



# MEASURING EFFORT RATHER THAN ASSUMING DEFICIT

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Moving beyond assumptions  
of disadvantage.

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*GetSmarter*

## INTRODUCTION - BEYOND IDENTITY MARKERS:

Higher Education policies and practices, whether in evaluating candidates for admission or in tailoring academic development to improve student success, often use proxies for the prior and continuing disadvantages that skew opportunity. The new and still-emerging field of Learning Analytics now offers the promise of replacing traditional proxies for disadvantage with far more accurate measures of individual effort.

For online providers such as GetSmarter, the use of analytics is essential for the continual improvement of course design and the alignment of programmes to learners' needs. In this paper, we focus on how Learning Analytics can be used to identify and support at-risk students without using contentious identity markers such as race, gender or ethnicity. We then go on to ask whether such approaches could be used to inform access decisions, resulting in fairer admissions, that are made on reliable estimates of potential rather than on assumptions of deficit.

Policies and practices that aim to support student inclusion are founded in the expansion of universities that began in the mid-twentieth century and that continues to gain momentum. The overall scope of these policies includes affirmative action in the United States, widening participation in the United Kingdom and current policies in a range of other countries. In South Africa, which is our focus here, academic development has been centred on the consequences of apartheid segregation and the continuing issue of economic inequality.

A common feature of these approaches has been their reliance on identity markers as proxies for disadvantage: race, religion, ethnicity, language, prior schooling and household location, and various categories of disability. In the absence of alternatives, this dependency has been unavoidable. However, the use of identity markers requires a set of assumptions that have become increasingly unreliable.

For example, through the early to mid 1990s, immediately after the dismantling of the apartheid education system in South Africa, the school that a university applicant had attended could be associated with an immediate history of unfair discrimination; applicants who had attended a school that had been administered by the former Department of Education and Training would have been racially classified as black and almost certainly needed additional support at university. Twenty years later, a large proportion of schools have been founded or restructured since the end of apartheid, there have been extensive organisational changes and apartheid-era bureaucratic affiliations have almost no value as proxies for making university admissions decisions. And, while universities are still required to record the race of students and staff for statistical purposes, there are significant complications – and many objections – to using race as an indicator of anything.

In the context of extreme economic inequality, the cliché of the level playing field is the wrong metaphor. For many students, access to Higher Education, along with subsequent success, is more like the challenge of climbing a mountain barefoot, without safety equipment, and while watching fully kitted out contemporaries swing by towards the summit. The problem is in identifying those climbers with both potential and the need for support, but without making inaccurate and derogatory assumptions based on identity indicators.

The use of identity markers in education is further complicated by the broadening application of theories of intersectionality; the recognition that social identities are complex and mutually independent in their perpetuation of discrimination. For example, in Britain universities may often assume that “BME” students will need academic support, implying that this identifier is applied to an educationally homogenous group. But as Oxford University’s admissions service explains:

“BME stands for Black and Minority Ethnicity, which includes members of the following British and international ethnicities: Bangladeshi, Pakistani, Indian, Indian other, Chinese, Asian other, Black African, Black Caribbean, other Black background, White and Asian mixed, White and African Caribbean mixed, other mixed background and other ethnic background” (Oxford University 2016).

In this definition, “BME” means little more than “non-white”.

In contrast to assumptions of need based on such a broad proxy, practice based on intersectionality theory works to understand how a wide range of identity indicators works together to establish a syndrome of prejudices. An example here is work at Middlesex University that is focusing on the intersection of ethnicity, gender and religion in order to understand the institutional practices that systematically disadvantage some students. By “understanding the ways in which students situate themselves in the classroom, and the extent to which different forms of oppression may intersect to hinder students’ ability to successfully engage and progress”, such research can “offer insights which can potentially inform practise. In turn, this may have an impact on departmental and university-wide progression rates, and degree classification awards” (Sanders-McDonagh and Davis 2014).

