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### Citation

Farrell, Tracie; Mikroyannidis, Alexander and Alani, Harith (2017). "We're Seeking Relevance": Qualitative Perspectives on the Impact of Learning Analytics on Teaching and Learning. In: EC-TEL 2017: Data Driven Approaches in Digital Education (Lavoué, Élise; Drachsler, Hendrik; Verbert, Katrien; Broisin, Julien and Pérez-Sanagustín, Mar eds.), 10474 pp. 397–402.

### URL

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# “We’re Seeking Relevance”: Qualitative Perspectives on the Impact of Learning Analytics on Teaching and Learning

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**Abstract.** Whilst a significant body of learning analytics research tends to focus on impact from the perspective of usability or improved learning outcomes, this paper proposes an approach based on Affordance Theory to describe *awareness and intention* as a bridge between usability and impact. 10 educators at 3 European institutions participated in detailed interviews on the affordances they perceive in using learning analytics to support practice in education. Evidence illuminates connections between an educator’s epistemic beliefs about learning and the purpose of education, their perception of threats or resources in delivering a successful learning experience, and the types of data they would consider as evidence in recognising or regulating learning. This evidence can support the learning analytics community in considering the proximity to the student, the role of the educator, and their personal belief structure in developing robust analytics tools that educators may be more likely to utilise.

## 1 Introduction and Motivation

Learning analytics intends to leverage the “collection, measurement, analysis and reporting of data” to “understand and optimize learning” [7]. However, the real impact of learning analytics has been difficult to determine, in particular with respect to the effects of personal agency and a lack of standardisation in how tools are used [5].

The study presented in this paper adopted a qualitative approach to this problem, based on Affordances, the “actionable properties” that an individual can perceive about a given object [9]. Educators’ perceptions of the “actionable properties” of learning analytics were derived from how they spoke about using them, now or in the future. The aim of this study was to probe the ideological and practical assumptions of educators, to determine how this relates to their understanding and intention to use learning analytics to support practice (personal agency). This knowledge can assist the learning analytics research community and other key stakeholders in making more accurate estimations of software engineering requirements, more effective measurements and evaluations of impact, and targeted approaches for deploying learning analytics tools.

## 2 Related Work

### 2.1 The Problem of Relevance

Institutions and educators are currently burdened with an abundance of data about their educational contexts [5]. For example, technology is used to gather and present trace data about learners' activities on the web [14] or within virtual learning environments [1][8], to collect data about learners' physiological responses [2], and even to highlight social interactions in learning processes [12]. However, researchers have illustrated that educators are likely to be most interested in using analytics data to interrogate the efficacy of *specific interventions* that they implement in their classrooms, whereas most of the tools with which they are presented are complex and overshoot their requirements [6]. These results indicate a necessity for deeper investigation into what kinds of data matter, to whom they matter and why they matter to support the search for relevance in this vast landscape of information.

### 2.2 Evaluating impact

Challenges of relevance are also manifested in how real impact on practice is evaluated. If the data is overwhelming, evaluations are likely to be either too broad or too narrow to get an accurate picture of an educator's *intentions* to use a given tool, their understanding of its utility and their *actual* use of the tool in an authentic environment. For example, research on disparities in how Learning Management System (LMS) tools are used showed that most disparities can be related to *specific* tool, task and interface combinations [11]. At the other end of the spectrum, a 2013 survey of 15 learning analytics dashboard applications for educators and learners found that evaluations of tools were primarily organized around usability studies and efficacy in controlled environments [13]. In a usability study, the perceived utility of the object at the time of evaluation is already provided to the user. This makes it difficult to ascertain how likely an educator is to incorporate the tool into their practice, even if the educator expresses confidence in the tool's utility. The knock-on effect of this tendency is that the research community knows much more about how tools could and should work, than how they *do* work.

## 3 Research Design

To prompt educators to articulate affordances, they were asked to reflect on their perceptions of challenges unique to their practice, their understanding of the "desired state" of successful learning and the steps they believe are necessary to achieve it.

1. *To which extent are educators able to perceive specific affordances of learning analytics? Will those affordances be linked to the educator's domain?*

2. *What recommendations can be made to learning analytics researchers and developers?*

We deployed a multi-stage, purposive sampling strategy to gain access to educators from various types of institutions (formal and non-formal), who embodied different roles within the institution (staff tutors, associate lecturers, facilitators, module chairs, etc.). The term “educator” was defined as any individual involved directly in the process of working with learners or developing their curriculum. We conducted 10, 60-minute interviews, concluding sampling through saturation and constant comparison among the transcripts [3]. We used an inductive qualitative analysis to expose and connect the research participants’ perspectives *ibid*. A second rater coded a random subset of 150 participant statements from 6 of the 10 interviews. We calculated interrater reliability (IRR) using the Cohen’s Kappa statistical test [4]. For the first coding procedure, kappa was .76, which rose to .87 after the two individuals coding the data negotiated some of the wording for descriptions of general themes. This study cannot generalise across a large number of educators and institutions. Rather, it explored the issues of perception and intention with regard to learning analytics.

