Stuck in the Middle? Making Sense of the Impact of Micro, Meso and Macro Institutional, Structural and Organisational Factors on Implementing Learning Analytics

Paul Prinsloo, University of South Africa, South Africa, Sharon Slade, The Open University, United Kingdom, Mohammad Khalil, Delft University of Technology, The Netherlands

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Introduction

Despite evidence that learning analytics has become institutionalised within higher education since its emergence in 2011 (Ferguson, 2012; Gašević, Dawson, & Siemens, 2015), there remain questions regarding its impact on informing curricula, pedagogy and ultimately, on student success (Ferguson et al, 2016; Ferguson & Clow, 2017; Kitto, Shum, & Gibson, 2018). A variety of factors may impact on the implementation of learning analytics (e.g., Leitner, Khalil, & Ebner, 2017; Lonn, McKay, & Teasley, 2017; Scheffel, Drachsler, & Specht, 2015). Despite its huge potential to inform and support learning, learning analytics may become stuck in the middle of, inter alia, the need to balance operational needs and resource allocation, and different perceptions of learning, agency and loci of control in learning, teaching and macro-societal factors. In this *conceptual* paper, we propose an institutional cartography of learning analytics and explore the impact of a number of micro, meso and macro institutional factors that may impact and shape the institutionalisation of learning analytics. As a conceptual basis for developing this cartography, we utilise the Subotzky and Prinsloo (2011) socio-critical model for understanding student success.

Academic and learning analytics: Spot the difference

As the availability of datasets has grown, higher education institutions have increasingly analysed educational data with a view to better understanding how effective learning takes place. Data mining first appeared as a means of analysing databases in order to uncover patterns within data. Educational data mining is particularly concerned with developing data mining and machine learning techniques with a view to better understanding students, and the settings in which they learn (Ferguson, 2012; Papamitsiou & Economides, 2014).

Analytics within higher education tends to be classified as either learning analytics or academic analytics (Siemens & Long, 2011). Although there may be datasets in common, the two terminologies largely reflect the different purposes to which student data might be put. Academic analytics generally refers to uses of (mostly aggregated) student data in courses, programs or qualifications, at an institutional or (inter)national level – at a meso or macro level. The purposes of academic analytics include regulatory reporting (for example, for funding purposes), and marketing (to potential students and alumni), as well as high level information on learner profiles (for example, to develop a national picture of student demographics), and staff records.

Fundamentally, learning analytics is designed to support greater insight into how students learn (Gašević, Dawson, & Siemens, 2015). This might include work at the individual (micro) student level: for example, tracking student progression with a view to improving completion or predicting student likelihood of completion in order to provide proactive support. Learning analytics also encompasses module or qualification wide (meso) analyses in support of curriculum design; for example, to facilitate implementation of assessment or tuition strategies which support student success. Often, when students at risk or with special needs are identified in learning analytics, institutional responses and where necessary, resource allocation, are approved at the meso level.

The issues and policies which impact on the collection, analysis and use of student data exist at micro, meso and macro levels. Developing a greater understanding of how these issues exist and operate across all three levels may help to reduce some of the complexities involved in successfully institutionalising learning analytics.

A social-critical understanding of successful learning

Central to learning analytics is learning and the effectiveness of learning (Gašević, Dawson, & Siemens, 2015). In the context of higher education, research into the effectiveness of learning is well-documented, as per the early theoretical models developed by Spady (1970), and Tinto (1975; 1988; 2006). Though these models form the basis of much of the research on student success, they also attract criticism. Some feel that such models over-emphasise student agency and the responsibility of students to “fit” into organisational cultures (e.g., Braxton, 2000), while others argue that they reflect North-Atlantic geopolitical, epistemological and social realities, and assume a universal validity (e.g., Subotzky & Prinsloo, 2011). Much of the published research focuses on selected individual variables, forgetting that student success is a complex and dynamic phenomenon found in the intersection of student's habitus, capital, prior educational experiences and life-worlds (micro), the character, values, processes, resources and efficiencies of institutions (meso), and "supra-institutional (macro-political and socio-economic factors)" (Subotzky & Prinsloo, 2011; p.179) (macro). Figure 1 provides an overview of the main tenets of Subotzky and Prinsloo's socio-critical model of student success (2011). The central "student walk" provides a linear view of student progression from the moment of registration up to successful graduation. The main agents in this "student walk" are students and the institution. Unique to this model is the third element of the broader societal context, impacting on both students and the institution.

