Emperor's new clothes: Speaking out about uses for predictive learning analytics

Nan Bahr & Peter J Cook

Abstract

As in the fable "The Emperor's New Clothes," there has been reluctance to draw attention to the problems with using predictive Learning Analytics by Universities as an evidence base for targeted interventions to support student success. We evaluate its effectiveness based on a comprehensive critique and review of contemporary literature in the field. Our examination focuses on the inherent limitations for equitable and efficient evidence in support of scalable and sustainable targeted interventions and the failure in scope for predictive Learning Analytics actually to identify those students who need support. We propose, instead that there is potential for more impactful and holistic support for student success with greater proactivity than most Learning Analytics approaches allow.

Introduction

From Hans Christian Andersen's "The Emperor's New Clothes (Keiserens nye Klæder)":

> *"So off went the Emperor in procession under his splendid canopy. Everyone in the streets and the windows said, "Oh, how fine are the Emperor's new clothes! Don't they fit him to perfection? And see his long train!" Nobody would confess that he couldn't see anything, for that would prove him either unfit for his position, or a fool. No costume the Emperor had worn before was ever such a complete success. "But he hasn't got anything on," a little child said."*

We contend that the promise of predictive Learning Analytics to provide supportive evidence to inform effective interventions for students at-risk, has obscured the reality; just like this scene from the famous short story about the Emperor and his new clothes from the early 1800s.

Learning Analytics is a comprehensive family of systems for data collection and analysis designed to guide the improvement of teaching and learning for higher education institutions. Institutional interest in Learning Analytics systems has grown dramatically in recent times, alongside the affordances of technologies to track learner behaviour and achievement. There are many different designs for Learning Analytics aligned directly with the types of questions that captivate each institution's leadership. Prominent among many topics is the quest for timely profiling of learners against performance risk markers to potentially rescue them from failure. It is this particular use that we critique in this paper. Substantively missing from the contemporary discourse around the use of Learning Analytics to guide learner intervention, is a reflection on first principles, that is, what exactly are we trying to achieve and is this the most efficient, equitable, scalable and sustainable approach.

Background

Universities have come to depend upon sophisticated data collection and correlation techniques to describe and predict the academic behaviour and performance of students as individuals and by cohorts. These Learning Analytics systems are diverse with respect to the array of data collected and their analyses. The popularity of the annual *International Conference on Learning Analytics and Knowledge*, now in its 10th year, is an indicator of the contemporary global interest level for Learning Analytics.

This particular conference (there are several international and national societies in the field) typically brings together over 500 researchers from across the globe to share and discuss Learning Analytics systems and impacts. In 2019, the program boasted 92 papers, selected from 384 submissions. The conference is scored with an H5 index of 36. An H5 score reflects the median number of citations for all papers in twelve months. For this conference, the H5 score has been achieved in just under six months since the conference was held. To achieve an H5 of 36 doesn't just indicate the popularity of the conference. It also shows that there have been many more papers published in the field across even for this brief period.

Learning Analytics research interest tends to consider the relationships between data, approaches to data analysis, and learning design, including the design of targeted support interventions for identified students. Interest also extends to the development of the sophistication, simplification and elegance of the Learning Analytics processes, tools, dashboards and interactivity. However, concerns are emerging in the discourse about the broad usefulness of Learning Analytics, and this may reflect the growing appetite for a silver bullet approach to improving retention and completion difficulties faced at many institutions. This is particularly true for Australian institutions (see West et al., 2015).

An important and well-cited review report of the success of Learning Analytics in higher education globally was provided by Sclater, Peasgood and Mullan (2016) for the Joint Information Systems Committee (commonly referred to as JISC) in the United Kingdom. They adopt the well-accepted definition for Learning Analytics, initially proposed by Siemens & Gašević, (2012):

> *Learning analytics is 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.*

The wording of this definition is important, particularly the statement of purposes for Learning Analytics. What is *not* said is that Learning Analytics can identify generalisable characteristics for predicting success. It is *not* suggested that there would be a link between profiles of data and performance or retention predictability. There is *no* hint that Learning Analytics have a role to incisively target learning support based on marker profiles.

In later publications, Gašević (2015) with co-authors Dawson, and colleagues actively warn against using retention and achievement data as a proxy for profiling or understanding learning. This issue was earlier recognised by Watters (2012), as well as Dietz-Uhler & Janet E. Hurn (2013), notably at the same time that the Siemens and Gašević definition for Learning Analytics was framed and adopted by the sector.