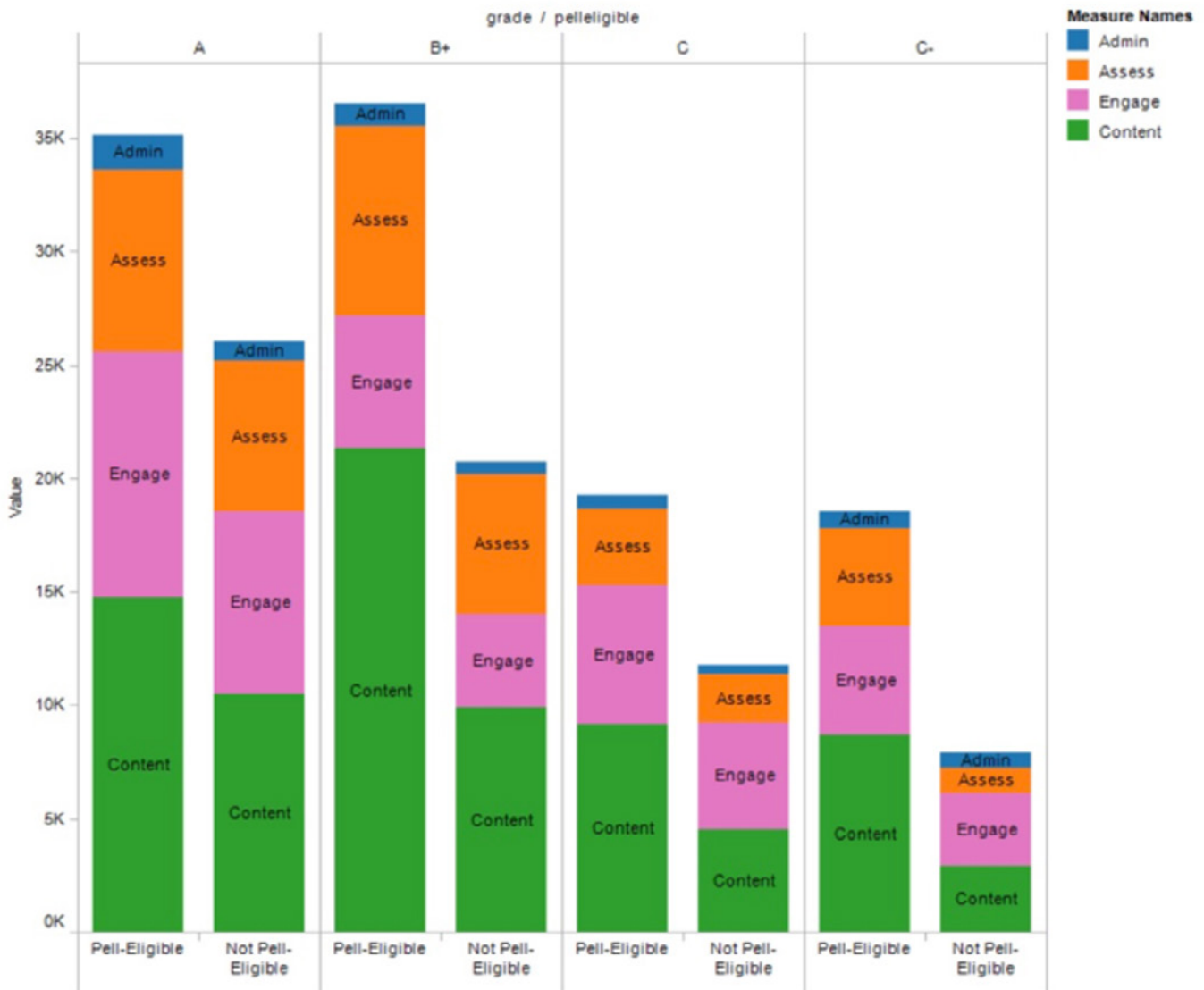
## INDIVIDUAL COMPETENCIES RATHER THAN ASSUMPTIONS OF DEFICIT:

Learning Analytics provides the means to take this approach further, allowing individual student requirements to be identified on the basis of their competencies and patterns of behaviour rather than on assumptions about who they may be. This is captured in a commonly used definition of Learning Analytics as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (SoLAR 2016). Deployed within appropriate fields of education practice, Learning Analytics can be used to provide support on the basis of individual student histories and requirements, rather than relying on increasingly contested markers such as race, gender and ethnicity.

