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Tracking (un)belonging: At the intersections of human-algorithmic student support

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Abstract

Central to this paper are the questions: How can open, distance and distributed learning use algorithmic decision-making systems to identify and respond to those students who may experience anomie and disengage from their studies before dropping out? What are the dangers, benefits and ethical considerations of using such systems?

The extent to which students become assimilated into the institutional, pedagogical, and disciplinary culture was and continue to be seen as key to understanding student success or failure. Research shows that students who do not 'fit', experience anomie, or have problems with assimilation have a greater probability of disengaging, failure or dropping out. Anomie or (un)belonging in open, distance and distributed learning environments may manifest in various ways, such as, but not limited to, the non-submission of assignments or tasks, absence from online discussion forums, etc. In courses with large student enrolment, *noticing* these disengagements or evidence of (un)belonging is often difficult, and clarifying the reasons underlying this behaviour, as well as responding to the data, is almost humanly impossible. So, how do we identify these students?

What data and systems will allow us to enter into a conversation *with them*, to explore ways of making them feel at home, whether in a disciplinary or delivery (online, blended or distance) context? Higher education has always collected, measured, analysed and used student data for a variety of purposes, such as operational planning, reporting to a variety of stakeholders, allocation of resources, and student support. Having access to increasing volumes of increasingly nuanced and granular data, from a variety of disparate sources, opens opportunities to proactively identify students who seem to have disengaged, or may experience feelings of anomie.

Despite well-documented concerns about, inter alia, the role of bias, lack of accountability and need for regulation, algorithmic decision-making systems offer huge potential to respond to evidence that students may be experiencing issues pertaining to student experiences of (un)belonging. In this conceptual paper, I will situate the potential and dangers of algorithmic decision-making systems in the context of the need to make the most of evidence that students may feel that they do not belong, or have difficulty in belonging.

Introduction

Using student data, whether through, inter alia, observation, assessments (formative and summative), quality assurance and accreditation, and/or behavioral change, has always been an integral part of teaching and learning. Student behavioral data provide insight with regard to the depth, frequency and linkages in students' (lack of) engagement and/or participation. As such, their lack of overt engagement or participation may be temporal, or may indicate and serve as an early warning that these students may experience issues with regard to, inter alia, not feeling at home in the particular context, or feeling that they do not fit in. Since the early models on student success and retention (Spady, 1970, Tinto, 1975) one of, and often the most important variable to indicate that students may fail, was the extent to which students 'fitted' into a particular (higher) educational, institutional, and disciplinary contexts.

As teaching and learning in higher education move increasingly online, institutions have access to an increasing range and scope of granular, varied, granular, and detailed data (behavioral and/or demographic), increasingly in real-time. Institutions combine these data with students' historical learning data to not only understand and explain their learning, but also to increasingly predict and prescribe their learning. Since the emergence of learning analytics in 2011 as a field of research and practice (Siemens, 2013), the measurement, collection, analysis and use of student data to understand and support their learning, has matured (Dawson, Joksimovic, Poquet & Siemens, 2019; Peña-Ayala, 2017). Realising its full potential to impact positively on student success is yet to materialise. There is, however, evidence that despite its imperfections, learning analytics assists faculty, support, and administrative staff to teach differently, to allocate resources more effectively and to respond to students' (learning) needs in (more) appropriate and ethical ways (Ferguson & Clow, 2017; Kitto, Shum & Gibson, 2018; Lim et al., 2019). Concerns regarding various the ethical issues are well documented and addressed through various frameworks and codes of practice (Sclater, 2016; Sclater & Bailly, 2018; Slade & Prinsloo, 2013).

While large classes are an increasing reality in many residential educational contexts, large groups of students are, for many if not most open, distance and distributed learning institutions, a frequent reality. It is very difficult, if not impossible; to identify *individual* students' learning needs in the context of large enrolments. Large enrolments makes it almost impossible to notice signs of disengagement or issues pertaining to students' feeling at home, whether in the discipline, pedagogical/delivery context or fitting into the institutional character. In these contexts, staff traditionally relies on evidence emerging from students' self-reporting, submitted assignments or the non-submission of assignments to notice that students may have problems fitting or belonging whether in the mode of delivery, in the pedagogical structure or disciplinary context.