However, Sclater, Peasgood and Mullan (2016) do not recognise these limitations in their report for JISC, and instead detail correlations between Learning Analytics processes with retention and achievement data for a range of international case studies. We note that JISC describes themselves as having a pivotal role to "champion the importance and potential of digital technologies for UK education and research" (JISC, 2020), which includes negotiation for sector-wide deals for higher education institutions with IT vendors and commercial publishers. This suggests a conflict of interests or at least a bias in their reporting of Learning Analytics success. This aside, Sclater, Peasgood and Mullan, usefully describe the three broad categories of uses and research into Learning Analytics. We refer to these as Learning Analytics for learning design; Learning Analytics for responsive pedagogy; and, predictive Learning Analytics.

Three categories for Learning Analytics

1. Learning analytics for learning design

First; those Learning Analytics systems aimed at monitoring student performance with different pedagogical approaches to inform future course innovation and development. This seems a defensible rationale for the analysis of an array of data to support innovation that is evidence-based and not merely change for change sake. Recent writers in this field, which we could call "*Learning Analytics for Learning Design*" include Wiley and colleagues (2020), and Hilliger et al. (2020). These researchers contribute to this body of literature concerning the value of performance and behavioural data for the support of learning design. The types of data considered are consolidated performance data sets, student evaluations, enrolment and re-enrolment figures, engagement profiles with Learning Management Systems, and the like.

2. Learning analytics for responsive pedagogy

Next; those Learning Analytics systems that enable academics to continually monitor their student engagement and performance to guide their timely responsive pedagogy with efficiency, which we could call "*Learning Analytics for Responsive Pedagogy*".

These systems provide academics with the learning pulse of their students. They alert them to signs of confusion or disengagement and provide them with insight to get a class back on track with their learning. Academics can be supplied with dashboards that profile the current usage rates for their class on the Learning Management System. Performance on diagnostic quizzes, engagement in discussion boards, and "pulse" questionnaires are the types of data that informs these systems for Learning Analytics.

Recent researchers reporting on these types of systems include Brown (2020) who writes about the usefulness of a data dashboard to support active pedagogical response with a large class. And also Shibani, Knight and Shum (2020) who report on the effectiveness of analytics derived from student use of an automated writing feedback tool for supporting academics to respond pedagogically.

3. Predictive Learning Analytics

Finally; and the focus for this paper, are those Learning Analytics systems designed to identify students that hit behavioural or performance markers indicating as red flags their need for supportive intervention. These "Predictive Learning Analytics" have a goal to efficiency through targeting the predicted points of weakness. However, we contend that it is counterproductive.

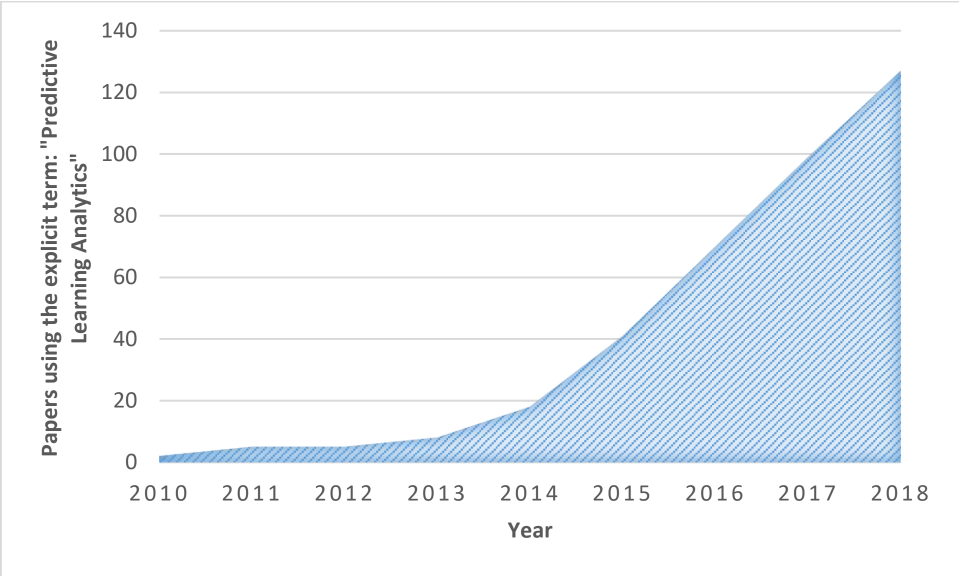

Figure 1: Profile of growth in interest for "Predictive Learning Analytics" 2010-2018

Figure 1 depicts the growth in publication numbers for papers identified in Google Scholar using the explicit search term "predictive Learning Analytics" for the past decade. From a zero base in 2010 and a gradual start, the number of papers for 2018 was 15 times that of four years prior, 2014. While not precisely exponential, the growth profile is dramatic, reflecting the quite recent fervent appetite for design and development of predictive Learning Analytics systems.