This potential has been demonstrated in a number of pilot studies. One of these was conducted at California State University, Chico; a medium-sized university with a high proportion of students who would characteristically be seen as “at risk”, and with a standard Virtual Learning Environment (VLE) and associated facilities (Whitmer, Fernandes and Allen 2012; Whitmer 2015). The CSU study is of interest here for two reasons. Firstly, it demonstrates that student use of the VLE can replace assumptions of deficits based on demographic indicators with direct indications of students’ in-course needs. Secondly, it shows how these insights can be linked with curriculum review and design to adapt courses to these needs.

At CSU, as with many universities, demographic indicators such as race, ethnicity and gender had been used to anticipate students needs. The Learning Analytics research found that these did indeed correlate with students’ success, represented by the final grades allocated to them. However, it was also found that measures of student use of the VLE were much stronger predictors of educational outcomes, suggesting that such measures are direct proxies of student effort. In other words, measuring the use of the VLE tells a university what students are actually doing while engaged in learning, rather than what it is assumed that they will do on the basis of sets of identity markers.

Secondly, the aggregation of records of student VLE use revealed new and unanticipated patterns that enabled educators to focus on particular aspects of provision as significant opportunities for improvement. This inductive approach is characteristic of “big data” research in general – the “fourth paradigm” that is transforming research across diverse fields, from medicine to climate change (Royal Society 2012). For example, CSU data on student grades was aligned with different kinds of VLE use and with the achievements of students from low income households (based on eligibility for Pell grants). The outcome is summarised in Figure 1, in which VLE use is broken down into routine administrative tasks, formal assessment exercises, collaboration (for example, in online forums) and time accessing course content.



**FIGURE 1:** California State University VLE use patterns (from Whitmer, Fernandes and Allen 2012).

This exercise shows that, when correlated with final course grades, low income students consistently spent more time accessing online content. This opened up a series of further, more focused issues for the improvement of course design, and the provision of support, based on the data patterns themselves rather than on prior assumptions of student need based on demographic characteristics:

“this finding raises more questions and suggests different potential actions to address the disparity. Perhaps these students need different study skills, or perhaps other background characteristics and academic experiences necessitate this extra study time. These findings can help us identify differences and target interventions to make the most difference for our students” (Whitmer, Fernandes and Allen 2012).

Here, and as the UK's Higher Education Commission has recently recommended, informed student consent is essential (Higher Education Commission 2016). This requires both consultation with student representatives and appropriate ethical policies and processes for data collection, management and protection at each institution (Sclater 2014; Sclater and Bailey 2015). In turn, the corollary of informed consent is the right to opt out – a right increasingly enforced by national legislation. This was highlighted in the California State University pilot, which required the navigation of the Family Educational Rights and Privacy Act (FERPA). In South Africa, all education institutions are subject to the Protection of Personal Information Act (PoPI), which requires consent for the re-use of any personal data record that is not “dis-identified”. Issues of data ownership and protection also need to be covered by appropriate policies at the institutional level. For example, partnerships with commercial organisations may require the surrender of control of data archives and of their use for other purposes. In addition, there need to be clear and transparent guidelines for the use of student data records for non-educational purposes.

## MEASURING EFFORT - THE GETSMARTER MODEL:

University of Cape Town (UCT) online short courses developed in partnership with GetSmarter provide another example of the use of behavioural metrics in favour of identity markers for identifying students deemed to be at risk of failing to complete or pass a course. The abbreviated time periods characteristic of the short course environment provide a quasi-experimental reference point from which insights gathered can potentially be extrapolated to online or blended credit-bearing courses.