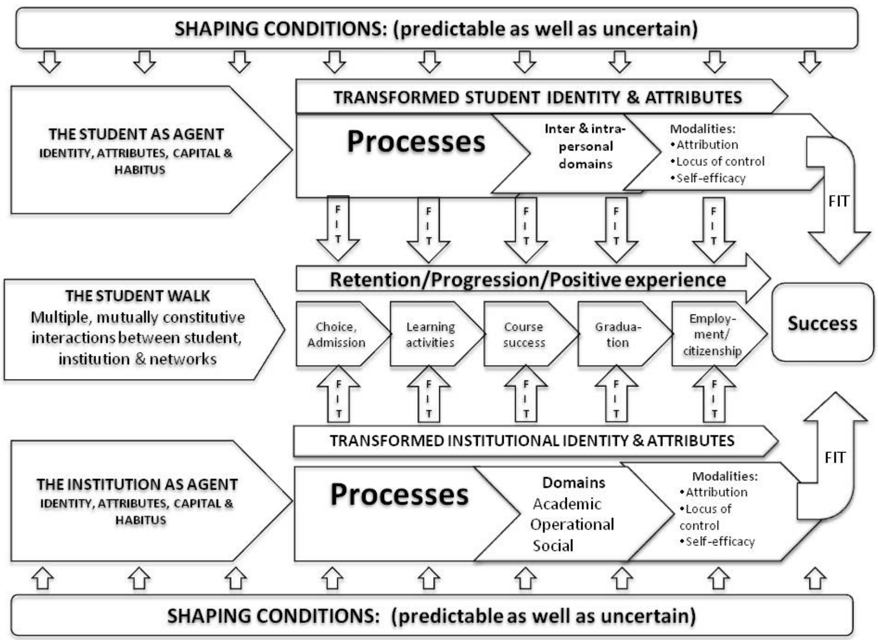

Figure 1. A socio-critical model of student success (Subotzky & Prinsloo, 2011)

Subotzky and Prinsloo's socio-critical model (2011) proposes a number of key constructs to understand the complexities and effectiveness of teaching and learning.

These are:

- *Situated agents: student and institution*. This construct emphasises that students are not helpless recipients of services but that they have some agency. However, we should also accept that the agency of both students and institutions is constrained. The situatedness of both means that "attributes and behaviours are strongly shaped by the structural conditions of their historical, geographical, socio-economic, and cultural backgrounds and circumstances. Nonetheless, as agents, they enjoy relative freedom within these constraints to develop, grow, and transform their attributes in pursuit of success" (Subotzky & Prinsloo, 2011; p.184). We note here that this model deviates from earlier models for understanding student success in the explicit recognition of student agency and responsibility.
- *The student walk*. Subotzky and Prinsloo (2011) refer to "the numerous ongoing interactions between student and institution throughout each step of the student's journey" as the "student walk" (p.185). What happens 'in the middle' between students and the institution is often mutually constitutive and interdependent. The 'student walk' and both parties' ability and responsiveness to the learning journey are shaped by connections on both sides to players and circumstances outside of that journey.
- *Capital*. This refers to the role of different kinds of capital, including financial capital but also "cultural, intellectual, organizational, and attitudinal forms of capital" (p.186) in the decisions and (in)actions of both students and the institution. Student capital is dwarfed by the symbolic and cultural capital of the institution.
- *Habitus*. Subotzky and Prinsloo (2011) refer to Bourdieu (1971) and Braxton (2000) and describe the notion of habitus as "the complex combination of perceptions, experiences, values, practices, discourses, and assumptions that underlies the construction of our worldviews" (p.186). The habitus of both students and the institution affect how they see risk, success, and the factors that shape the chances of dropout or success. Early models of student success and failure (Spady, 1970; Tinto, 1975) normalised students' chances of success as their (in)ability to be assimilated into accepted norms, worldviews, and assumptions undergirding student learning. When students enter higher education, they do not leave their habitus at the door. Often their habitus (ontologies and epistemologies) will collide with that of the hosting institution. Then, depending on their capital and loci of control, they will negotiate a way through the "student walk".