Much of the literature in this area reports on the design of Learning Analytics systems and the way they guide particular interventions such as Student Success Advising (e.g., Dietz-Uhler & Hurn, 2013), Learning Coaches (e.g., Dawson et al., 2017), mentoring schemes (e.g., Lonn et al., 2012), and so forth. Using four distinct lenses; efficiency, equity, scalability, and sustainability, we review and critique these types of uses for Learning Analytics.

Efficiency

At face value, it seems efficient to target learner support interventions based on evidence from predictive Learning Analytics systems. The notion is that it may be possible to aim scarce support resources at the heart of the risk for students who are most likely to separate from their studies. This is arguably more efficient than attempting to provide the same level of support more broadly across a cohort. Therefore this is very attractive to institutions: a positive value proposition. The idea is to make the most significant impact by incisively working with those who will most benefit from support. The problem is that it is notoriously difficult to predict with any degree of certainty, who is on the path to disengagement and failure. Several recent articles talk of this difficulty.

Dawson and colleagues (2017), for example, implemented a large scale intervention for 1868 college students identified at-risk of failure from a population of 11,160, over two years at one institution. The results of their impact analyses led them to conclude that the positive association between the intervention and academic performance had an effect size that was too low for confidence that the intervention explained the variation in data.

Very recently, Foster and Siddle (2019) demonstrate that the impact of at-risk interventions based on Learning Analytics depends on the nature of the data being used. Indeed, although predictive Learning Analytics promote a data-driven intervention evidence base, there is little agreement across the sector on the most useful data to inform actions, nor how these might inform supportive interventions.

There is some argument that reliance on predictive Learning Analytics systems might be unhelpful or worse, harmful (Dringus, 2012), because they may focus attention on the improvement of the metrics rather than student learning and development. This could lead to support models that prioritise the improvement of the product of assessment deliverables, rather than the development of vital processes required for longer-term academic achievement. But this idea has largely been ignored.

We assert that, from an efficiency perspective, there may be only marginal or even negligible impact of intensive interventions on the most effective academic behaviour and performance of students identified as at-risk. If so, then the value proposition for the entire process is undermined. Further, if the success of the venture focuses on evidence for achievement of performance rather than mastery goals, then the long term impact of the intervention will be minimised, and so the cost-benefit relationship is damaged. Students may come to believe in the importance of performance indices rather than their knowledge and skills.

So why do researchers report success for their support interventions for learners identified through Learning Analytics systems? Ferguson and Chow (2017), reflect on the possibility that there may be a “Hawthorne effect” in play. The Hawthorne effect, first identified in 1925, saw a change in worker behaviour simply because they became aware that they were being observed. A Hawthorne effect could mean that reports of improvements or change in student behaviour and achievement may be unrelated to the effectiveness of interventions dependent on a predictive Learning Analytics system. There may also be a “Halo effect”, a term first coined by Thorndike a century ago (1920) to describe an observer expectancy bias. That is, where there is an expectation or desire for change, and so there is heightened importance placed on any effects observed co-incident with an intervention.

So, what data is the best data for predicting effectiveness for targeted intervention? This question remains unanswered. Therefore, there can be no argument for the efficiency of any particular intervention approach, as we cannot be sure that the students identified for interventions are the ones most likely to benefit from the work, or are the ones most likely to disengage or fail.

Equity

The use of predictive Learning Analytics to identify individuals for intervention privileges some students by providing them with access to supports not available to others. This is patently inequitable. Further, if there is an uncertain alignment between the indices from the predictive Learning Analytics system and actual student behaviour, students who may benefit from support may languish, and probably do.

The affordances of technology provide us with an opportunity for visibility and trend tracking of student digital footprints. But these digital footprints don’t reveal what we know are commonly reported reasons given by students who decide to withdraw from their studies, or who fail. These reasons include things like feeling overwhelmed, lethargy, mismatched expectations and reality, chronic illness, anxiety, and family responsibilities, (e.g., Bakker et al., 2019; O’Keeffe et al., 2019) situations that do not shine through on predictive Learning Analytics.

