. Use data to modify instruction or lessons plans for future students.
18. Use data to modify instruction or lesson plans for current students.
19. Use data to set student performance goals or targets.
20. Use data to select which content to teach.
21. Use data to differentiate instruction.
22. Use data to select scaffolds to provide.
23. Use data to identify student learning needs.
24. Use data to communicate student performance.
25. Use data to give feedback to students.
26. Use data to assign grades.
27. Use data to identify gaps in student knowledge.

B. 3D-MEA Assessment

Rating scale: Strongly disagree (1)*, Disagree* (2)*, Neutral* (3)*, Agree* (4)*, Strongly agree* (5)

Data Access & Retrieval Confidence

1. I am confident in my ability to access assessment results for my students.
2. I am confident that I know what types of data or reports I need to assess group performance.
3. I am confident that I know what types of data or reports I need to assess student performance.
4. I am confident I can use the tools provided by my university data technology system to retrieve charts, tables or graphs for analysis.
5. I am confident I can use the tools provided by my university data technology system to filter students into different groups for analysis.
6. I am confident that I can use my university's data analysis technology to access standard reports.

Data Interpretation Confidence

7. I am confident in my ability to understand assessment reports.
8. I am confident in my ability to interpret student performance from a scaled score.
9. I am confident in my ability to interpret subtest or strand scores to determine student strengths and weaknesses in a content area.

Data Application Confidence

10. I am confident that I can use data to identify students with special learning needs.
11. I am confident that I can use data to identify gaps in student understanding of curricular concepts.
12. I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress.
13. I am confident I can use assessment data to identify gaps in my instructional curriculum.
14. I am confident that I can use data to group students with similar learning needs for instruction.
15. I am confident in my ability to use data to guide my selection of targeted interventions for gaps in student understanding.

Data-Related Anxiety

16. I am intimidated by statistics.
17. I am intimidated by the task of interpreting students' state level standardized assessments.
18. I am concerned that I will feel or look "dumb" when it comes to data driven decision-making.
19. I am intimidated by my university's data retrieval technology.
20. I am intimidated by the process of connecting data analysis to my instructional practice.

D. Education & Follow-up

1. Please describe any other specific opportunities you had to learn about assessment and data during your teaching preparation program. [Open-ended]
2. Please describe any other specific opportunities you had to learn about assessment and data after you started teaching. [Open-ended]
3. Would you be happy to be contacted if we have additional questions about any of your answers? If so, please leave your email address. [Open-ended]

Appendix B

Interview Guide: Data Use in Instruction

A. Introduction

1. Please briefly describe your role and responsibilities concerning data use in instruction at your institution.

B. Understanding and Context

2. Can you tell me where you learned about student data? What do you know about data available and how do you know about that? How has it changed since you started and why did it change?

C. Practical Applications

3. Talking about students data, can you tell me what kind of student data you are using in your teaching practice?

D. Pedagogy and Data Preferences

4. In terms of your teaching priorities, is there data you wish you could have access to, that you do not currently?

E. Confidence and Skills

5. How did you build your confidence in accessing and interpreting assessment results?
6. Are there any specific training programs or resources you wish were available to further improve your data literacy?

F. Institutional Support

7. How does your institution support data-driven instruction? Are there any policies in place?
8. Are there any collaborative efforts within your department or between departments to share best practices on data use?

G. Reflection and Future Outlook

9. How has your understanding and use of data evolved since you began teaching?
10. What advice would you give to instructors who are hesitant or new to using data in their teaching?

H. Closing

11. Is there anything else you would like to add that we have not covered regarding your experience with data use in instruction?