- *The domains and modalities of transformation*. In reference to students, Subotzky and Prinsloo (2011) refer to intra- and interpersonal domains and how these shape students' approaches to, and strategies in, their learning journey. In respect of the providing institution, the three domains of academic, administrative, and non-academic social domains of institutional life interact with students' intra- and interpersonal domains in complex and often interdependent ways.
- *Student success*. The sixth construct suggests that "student success" may not be fully understood. Measuring student success is commonly assumed to refer to course success or successful graduation (measured as time-to-completion). With an emphasis on student satisfaction in higher education, there is also the possibility that success can be defined as a satisfactory experience. Finally, student success may also refer to the "successful fit between students' graduate attributes and the requirements of the workplace, civil society, and democratic, participative citizenship" (Subotzky & Prinsloo, 2011; p.188).

Mapping macro, meso and micro institutional structural and organisational factors

Much of the literature around learning analytics assumes that outcomes are determined either by the actions or characteristics of the individual – the student – or by the behaviours of cohorts of students at a module or subject level. Subotzky and Prinsloo's socio-critical model (2011) provides a useful framework to examine a range of factors at micro, meso and macro levels which have the potential to impact and shape the institutionalisation of learning analytics.

Macro factors

At first glance, it may appear that few issues have any real impact on the implementation of learning analytics at a macro level. In this section, we make the case that the concept of habitus - the habits, skills, and dispositions shaped by life experiences – has relevance at each level – micro, meso and macro. At an institutional level, habitus will be influenced by the national context as well as by the views and perceptions of senior management. These will shape how data are defined, what data are collected and the underlying beliefs around what that data represents. In the context of learning analytics, analysis and action are often driven by available data rather than actual need. This can be exacerbated by a lack of political will to engage students in the meaning of their data, on what is collected, when it is collected and what other data may provide both the institution and learners with a more comprehensive view of students' habitus and capital in the *student walk* (Prinsloo, 2017).

Similarly, the notion of capital – the assets that a party can bring to bear – has application across each level. The acquisition of capital is likely to be impacted by socio-economic and cultural contexts. It has been argued elsewhere that institutions have a fiduciary and moral duty to use their capital to ensure effective, ethical and caring and appropriate learning experiences (Slade & Prinsloo, 2013; Prinsloo & Slade, 2016). Not only must institutions provide ethical oversight on the collection and analysis of students' data to establish the scope and value of their *capital* (Willis, Slade, & Prinsloo, 2016), but they should also accept a contractual and moral responsibility to ensure the ethical allocation of resources in response to the analysis of student data (Prinsloo & Slade, 2017).

Learning analytics is often used to examine students' behavioural data which, in many respects, are the outcome of the interplay of their different kinds of capital in response to pedagogical strategies, curriculum coherence, stimuli and events in their life-worlds outside of their studies. It is pertinent to note that there is little evidence of equivalent reflection of the institutions' capital and how that capital is used to support and ensure effective, appropriate and high-quality learning journeys via the systematic collection, analysis and use of institutional data, across and between strategic and operational silos.

Institutions are often faced with regulatory issues, such as changes in the funding regime, which seriously impact and hamper both their offer and their response to operational challenges, increasing competition and supporting students. As Prinsloo and Slade (2017) indicate, institutions' ability to respond to students' identified risks and support needs, is, in many respects, "an elephant in the learning analytics room" (p.1).

Meso factors

Although students have a clear responsibility to contribute to their own student walk, there is less attention directed to other partners in that walk, namely faculty and support staff, and the institutions themselves. The current drive to collect as much student data as possible (without always knowing its potential purpose) is starkly juxtaposed by the lack of an institutional commitment and resource allocation to keep track of, surveil and build institutional profiles of actions taken by course teams and the ways in which support and study resource are allocated within courses and faculties. It is likely also that the existence of departmental silos leads to a loss of shared insight as well as subsequent inefficiencies and a lack of real understanding of both the raw data and the subsequent analysis.

Learning analytics can get “stuck in the middle” as a result of a focus on role of the student without equal consideration of the (in)actions of others in the learning journey. Similarly, the social domain of the institution – its culture, power relations, and dominant ideology – has a significant impact on academic and administrative strategy. Recognizing and addressing this is an essential feature of the socio-critical model (Subotzky & Prinsloo, 2011).

The construct of *situatedness* has important implications for the potential of learning analytics to effectively address students’ needs and risks. Learning, as proposed by Subotzky and Prinsloo (2011), is caught between the constrained agency of two players, namely students and the institution. However, given the asymmetries in the power relationship between students and the institution, and the ways in which institutional processes, rules and regulations impact on student learning, it would not be reasonable to take an approach to learning analytics which focuses only on what students do or don’t do. Though students have agency, such that some of their decisions about learning fall within their loci of control, in practice their agency and loci of control are constrained. What students do or don’t do is often in response to instructional and institutional intentions and (in)actions.