The first amongst these is the feeling of being overwhelmed (Ashour, 2019). There are many causes for a student to feel overwhelmed. An example that would elude predictive Learning Analytics is enthusiastic and anxious students. These students may feel overwhelmed due to almost fanatical engagement with discussion boards, reading lists, with controlling peers for group work and so on. Their fanaticism, drawing on their desire for excellence, would create a positive footprint on learning systems and yet they may well also be at risk of failure as the weight of their heightened engagement takes its toll.

Scalability

Wong and Cheong Li (2018) have noted that interventions for just-in-time, personal learning support have not yet been successfully implemented at scale. This is because intervention efforts connected to alerts from predictive Learning Analytics tend to be intensive. Identified students at-risk are typically provided with one to one support in the form of advisory interviews, feedback on draft work, assistance with work planning, direct mentoring, and emotional support. This often takes the form of a sequence of meetings for weeks with a skilled adviser. Apart from the sense of dependency that this can foster, significant weakness is that it is rarely plausible to provide such support at scale.

Sustainability

Predictive Learning Analytics systems need to be responsive to changing student profiles. This requires constant technological attention, monitoring, designing and redesigning mechanisms and dashboards, selecting and re-selecting metrics and evaluating for application to a continually evolving student body. This agility is resource-heavy. The interventions themselves are also resourced heavy. Given the issues raised regarding the inequity, inefficiency, and lack of scalability, the use of predictive Learning Analytics systems is clearly unsustainable for contemporary institutions.

To try and alleviate the expense, many institutions have sought guidance from reported Learning Analytics work from across the sector. Yet there can be no “off the shelf” system for predicting academic success for a cohort or individuals. Each institution, each student cohort, each student, is unique and dynamic. Dimensions such as regionality, modes of learning, course structure, access to co-curricular induction programs, domestic stability, cohort age profile, and family responsibilities vary markedly between institutions and demand bespoke predictive Learning Analytics systems. The ongoing expense of a unique and agile predictive Learning Analytics system design is prohibitive, and we argue, for most institutions, unsustainable.

First-principles

We have outlined some difficulties in the use of predictive Learning Analytics. Still, the most significant problem with the use of predictive Learning Analytics is the fundamental premise that it can be helpful to intervene in targeted ways to support individual students. We argue that it is not beneficial at all, that it is instead typically, harmful. There are eight points of failure that suggest we should return to first principles; that is, what exactly are we trying to achieve. The points of failure are:

1. A rise in the incidence of student dependency,
2. A focus on products and performance rather than processes and mastery,
3. The emergence of “failing forward” cycles and traps,
4. Pigeon-holing of students into dichotomous successful and unsuccessful typologies,
5. Belief in metrics as imperfect proxies for understanding the learner and their learning,
6. Neglect of the emotional needs of students,
7. Inattention to the development of self-regulatory skills and approaches, and
8. Lack of attention to the establishment of a growth mindset.

The first three of these have not yet been addressed in this paper.

Dependency

Students who have the benefit of a personal tutor can develop a deep sense of dependency (Mazenod et al., 2019), especially if the direct support reaps academic success beyond their expectations or previous experience. High levels of engagement with individual and personal support that focuses on the completion of assessment tasks can promote a sense of external locus of control. That is, a student can develop a belief that their success is reliant on the support relationship. They may become reluctant to take the lead for their learning through assessment.

Performance goals

Predictive Learning Analytics systems often profile the prior academic achievement of students. And this leads to personal just-in-time, just-for-me, learner support provided after the beginning of a teaching session. To make an impact on their achievement, this support necessarily circles around the importance of performance on assessment tasks. The risk here is that students can see the performance on assessment as the target rather than mastery of the underlying processes. For example, timing often precludes longer-term planning for progressive task completion.

Failing forward

Support for students who have begun to fail often involves acceptance of full drafts, extensions of submission dates, supplementary assessment opportunities, and resubmission allowances. Such leniency is imagined to help enable the engagement with personalised support. However, such leniency tends to concertina or overlap assessments such that struggling students are faced with a higher workload than their more successful peers. Such leniency, therefore, creates a "failing forward" cycle whereby a student can be attending to the completion of work from a previous session during the time they should be attending to their next assessments.