## 4 Findings

Participants consistently framed their arguments about the challenges they perceive, their ideas of the “desired state”, and the ways in which they monitor their progress in terms of their *personal* beliefs about learning and the *goal* of education. Goals tended to cluster around one of three general categories: *to develop strong minds, to prepare learners for practice and to satisfy the learner*. Domain differences were noted in that the goal to develop strong minds was exclusively found among educators working in the social sciences, arts and humanities. STEM educators primarily described preparing learners for practice. Educators with the goal of satisfying learners all had class sizes of 1000+ students (regardless of platform or domain). The domain differences prompted us to conduct an analysis of the modules in which the educators were involved, using the learning design taxonomy provided by the Open University Learning Design Initiative [10] and comparing this to how educators described the classroom experience in the interview evidence. There was consistency between goals and activities for all of the educators’ interviews, indicating a conscious learning design, on behalf of the educator, and an expression of their educational epistemology. Interview data suggested that educators with different educational epistemology have significantly different priorities and viewpoints on challenges and success in education. To triangulate these findings, we conducted a frequency analysis of the open codes and discovered that educators with a shared epistemology also tend to share a similar perspective on challenges and desired states. For example, learner background and agency is of particular concern to educators preparing learners for practice, whereas communication and interaction are consistently mentioned as challenges by educators from the social sciences, arts and humanities, who aim to develop strong minds. Analysis of educators’

statements of the "desired state" also mirrored educators' goals. For example, educators who are preparing students for practice tended to connect performance with having a strong motivation for learning and identification with a specific career objective. Educators who felt they were responsible for developing strong minds tended to determine their success through energy and euphoria in the classroom, particularly in the presence of lively, rich discussion.

#### 4.1 Sources of Data and Affordances of Learning Analytics

An analysis of the kinds of data educators use or need also showed continuity from personal belief structure, through to the affordances that educators perceived in learning analytics. For example, educators preparing their learners for practice appear to focus on the hard evidence that they can see, e.g. if the learner is able to demonstrate skill, if the learner is active in the VLE. While they did show interest in the personal lives of learners, in terms of stress and time management, educators did not see many opportunities for gathering data about learner emotions, unless the student provided it directly. Thus, educators preparing for practice relied more on institutional analytics that predict learner performance or activity. Educators that wished to develop strong minds focused much more on their intuitions about learners and what they can observe in the class. Educators in this category had sincere and significant reservations about how their learners are assessed and whether or not it is a meaningful measure of what they have learned. For this reason, educators with this goal wondered if institutional analytics could collect enough relevant data to support their practice. Figure 1 shows the breakdown of mentions of learning analytics by educational goal. 7 major themes were identified in the transcripts regarding how educators use learning analytics: to understand learner engagement, learner performance, learner motivation and use of resources, to uncover more about the social interactions between learners, to interrogate and modify learning design, and to predict performance.

One unexpected finding was that only educators in senior roles or with class sizes of 1000+ provided *unprompted* affordances of learning analytics for understanding or improving their practice. This included predictive analytics, which was surprising because tutors and assistant lecturers are responsible for making interventions on the basis of the predictions. Instead, participants described having access to this data as overwhelming and they were unsure of how to interpret it or develop a response. A preference for having the management of this data lie in outside of their own remit was evident.

## 5 Recommendations for Learning Analytics Research

The tension between having too much and too little data, as described in the previous section on related work, was reflected in our findings. Educators are looking for *relevant data* that is appropriate for their role within the institution, makes sense within the context of their *domain* and their *learning design*, and

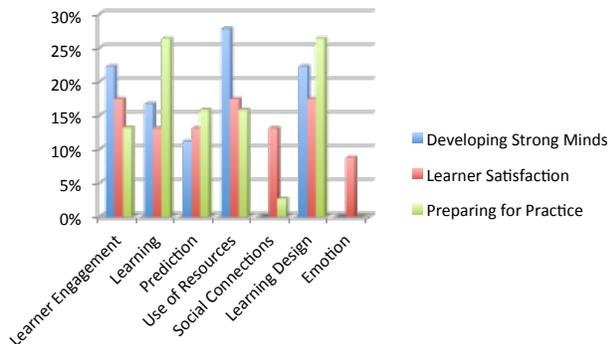


Fig. 1: Affordances by Educational Goal

meets their *specific needs* with regard to those contexts. To help educators reduce cognitive load in dealing with analytics data, we recommend that developers and institutions begin to filter educator requirements according to epistemology and learning design. With a clear line from goal to outcome, the path to understanding the impact of learning analytics tools (as a source of actionable information) would be much clearer. It would also provide a mechanism for refining specific analytics that interrogate certain types of learning designs and classroom orchestrations. Finally, it would also make it easier for institutions and developers to build stakeholder buy-in for learning analytics initiatives, by targeting tools toward the most appropriate academic communities.

Research in progress at the time of writing includes a more in-depth case study of the Open University UK, in which several learning analytics initiatives have already been launched and evaluated.<sup>1</sup> This case study involves both educators and students, connecting affordances of learning analytics with personal educational goals for more specific software engineering requirements within the OU.

## 6 Conclusion

The research study described in this paper was designed to explore connections between educators' beliefs about their work and how they perceive and utilise learning analytics. Applying Affordance Theory to the evidence highlighted how the participants in the study are currently using learning analytics and their specific reasons for doing so. The findings indicate that an educator's personal, background and belief structure, professional domain, and role within an institution all play a part in their willingness and ability to use learning analytics as a resource for understanding and optimising learning. The learning analytics

<sup>1</sup> <http://www.open.ac.uk/iet/main/research-innovation/learning-analytics>

community can use this research to help filter requirements and provide more targeted tools that assist educators in fulfilling the responsibilities of their role.

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