Caring Pedagogies in Action: Utilising Student Engagement Data to Develop Sustainable Learning Environments

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Abstract

In the context of growing class sizes and limited institutional resources, student-centred and responsive education is increasingly important although challenging to implement effectively. A central part of responsiveness involves interpreting and acting on student-generated data -a task that can be particularly challenging for novice engineering educators, as their background and training often guide both how they understand the data and how they respond to it. This paper reflects on our experiences, as teaching assistants and course lead, in developing and running a data analysis process for a large-scale problem-based learning engineering mathematics course. Using autoethnographic data from written reflections and transcripts, we applied an adapted version of Sochacka et al.'s (2009) three-tier reflexivity model to analyse how our understandings evolved regarding (i) what counts as data, (ii) how it can be interpreted, and (iii) what matters in its analysis. Through dialogic exchange, we identified significant shifts in our conceptualisations of the task of educational data analytics, as well as the value we placed on the different types of data.

Keywords: Learning analytics, virtual learning environments, adaptive learning, reflexivity in educational research, critical quantification

1. Introduction

The integration of virtual learning environments (VLEs) in higher education offers valuable opportunities to collect and analyse educational data for monitoring and improving teaching and learning strategies (Siemens & Long, 2011). However, ethical concerns around privacy, consent, and bias still remain prominent (Floridi & Taddeo, 2016) with the British Educational Research Association calling for transparency, accountability, and respect of student rights. Meanwhile, educators must reflect on how their own values can influence the data interpretation and pedagogical decisions (Denscombe, 2003).

For engineering educators, reflecting on personal values and biases can be particularly challenging, given a professional background that tends to prioritise positivist, pragmatic, and numerical data analysis over interpretive, contextual, and qualitative understandings. This tension between technical rigour and interpretive approaches has already been noted by engineering education researchers, who suggest that engineering faculty are often trained to prioritise quantitative precision over interpretive rigour (Borrego, 2007; Koro-Ljungberg and Douglas, 2008).

Responding to these challenges, this paper reflects on our collective experience over three years designing, and implementing data analytics processes to support a large-scale engineering mathematics problem-based learning (PBL) module delivered through a flipped classroom format. Our main practise question is:

What have we learned from this collaborative process, and how has this shaped our current identities as engineering educators?

Through writing and collaboration, we aim to make visible how our perspectives on educational data interpretation have evolved and to encourage other educators engaged in student data analytics to adopt reflexive practices. Finally, we draw practical implications for data-informed PBL approaches and for training and onboarding teaching assistants involved in interpreting student data collected via virtual learning environments (VLEs).

2. Institutional Context

The study is situated in a faculty-wide, first-year mathematics course with approximately 900 students across eight engineering departments at University College London. The module covers calculus, linear algebra, complex numbers, differential equations, mathematical modelling, and data analysis, using a flipped-classroom format: students complete self-paced online activities before participating in face-to-face departmental workshops, where they collaboratively solve real-life engineering mathematics problems. The online module material, hosted on Moodle®, generates both quantitative data (grades, completion rates) and qualitative inputs (short-answer responses, uploaded diagrams, perception surveys). In 2022, a small data analysis team, formed by two teaching assistants (TAs), was created to process and analyse this data weekly, producing reports for teachers leading the module's problem-solving workshops and for the course lead who oversees the teaching delivery, faculty-wide.

3. Methodology and Reflexivity Framework

To answer our practice question, we produced autoethnographic data through written reflections and "think-aloud" dialogic meetings with automatic transcription. Our reflections were prompted by three activating questions, initially answered individually in writing and then discussed collectively over the course of two meetings:

- What did you expect this data analytics role to involve when it started?
- How has your understanding of the role and of data analysis changed over time?
- What is the engineering educator identity that you developed through this role?

The autoethnographic data was then analysed deductively through an adaptation of the three-tier model of reflexivity designed by Sochacka et al. (2009) in an attempt to help engineering education researchers examine how their disciplinary background, personal values and experiences shape their research in interpretive contexts. We made minor *a priori* adaptations to the framework which originally consisted of ontology and epistemology as the first dimension, values (axiology) as the second, and lived experiences as the third. In designing this study, we decided to split the first dimension and merge the second and third, where our reflexive framework consisted of:

- Ontology: the things that exist, what they look like, and how these things interact with each other.
- Epistemology: how can we gain knowledge about something, and what are the criteria for this knowledge to be valid.
- Axiology: how our values, orientations and lived experiences shape our actions in the educational environment.

This split follows Bhaskar's (1975) critical realist position that ontology (what exists) and epistemology (how we know) are distinct domains of inquiry.