In this paper, I propose that a change of behaviour or inactivity *opens the opportunity for a discussion or engagement* in the light of higher education's fiduciary duty of care (Gašević, Dawson & Siemens, 2015; Prinsloo & Slade, 2016, 2017). Considering the scale or numbers of students often enrolled in open, distance and distributed learning environments, we need to seriously consider the potential of various options in human-algorithmic decision-making systems to not only help us notice and respond, but also to understand the complexities of students learning in open, distance and distributed learning contexts. In the first section I briefly introduce the notion and importance of (un)belonging in understanding student retention and success, before introducing a tentative framework for human-algorithmic decision-making as a way towards not only tracking (un)belonging but framing appropriate, ethical, and effective responses. There are, however, important caveats in employing human-algorithmic decision-making systems and I briefly discuss some of these concerns. I conclude this paper with some pointers for consideration.

On (un)belonging

Several historical and current conceptual and empirical models attempt to map and explain the various factors affecting student retention and success in higher education. Since the early models proposed by Spady (1970) and Tinto (1975, 1988), the notion of students' sense of belonging, whether in the delivery mode, the institutional character and values, and/or disciplinary and pedagogical context has been a recurring element in many of the subsequent models. Though Spady (1970) and Tinto (1975, 1988) proposed their models based on research in *residential* face-to-face institutions, the elements in these models *also* informed and continue to inform understandings of student belonging and success in distance, open and distributed learning environments (Kember, 1989; Kember, Lee, & Li, 2001; Kember & Leung, 2004; Subotzky & Prinsloo, 2011).

In his early model on student success Spady (1970) emphasised the integration of students as a vital precursor for student success. Central in understanding student dropout according to Spady (1970), is the "interaction between the individual student and his [sic] particular college environment in which his attributes (i.e., dispositions, interests, attitudes, and skills) are exposed to influences, expectations, and demands from a variety of sources (including courses, faculty members, administrators, and peers)" (p. 77).

It is important to note that both Spady (1970) and Tinto (1975) based their understanding and explanation of the importance of 'assimilation' on the work of Durkheim (1897) on suicide and specifically the role of feelings of *anomie*. Anomie refers to feelings of un-belonging when relations between an individual and his/her community break down. Tinto (1975) combined the importance of Durkheim's (1897) emphasis of the role of assimilation and anomie, with the work of Van Gennep (1960) who emphasised the role and impact of transitions, or 'rites of passage; when individuals moved between groups and/or contexts. Van Gennep was interested in "life crises" that occurred during an individual's life over the course of a lifetime and he "saw life as being comprised of a series of passages leading individuals from birth to death and from membership in one group or status to another" (Tinto 1988, p. 440). Van Gennep identified three distinct phases, namely separation, transition and incorporation (in Tinto 1988, p. 440). Applying these to understanding student success, Tinto (1988) applies these stages to the number of transitions, or "rites of passage" students experience as they leave behind their previous life-worlds and relocate to another context. These transitions also encompass transitions from previous beliefs and epistemologies to different ways of being and thinking and may result in intense disorientation and disequilibrium as well as feelings of loss and bewilderment (for example, Aikenhead, 1998).

These understandings as proposed by Spady (1970) and Tinto (1975, 1988) still inform much of our understanding of students' assimilation into higher education, also in distance education (Kember, 1989). It is also crucial to acknowledge a range of criticisms against these understandings, inter alia, the concern that these models over-emphasise students' agency and *their* responsibility to 'fit' into organisational cultures (Braxton, 2000). There are also concerns that these models reflect North-Atlantic geopolitical, epistemological and social realities, and assume a universal validity (Subotzky and Prinsloo, 2011). While no one contests the importance and role of assimilation, anomie, and (un)belonging as one of the factors in explaining student failure, success or drop-out, we must acknowledge how assimilation and anomie play out in the specific context of open, distance and distributed learning (see Kember, 1989; Kember, Lee, & Li, 2001; Kember & Leung, 2004; Subotzky & Prinsloo, 2011). It is also important to note that (un)belonging and its impact should be understood in the context of understanding student success as a dynamic, fluid and complex phenomenon found in the intersection of the students, institutions and macro-political and socio-economic factors (Subotzky & Prinsloo, 2011).

Signs of (un)belonging in open, distance and distributed learning

Considering the work of Spady (1970), and specifically Tinto's (1975, 1988) application of tracking students' assimilation as 'rites of passage', it is useful to consider how students' anomie or feelings of not fitting in, or (un)belonging would manifest in open, distance and distributed learning environments. How these would manifest will depend on several factors such as pedagogical strategies (e.g. number and format of formative assignments), the involvement of tutors or assistance faculty (student: instructor ratios), delivery mode (offline, digitally supported, internet supported, internet-dependent, and/or face-to-face tutorials) or combinations of these. Despite the proliferation of online learning, we must acknowledge the reality that many open, distance and distributed learning institutions, especially in emerging economies are still, mainly, offline or at most, internet-supported. In the light of the various nuances of interactions and forms of delivery and support, it is almost impossible to define what (temporary) disengagement, anomie or (un)belonging will look like taking into considerations the different modalities in educational delivery.