Another issue in the context of student (constrained) agency is that of student consent. Generally, it is assumed that students’ acceptance of the Terms and Conditions at the moment of enrolment provides the institution with blanket permission to have their data collected, analysed and used. While the use of student aggregated data (as proposed in Academic Analytics) is provided for in the contractual, fiduciary duty of the institution, the ethics around the collection, analysis and use of individualised and identifiable student data to shape their learning is unclear (Willis, Slade, & Prinsloo, 2016). With changes in international data regulations (e.g., the European General Data Protection Regulation, GDPR), there is increasing pressure on higher education to develop a nuanced regulatory framework to ensure the legally compliant, but also morally justifiable option to allow students to opt-out of the collection, analysis and use of their data (Sclater, 2017).

Micro factors

We have access to increasing volumes of student data, and also to a greater variety, velocity and granularity of student data. Institutions harvest and analyse behavioural data, and combine this with demographic and historical learning data, and data from sources such as the library, student counselling, and, increasingly, from social media. As such we have increasingly detailed views of individual student identities, behaviours and networks. We use this data to understand and describe student learning, to diagnose their needs, risks and potential, to predict chances of success, failure and their need of institutional resources, and increasingly to prescribe personalised / individualised curricula, assessment, learning pathways and future enrolments. Such determinations are weakened when data is not complete or where proxies are used to substitute for missing datasets. Where data proxies are used in predictive analytics, there is also a danger of creating false positives, identification of individual students deemed to be at risk as a result of unrepresentative datasets.

In a learning analytics context, less attention is paid to the intra-personal domain of the student – the range of individual psychological attributes required for successful study, such as positive attitude and beliefs, self-discipline, motivation, and confidence since these are not routinely captured nor easily measured. There is a growing focus on the inter-personal domain – the social interactions which can support learning and understanding (Ferguson & Shum, 2012; Perrotta & Williamson, 2016).

Subotzky and Prinsloo (2011) discuss how notions of causality and attribution, control and efficacy play out in the student walk. In the field of learning analytics research, there are concerns that data are used, incorrectly, to prove causality rather than simple correlation (Ferguson et al., 2016). For both students and institution, there are factors within the control (or perceived control) of students and/or the institution, but also many that fall outside the loci of control of both students and institution. It is often assumed that the mere act of identifying a factor in a student's strategies or learning behaviours, will allow that student to make a change. Although we should not label students as helpless, we should also not underestimate the impact of intergenerational, context-specific and structural elements which may constrain their self-efficacy and loci of control.

Subotzky and Prinsloo's five constructs (2011) culminate in the concept of student success. One of the many attractions of learning analytics is its promise of identifying students at risk of not being successful. Models of student success are often comparative – measuring current students against the characteristics, demographics and behavioural data of students who have previously successfully completed a course or programme. This can result in such feedback as “our research indicates that students like you…”. There is a danger in equating a predicted outcome based on historical student behaviours and characteristics with an actual outcome, effectively pre-labelling students as successful or not. In addition, Woodley (2004) warns that we should not pathologise student dropout in distance education contexts because the motivations and individual measures of what makes for successful study may vary. In this case, it becomes difficult to use the statement ’students like you’ in any meaningful way.

(In)conclusions

Learning analytics as a practice, discipline and research focus has matured. There are however concerns regarding a lack of evidence of its ability to impact positively on students learning (Ferguson & Clow, 2017), and suggestions that learning analytics is, in many respects, *imperfect* (Kitto, Sum, & Gibson, 2018). Though there is research that maps and explores the many factors that impact on the institutionalisation of learning analytics (Ferguson, 2012; Scheffel, Drachsler, & Specht, 2015), this paper provides a perspective on three levels – micro, meso and macro – of factors that shape and impact the effectiveness of learning analytics. Much of the learning analytics literature is focused on the individual student, at a micro level, and on how student characteristics and behaviours determine outcomes. This paper suggests that such a focus may be misguided. In viewing the factors which impact on student learning from a *socio-critical* perspective, we find that many (as identified through learning analytics and communicated to students, faculty and support staff through dashboards and early warning systems) may fall outside students’ loci of control.

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