Summary and conclusion

We call for a return to first principles, what are we trying to achieve? If the answer is better learning outcomes for all students, then we need to take care. While Learning Analytics for learning design and responsive pedagogy holds great promise, there is danger in the use of predictive Learning Analytics. Using Predictive Learning Analytics to identify students for target learning support interventions is inequitable, inefficient, un-scalable, and unsustainable. Further, we conclude that there can be a harmful impact on the development of a mastery focused and academically achieving student who can reach their potential. And so, like the small child in Hans Christian Andersen's short story, we draw attention to the negative reality of using predictive Learning Analytics for targeted learning support initiatives.

References

Ashour, S. (2019), "Analysis of the attrition phenomenon through the lens of university dropouts in the United Arab Emirates", *Journal of Applied Research in Higher Education, Vol. 12* (2), 357-374.

Bakker, E. J., Verhaegh, K. J., Kox, J. H., van der Beek, A. J., Boot, C. R., Roelofs, P. D., & Francke, A. L. (2019). Late dropout from nursing education: An interview study of nursing students' experiences and reasons. *Nurse education in practice, 39*, 17-25.

Brown, M. (2020). Seeing students at scale: how faculty in large lecture courses act upon learning analytics dashboard data. *Teaching in Higher Education, 25*(4), 384-400.

Dawson, S., Jovanovic, J., Gašević, D., & Pardo, A. (2017, March). From prediction to impact: Evaluation of a learning analytics retention program. *In Proceedings of the Seventh International Learning Analytics & Knowledge Conference* (pp. 474-478). Retrieved from:

Dietz-Uhler, B., & Hurn, J. E. (2013). Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of interactive online learning, 12*(1), 17-26.

Dringus, L. P. (2012). Learning analytics considered harmful. *Journal of Asynchronous Learning Networks, 16*(3), 87-100.

Foster, E., & Siddle, R. (2019). The effectiveness of learning analytics for identifying at-risk students in higher education, *Assessment & Evaluation in Higher Education. Retrieved from: https://www.tandfonline.com/doi/full/10.1080/02602938.2019.1682118?casa_token=J8AoThD9eaQAAAAA%3AXmq3IsTVfeUdrady09wBPr6eSVekJKB56Z4Q9n0HE-6q41SZjuh4NN4UPj6PucXim-yXCmxdLKEXx4Q*

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64-71.

Hilliger, I., Aguirre, C., Miranda, C., Celis, S., & Pérez-Sanagustín, M. (2020, March). Design of a curriculum analytics tool to support continuous improvement processes in higher education. *In Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 181-186). Retrieved from: https://dl.acm.org/doi/abs/10.1145/3375462.3375489

Lonn, S., Krumm, A. E., Waddington, R. J., & Teasley, S. D. (2012, April). Bridging the gap from knowledge to action: Putting analytics in the hands of academic advisors. *In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 184-187). Retrieved from: https://dl.acm.org/doi/pdf/10.1145/2330601.2330647

Mazenod, A., Francis, B., Archer, L., Hodgen, J., Taylor, B., Tereshchenko, A., & Pepper, D. (2019). Nurturing learning or encouraging dependency? Teacher constructions of students in lower attainment groups in English secondary schools. *Cambridge Journal of Education, 49*(1), 53-68.

O'Keeffe, S., Martin, P., Target, M., & Midgley, N. (2019). 'I just stopped going': A mixed methods investigation into types of therapy dropout in adolescents with depression. *Frontiers in Psychology, 10,* 75.

Shibani, A., Knight, S., & Shum, S. B. (2020). Educator perspectives on learning analytics in classroom practice. *The Internet and Higher Education*, 46, 100730.

Thorndike, E. L. (1920). A constant error in psychological ratings. *Journal of Applied Psychology, 4*(1), 25-29.

Watters, A. (2012). *Learning analytics: Lot of education data...Now what?* Hack Education. Retrieved from http://hackeducation.com/2012/05/04/learning-analytics-lak12/

West, D., Huijser, H., Lizzio, A., Toohey, D., Miles, C., Searle, B., & Bronnimann, J., (2015). *Learning Analytics: Assisting Universities with Student Retention, Final Report (Part 1)*, prepared for the Australian Government Office for Learning and Teaching. Retrieved from https://ltr.edu.au/resources/SP13_3268_West_Report_2015.pdf

Wiley, K. J., Dimitriadis, Y., Bradford, A., & Linn, M. C. (2020, March). From theory to action: developing and evaluating learning analytics for learning design. *In Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 569-578). Retrieved from: https://dl.acm.org/doi/abs/10.1145/3375462.3375540

Wong, B. T., & Li, K. C. (2018, July). Learning analytics intervention: A review of case studies. In *International Symposium on Educational Technology (ISET)* (pp. 178-182). IEEE.