Thinking of student learning as several processes or steps from registration, to the first assignment or activity, to the second, etc., as rites of passage (Tinto, 1988), anomie, disengagement or (un)belonging may manifest in particular ways (Subotzky & Prinsloo, 2011). For example, when students do not submit a first task or assignment (whether online or offline), or when students do not log in to the institutional learning management system (LMS) in the early stages of the semester, it may be evidence of students' adaptation or balancing various priorities, or it may signify a deeper, possibly important marker. As stated earlier, it is crucial that we do not make assumptions about these manifestations. We will only know what these manifestations mean if we see these markers or manifestations as *the start of or invitation to a conversation* (Prinsloo, 2017b).

Of particular interest in this paper is not only how we will notice these manifestations of disengagement, anomie and/or (un)belonging, but *who* will notice these? A range of individuals or systems (administrative, support, tutorial and/or faculty) may notice and respond to these manifestations. Considering the scale (i.e. course enrolments) and scope (geo-political distribution) of many courses in open, distance and distributed learning contexts, the possibility that humans may notice one of the possible manifestations of anomie or (un)belonging and have the understanding and resources to respond in appropriate, ethical, and effective ways, *is an open question* (Prinsloo & Slade, 2017).

In the next section, I explore a tentative proposal for considering the potential of human-algorithmic decision-making to respond and address anomie and (un)belonging in appropriate, ethical, and effective ways.

Responding to (un)belonging: the promise of algorithmic decision-making

To understand the potential and perils of algorithmic-decision-making systems in broader society, and specifically in education, we must acknowledge not only the hype and imaginaries surrounding Artificial Intelligence (AI), but also the increasing impact of how a variety of automated digital processes already shapes our lives (Beer, 2019). We also need to consider expressed concerns about the (inherent) bias, discrimination, and opacity that surround AI, its design, processes and impact (Beer, 2019; Pasquale, 2015).

There are also claims that algorithmic decision-making will be 'intelligence unleashed' (Luckin, Holmes, Griffiths, and Forcier, 2016), and replace teachers (Clark, 2016a, 2016b). In the context of learning analytics, algorithms are increasingly central to the design and execution of learning analytics. Williamson, Knox and Doyle (2014) therefore warn that: "[the] algorithms that enable learning analytics appear to be 'theory-free' but are loaded with political and epistemological assumptions. The data visualisations produced by learning analytics – data dashboards as they're frequently described – also act semiotically to create meanings" (para. 9).

Let us return, for a moment, to the central proposal of this paper and its problem statement: Student (dis)engagement, anomie and (un)belonging are important variables in determining students' decision to drop-out or students' failure. Depending on the form of delivery (from offline to fully online or variations thereof), there may be different and a variety of markers or manifestations that act as proxies of students' (dis)engagement, anomie and/or feelings of (un)belonging. With the scale and scope of course enrolments in open, distance and distributed learning contexts, there are concerns that we may miss these markers or proxies and, as such, not respond, or not respond appropriately, ethically, or effectively.

Without ignoring the expressed concerns surrounding algorithmic decision-making systems, we also must acknowledge its potential in the context of student (dis)engagement.

A tentative framework for using algorithmic decision-making

Danaher (2015) classifies four essential components in human decision-making, namely sensing, processing, acting, and learning.

- *Sensing* – referring to the collection of data from sources
- *Processing* – organising the collected data into useful chunks/patterns as related to categories, goals, or foreseen actions
- *Acting* – using the outcome of the processing to implement a course of action
- *Learning* – the system learns from previous collections/analyses and adapts accordingly

To apply this to a pedagogical situation, and to illustrate the four elements, we have to think of an educator 'seeing' a change of behavior (e.g. the non-submission of an assignment), 'processing' the information (e.g. classifying the student as at-risk of failing and in need of follow-up), 'acting' (sending the student a reminder or query pertaining to the non-submission), and 'learning' (making sense of whether the reminder or query makes a difference in the student's behavior).

What will happen if/when one or more of these elements are shared or taken over by an algorithm? An algorithm may, for example, 'sense', or 'notice' the fact that certain students have not submitted their assignments or have not logged on for period. The algorithm then alerts the educator, who *processes* the information (e.g. what steps to take) and how to act (e.g. make a phone call or send an email). When considering courses with large enrollments, algorithms can be programmed to also *process* the information within set parameters and *act* by sending these identified students a personalised email offering a range of options and care. This information is then recorded by the lecturer (if s/he sensed, processed, and acted), or stored by the algorithm. Whoever/whatever sensed, processed, and acted then opens the possibility to learn from not only what was done but also how students who were identified, responded (or not) to this intervention. Table 1 illustrates a matrix of different possibilities ranging from humans (1) doing all the tasks (sensing, processing, acting, and learning; or (2) sharing any or most of these tasks with an algorithm; (3) the algorithm does some/most/all of these tasks but is overseen by a human; to (4) where the algorithm senses, processes, acts and learns autonomously.