4. Discussion and Findings

Throughout our discussions, we identified clear shifts across all three tiers of reflection. A central theme was our relationship with quantifiable data such as grades in formative activities, completion rates at departmental and faculty level, and how these indicators changed over time. At first, we treated them as direct measures of learning and engagement. Over time, we came to see them as partial signals that hide important aspects of student experience. A low completion rate, for instance, might reflect conceptual difficulty, time pressures, digital literacy issues, or alternative learning strategies. None of these factors, however, are visible in the numbers alone. We interpreted this as our ontological shift from assuming "the data tells the whole story" to recognising that "data have blind spots" and must be interpreted in context.

This recognition prompted an epistemological shift in how we interpreted and acted on data. Early on, our approach was to focus on what the data showed. If completion rates dropped or grades decreased in a certain topic, we responded directly by encouraging students to complete preparatory work or spending more class time on problems with low average grades. Later, we began asking why these changes occurred and how the data might meaningfully inform teaching. That is, the initial focus on metrics on their own changed to a focus on what the metrics could be an indicator of, which requires interpretation.

Our most important epistemological shift was that patterns in performance were sometimes more reflective of the structure or validity of the assessment items than of student understanding, and that engagement rates were not necessarily related to motivation, interest, or conscientiousness as initially assumed, but more so of the clarity and accessibility of the digital activities. For example, coding activities by theme revealed that questions with numerical answers had consistently higher average scores than questions with symbolic answers, prompting us to reconsider how we interpreted grades, now including the "type of answer" as an important explanatory variable.

Going back to the theme of "invisibility in data" identified in our reflections, we also considered whether VLE-generated statistics were representative of the student population at all. One of the team members mentioned "a constant left-skew" in the data, meaning that most completions were concentrated at high grades with few at the lower end of the distribution, which could indicate a type of "self-selection" bias where there is a possibility that proficient students completed the activities possibly to confirm their ability, whilst students struggling decided not to complete them to avoid receiving low formative grades. Although this inference was made as a possible explanation to the behaviour observed, it suggests that the common frequentist statistics performed on the data might be inappropriate to yield valid and actionable educational insights.

Recognising that important aspects of student experience lie beyond the scope of our datasets (ontology) forced us to rethink how we interpret and act upon those datasets (epistemology). Taken together, these shifts reshaped the values we brought to our data-informed practice (axiology) and to our identities as educators. As we became more critical of what our analytics could and could not reveal, we placed increasing emphasis on fairness, transparency, and relational aspects of data-informed education, which formed the basis of our reflections on axiology and lived experiences.

We became more deliberate in ensuring that analytics were used to support learning rather than to police or punish. Respecting student agency meant recognising that non-engagement could be a valid strategic choice rather than simply a deficit. For example, in the weeks prior to multiple deadlines we started to expect a drop in completion rates. We also prioritised transparency about what data was collected and why, which was ultimately to uphold our values of student-centred learning experiences. For example, instead of uniformly redesigning workshops based on aggregate data, we considered the diversity of student circumstances and used targeted, non-punitive interventions.

Relational and pastoral considerations became central to our practice. Building rapport and approachability in classes, responding to individual circumstances with empathy, and creating psychologically safe spaces for feedback and discussion all became priorities. A clear shift in values occurred from attempting to “fix” what the numerical data indicated as problems to facilitating conditions for students to succeed, combining analytics with dialogue to understand the stories behind worrying numbers. As one of the team members put it, we learned to “believe people, not numbers”. This included targeted one-to-one support for persistently low-engagement students, and practising triangulation by weighing quantitative indicators against qualitative accounts. These changes marked our evolution from technically oriented data analysts to reflective educators, comfortable with the ambiguity of data, and committed to co-constructing interpretations and actions with students.

5. Conclusions

In this paper we have explored challenges of using data analytics in a large-scale, hybrid mathematics course through the lens of Sochacka et al.'s (2009) three-tiered model of reflexivity, focusing on how ontological and epistemological assumptions, underlying values, and lived experiences shape the collection and interpretation of student data. Our findings suggest that while data analytics can offer insights into student engagement and learning, their effectiveness depends not only on technical accuracy but also on a deep awareness of the assumptions and values embedded in the process.

The paper argues that the value of educational data lies not in its capacity to classify or measure students, but in its potential to inform thoughtful, dialogical, and values-driven educational practices within problem-based learning environments. For educators working with large and diverse cohorts, especially in engineering education -and for teaching assistants- this approach offers a valuable model for including reflexivity and care into data-informed teaching.

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