GetSmarter's model for identifying at-risk behaviour is based on this premise that student effort is a stronger predictor of success than traditional student demographic data. Research from Purdue University's frequently cited Signals Project that used a traffic light system to indicate level of risk supports this obvious yet necessary hypothesis: 'a student with average intelligence who works hard is just as likely to get a good grade as a student that has above-average intelligence but does not exert any effort' (Arnold and Pistilli, 2012). The VLE is a rich data source, and thus provides a number of different options for measuring student effort. Variables selected should be an accurate reflection of the construct under scrutiny (effort) and on a practical level accessible via the current system's functionality. The variables included in the model were based on both institutional experience and previous studies conducted. This model includes three measures of student effort: VLE access, assignment submission and discussion forum engagement.

A study conducted by the University of Maryland, Baltimore County (UMBC) also supports the inclusion of VLE access to measure student effort. This data confirms nothing more than the fact that a student has logged onto the VLE and, as such, is a crude proxy for effort. However, the research conducted at UMBC revealed that students who obtained D and F grades used the VLE 40% less than students who achieved A, B and C grades, and that this finding was consistent year after year (Fritz 2013).

This consistent correlation between grades and effort justified the inclusion of VLE access in the GetSmarter model. While time spent on the VLE may be a more accurate measurement of effort, current systems lack the functionality to measure this variable easily. VLE Access, however, merely begins to paint the full picture of student effort. Assignment submission measures effort more directly. The Open University, which has a long-standing history of online education provision, uses assignment non-submission, and in particular non-submission of the first assignment, as an indicator of risk (Sclater 2014). Since GetSmarter short courses include at least one assignment in each week-long module, assignment submission has been adopted as a measure of on-going effort.

Similar to the way that a teacher or tutor would be interested in measuring contribution to class discussion in the traditional classroom, in the online classroom an equivalent measure is engagement in discussion forums. Wollongong University has developed the Social Network Analysis and Pedagogical Practices (SNAPP) tool to monitor discussion dynamics and intervene in cases where students are isolated from group conversations (Bakharia and Dawson, 2011). The GetSmarter model combines the data used to generate the SNAPP diagram (based on the number of discussion forum posts) with VLE access, assignment submission data and grades to monitor student at-risk behaviour at any given time.

While VLE data is effective in highlighting certain behaviours, the GetSmarter approach is further enhanced by a high touch model that emphasises the value of human interaction. Course Coaches work with a given number of students to encourage and motivate them to engage with the course material and with their peers. Course coaches communicate via telephone and email to establish one-on-one relationships with students who have elected to make use of this service based on a self-assessment of their own needs. This means both reinforcing positive behaviour and encouraging students to alter negative patterns that result in less than optimal performance.

During any given week, a Course Coach needs to be able to identify the students who are most at risk of failing or dropping out and to contact them. More importantly, this behaviour should be identified before a student has fallen too far behind. The at risk model provides the Course Coach with a tool to identify these students (Figure 2).

Course: UCT Advance ▾ Module: All ☀ Post: All ▾ No Login: All ▾

No\_Submissions: All ▾ Grade\_Average: All ▾

	Name ↓	Email ↓	Phone ↓	Average Grade ↓
1	[REDACTED]	[REDACTED]@omwea	+27 83 [REDACTED]	65.23413150000002
2	[REDACTED]	[REDACTED]@gma	+27 71 [REDACTED]	49.84791450000001
3	[REDACTED]	[REDACTED]gmail.co	+27 79 [REDACTED]	59.366460499999995
4	[REDACTED]	[REDACTED]whereismytranspor	+2721 [REDACTED]	78.358533999999999
5	[REDACTED]	[REDACTED]@shell.com	+27 [REDACTED]	45.025788947368426
6	[REDACTED]	[REDACTED]gmail.com	+264 [REDACTED]	54.782539500000006
7	[REDACTED]	[REDACTED]gmail.com	+27 [REDACTED]	67.89306200000001
8	[REDACTED]	[REDACTED]@transhex.co.za	+27 [REDACTED]	71.25833
9	[REDACTED]	[REDACTED]@hotmail.com	+27 [REDACTED]	72.7999985

**FIGURE 2:** GetSmarter at risk tool for Course Coaches.

Course Coaches select the current module of the course and check which students have failed to log in to the VLE, post comments on the discussion forums or submit assignments. Over and above being able to identify behaviours that signal a lack of effort, Course Coaches also have sight of how this behaviour has affected individual students' grades. The filtering mechanism gives the Course Coach a basis for applying triage principles in selecting which students should be called first. For example, a student who has not logged in for seven days, has not submitted the assignment for the week and has not engaged in the discussion forums would be contacted ahead of a student who is passing the assignments but not engaging in the forums.