Table 1. Human-algorithmic decision-making grid (adapted from Danaher, 2015).

	(1) Humans perform the task	(2) Task is shared with algorithm	(3) Algorithms perform task with human oversight/ supervision	(4) Algorithms perform the task independently/ autonomously – no human input
Sensing	Yes or no?	Yes or no?	Yes or no?	Yes or no?
Processing	Yes or no?	Yes or no?	Yes or no?	Yes or no?
Acting	Yes or no?	Yes or no?	Yes or no?	Yes or no?
Learning	Yes or no?	Yes or no?	Yes or no?	Yes or no?

The different options and combinations between human and algorithm amount to 256 logically different possibilities ranging from an exclusively human-driven process, to where one or more of the elements is/are shared with an algorithm or set of algorithms. The final combination resembles a total, autonomous algorithmic decision-making system with no human involvement.

As indicated earlier, the exact configurations and potential of the above combinations will depend, inter alia, on access to student data, the size of the class or course cohort, the ratio of students to instructors or faculty, and curriculum, pedagogy and assessment structures and regimes. In the context of teaching courses with high enrollments in a resource-constraint environment, and with access to student data – from the (non)submission of assignments, to daily behavioral logs and student feedback – it is almost impossible for an individual or groups of faculty to, personally, notice (sense), process, respond and learn in response to student (in)activity (Prinsloo, 2016). (Also see Prinsloo, 2017a).

Facing the dark side of algorithmic decision-making

In the context of learning analytics, ethical concerns, and various frameworks to address these concerns are an established and respected part of the learning analytics field (Pardo & Siemens, 2014; Khalil & Ebner, 2015; Sclater, 2016; Slade & Prinsloo, 2013; Prinsloo, 2017b). While these principles and frameworks also apply to algorithmic decision-making, there are very specific concerns in respect of algorithms in general (Amoore & Poitukh, 2016; Ananny, 2016; Citron & Pasquale, 2014; Pasquale, 2015), and specifically in the context of education (Ekowo & Palmer, 2017; Prinsloo, 2017a; Williamson, 2016a, 2016b). It falls outside the scope of this paper to mention and discuss all of these concerns. What is possibly more valuable is not only to acknowledge these concerns but to accept the responsibility to "care for our technologies as we do our children' (Latour, 2012, para.1) however uncomfortable this may be. Shellenberger (2012), in reflecting on Latour's (2012) proposal, states:

> Our technologies, like our children, go wrong. They will create new problems. We cannot create perfectly formed new technologies, only flawed ones. We must, thus, continually care for and improve them, just as we do our children (para.12).

In addition to various frameworks and codes of practice, in in following Crosslin (2019), we have to consider:

- We cannot design and employ algorithmic decision-making systems without an informed understanding of "the history of educational research, learning theory, educational psychology, learning science, and curriculum and instruction."
- We cannot and should not ignore the history and continued reality of "structural inequalities and the role of tech and algorithms in creating and enforcing those inequalities."
- We have to "be honest about the limitations and bias" inherent in learning analytics (also see Kitto et al., 2018).
- The design and use of algorithmic decision-making systems necessitate an inter-disciplinary team approach
- Algorithmic transparency and accountability

[Also see the "Toronto Declaration: Protecting the right to equality and non-discrimination in machine learning systems" (Amnesty International, 2018); and Zaidi, Beadle and Hannah, (2018)].

(In)conclusion

Central to this paper is the acceptance that higher education has a fiduciary duty of care to not only ensure the quality and effectiveness of teaching and learning, but to take the necessary steps to intervene within their locus of control, to students who exhibit behaviour that may indicate a sense of anomie or (un)belonging. In open, distance and distributed learning environments, the identification of such experiences of (un)belonging may be more difficult, if not impossible. The fact that many courses in open, distance and distributed learning environments may also have large enrolments, makes the identification of students-at-risk not only more difficult, but also more important.

In this paper I outlined the potential, but also the risks of using algorithmic decision-making systems in identifying students who exhibit behaviour that may indicate experiences of anomie or (un)belonging. Crucial in the paper is the consideration that the identification of such behaviour is an invitation to a conversation to clarify, confirm and offer support. Designing and employing such systems may assist institutions to respond appropriately and ethically.

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