Bringing together earlier and contemporary approaches to student support with such early outcomes from the use of Learning Analytics opens up the possibility of widening participation in Higher Education by using more accurate information that does not run the risk of stereotyping by the continued use of simplistic, singular identity markers that may lack validity as proxies and which may be offensive. Instead of making assumptions about a student's future success based on who they are – their race, gender or socioeconomic background, for example – Learning Analytics allows in-course interventions based on what all students, irrespective of identity markers, actually do. While effort and ability are not synonymous, research conducted to date has demonstrated – convincingly, we believe – that measures of effort derived in real-time from a student's digital footprint allow effective and targeted interventions that are free of identity assumptions.



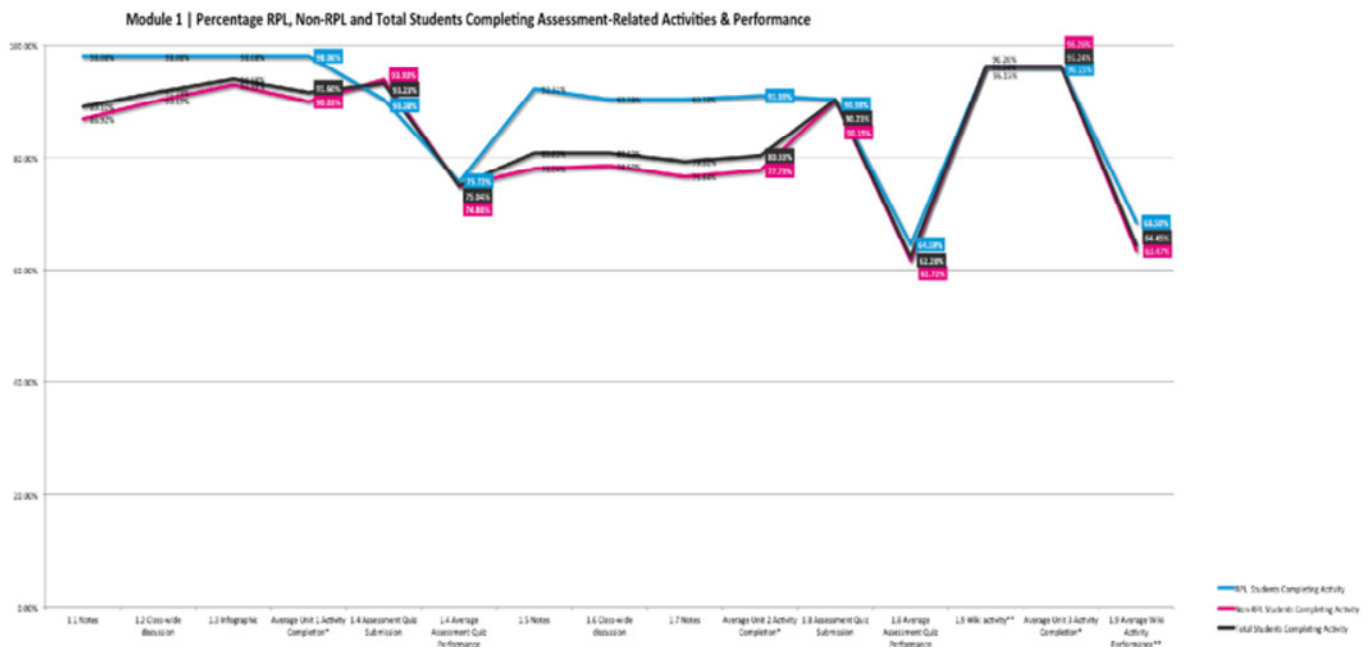
## LOOKING AHEAD: FAIRER ADMISSIONS POLICIES?

Looking ahead, an obvious question is whether these advantages can be extended to application processes and admissions decisions. Here, the reliance on prior identity markers is just as controversial. In the UK, the use of “contextual” admissions processes, that take account of an applicant’s socio-economic circumstances in weighting the value of their prior education qualifications, remains contentious. In the US, affirmative action admissions policies are under almost continuous review by the Supreme Court. In South Africa, the use of racial identifiers in making admission decisions is attacked on all sides (UCT 2014).

Here, a useful baseline is the set of general principles for making a fair admissions decision, whatever the programme, institution or national jurisdiction. These were well laid out in the 2004 Schwartz recommendations for the UK. Contrary to widely held assumptions (not least by applicants and their families) admission to a university should not be a reward for prior education attainment. A fair admissions decision should rather be based on a professional evaluation of the applicant’s potential to complete course requirements and graduate. As such, a fair admissions decision can be based on any evidence that is a reasonable and proven basis for prediction.

School leaving results or their equivalents are, like identity markers, proxies for the combination of ability, experience, maturity and commitment that will be required to successfully complete a Higher Education qualification. As such, they are often inaccurate. For example, in an early use of Learning Analytics Bowen, Chingos and McPherson used a large sample of progression and completion data across a range of public universities in the US to test whether SAT scores were reliable predictors of graduation outcomes. They found that they were not and that high school grade point averages were far better indicators of a candidate’s preparedness for university: “we believe that the consistently strong performance of high school GPA as a predictor of graduation rates derives in large part from its value as a measure of motivation, perseverance, work habits, and coping skills, as well as cognitive achievements” (Bowen, Chingos and McPherson 2009). In South Africa, recognition of the limited predictive value of the National Senior Certificate has long been known and has promoted the development of alternative admissions testing and the National Benchmark Test facility (<http://www.nbt.ac.za>; Yeld 2001)

The growing urgency for the reform of Higher Education admissions systems in South Africa is again demonstrated by recent profiles of learning patterns through a UCT postgraduate course, designed and delivered by GetSmarter, that makes use of finer-grained analysis. This Advanced Diploma programme offered a dual admissions route; prior attainment of formal qualifications, and Recognition of Prior Learning (RPL). RPL applicants were required to take a two week online pre-admission course with a summative assessment to establish potential to successfully complete the Advanced Diploma. Learning Analytics were then used to map every student’s work on every task in each successive weekly module, allowing the engagement, progression and outcomes for the RPL group of students to be compared with those admitted on conventional criteria.



**FIGURE 3:** UCT Advanced Diploma. Student engagement levels.

An example of this analysis is shown in Figure 3. This shows RPL activity completion rates (blue line) compared with both non-RPL activity completion rates (red line) and the activity completion rates for the class as a whole (black line) tracked across 15 engagement points in a single week. This in-course data showed that, over all modules, a consistently higher proportion of RPL students completed learning activities, that in almost all cases RPL students outperformed conventionally-admitted students in assessments, that RPL students were more persistent in their levels of engagement across the academic programme as a whole and that a far greater proportion of RPL vs. non-RPL students initiated discussion topics on the forums, as well as contributed to existing discussion threads initiated by others.

Taken together, these diverse studies point to a new frontier for Learning Analytics – contributing to equitable admission policies for Higher Education. Combining this need with the insights that are being gained in tracking the detailed performance of students who are already enrolled in Higher Education suggests that investment in measuring the learning behavior of applicants prior to admission would be well worthwhile. In the example used here – UCT’s Advanced Diploma – GetSmarter provided an online pre-course for applicants who lacked traditional prior qualifications. Given the subsequent success of these students in matching, and sometimes , exceeding the performance of their “traditional” contemporaries, it is a reasonable inference that a person’s aptitude for learning can be assessed on their unique performance, again without using proxies for whom they are believed to be.

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