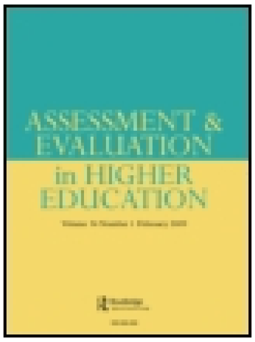

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A systematic review on the deployment and effectiveness of data analytics in higher education to improve student outcomes

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ABSTRACT

This is a systematic review conducted of primary research literature published between 2007 and 2018 on the deployment and effectiveness of data analytics in higher education to improve student outcomes. We took a methodological approach to searching databases; appraising and synthesising results against predefined criteria. We reviewed research on the effectiveness of three differentiated forms of data analytics: learning, academic and learner analytics. Student outcomes are defined as retention, academic performance and engagement. Our results find that three quarters of studies report the use of educational data analytics to be effective in improving student outcomes but their relationship with student outcomes requires further and more robust investigation and assessment. We argue that research must interpret and communicate effectiveness qualitatively, as well as quantitatively, by including the student voice in assessments of impact.

KEYWORDS

Learning analytics; academic analytics; learner analytics; educational analytics; educational data mining

Introduction

The 'intensification and spread of data analytics' (Beer 2017: 21) in business and society is gathering pace due to advancements in technologies designed to exploit increasing volumes of data capital (Francis and Foster 2019). As higher education institutions face numerous challenges in an increasingly capitalist market (Marginson 2013), big data and analytical based methods are being implemented across a raft of provision. This is unsurprising when the globalisation and massification of higher education is coupled with an increased emphasis on value for money with limited resources (Daniel 2017); analytics affords an opportunity to meet large scale demand. The theory of data analytics in higher education is that the collation of data and its analysis can deliver improved student outcomes by enabling personalised student learning environments, and delivering evidence based, 'what works' approaches (Harrison and Waller 2017: 81). Learning analytics is the term used to describe this process although other terms often include academic analytics and learner analytics (Piety et al. 2014). The four key elements of learning analytics are the measurement, collection, analysis and reporting of student data (Long et al. 2011). Siemens (2013, 1382) acknowledges that learning analytics 'is more concerned with sensemaking and action' rather than just data, and Reimann (2016: 131) decouples data collection from the process to take learning analytics 'closer to foundational research on learning'. As the use of data analytics in higher education has evolved so too has its complexity (Brouwer et al. 2016).

This article reviews the evidence of the use and impact of learning analytics in higher education with the aim of contributing to a student-focussed, research-informed debate about developments in

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this area. It presents the findings of a systematic review carried out in 2018 to inform the development and implementation of a learning analytics project aimed at improving student outcomes (Francis and Foster 2018; Foster 2018; Francis and Foster 2019). To inform our approach we reviewed the research that had been undertaken on the deployment and effectiveness of learning analytics in higher education, with the intention of avoiding any reported pitfalls, and to learn from 'good practice'.

What was clear from a cursory glance at the literature was that both data analytics and learning analytics were starting to receive considerable academic focus across the education sector. But on further examination, what was also evident was that much that had been published was not empirically based, of high quality or peer reviewed. Articles could be found in low quality academic journals and their focus was often wider than higher education, relating to particular industry and disciplinary organisations. Other articles were as likely to focus on the wider legal, theoretical and ethical issues relating to the use of data and its analysis for student outcomes, lacking the empirical rigour and evidence we needed to inform the specific activities of our project.

Other academics have undertaken reviews of this literature, often but not exclusively using systematic review methodologies (see Bienkowski et al. 2012; Romero and Ventura 2013; Papamitsiou and Economides 2014; Ferguson and Clow 2017; Ahern 2018; Sonderlund et al. 2018; Vieira et al. 2018; Robertshaw and Asher 2019). Reading these enabled us to understand the focus of other research, the questions being asked and the empirical findings reported. Importantly we gained insight into these authors' assessment of the quality of the articles and the underlying research.

Many of these systematic reviews report the positive impact that learning analytics is having in higher education, but often lack critical assessment of the research undertaken. Particularly noticeable is that the authors rarely, if at all, reflect upon the research design and theory of change in the studies. Furthermore, a critical assessment of the relationship between inputs, outcomes and benefits, as well as of causality and correlation, is limited. What is too often presented are summaries of the findings in the form of descriptive statistics and evaluations which lack an interrogation of the methodological approach alongside critical insight into why learning analytics worked in each setting. It is important to us to focus on the relationship between the data, the analytics and the interventions in light of their effectiveness.

Our aim was to systematically review the primary research literature on the deployment and effectiveness of what we have termed Educational Analytics (Francis and Foster, 2018) to improve student outcomes by enabling targeted academic and professional support interventions in universities. We have outlined in detail the key findings as they relate to the 34 relevant research studies. The article concludes by bringing together the emergent themes from the review to provide both a critical assessment of and initial reflections on the state of evidence for educational analytics.

Methodology

We deployed a systematic review methodology, informed by critical realism and its application in the social sciences (Pawson 2005). Our methodology thus produces a systematic review that is 'transfactual' (Price and Martin 2018: 90) in that its assessment of the empirical research literature goes beyond the reported outcomes to the underlying processes and conditions of practice which are fundamental. This section describes each stage and offers our reflections on the efficacy of the methodology.

Definitions

From the outset, a shared understanding of the terms used in the inclusion criteria was essential, as multiple and conflicting terminologies can be found within the research literature (Piety et al. 2014). This systematic review uses the following definitions:

- Educational data mining (EDM) is defined as the application of analytics methods on big data which has been collected from the learning environment and processed in order to report, monitor, identify patterns and generate insights.
- Learning analytics methods are defined as the generation of targeted personal, pastoral, wellbeing or other support interventions, delivered by academic or professional support staff through the application of EDM.
- Academic analytics methods are defined as the generation of academic interventions such as changes to course or curricula design, assessment and feedback, pedagogies, or other learning and teaching enhancement activities through the application of EDM.
- Learner analytics methods are defined as the direct-to-student communication and visualisation of personalised data and insights derived from the EDM process for the purpose of positively influencing learning behaviour. Deployment involves actively applying learning analytics methods in a live university environment either on campus, via distance or blended learning or massive open online courses (MOOCs).
- Academic and professional support interventions are defined as coordinated institutional or faculty led initiatives designed and delivered by utilising insight from the educational analytics process and targeted at students for the purpose of positively influencing their behaviour and or performance.
- Student outcomes are defined in terms of retention, achievement and engagement.

For clarity, learning analytics, learner analytics and academic analytics in this study excludes the application of EDM techniques for the purpose of improving student outcomes through the deployment of:

- institutional analytics, defined as the improved utilisation of physical, spatial, technological or digital resources;
- adaptive analytics, defined as the latent application of educational data mining and associated techniques to provide a real-time personalised learning environment.

Of equal importance to defining the terms was setting out the inclusion criteria for the systematic review. For the purpose of this systematic review, primary research literature is defined as that which reports on an original primary research study, published between 2007 and 2018, and categorised by the relevant online database as one of the following:

- conference paper
- journal article
- article (including those in press)
- reports – evaluative and research
- case study
- dissertation or thesis

Upon agreeing the parameters, the systematic review adopted a three-stage approach to collecting and reviewing research literature: search, sift and record. As the two of us were working simultaneously, we built into each stage a quality assurance process to ensure consistency in the interpretation and application of the agreed methodology.

Searching

The definition of terms and inclusion criteria informed the generation of the search terms outlined in Table 1. An asterisk denotes that the term was truncated to its root form; this maximises the possible returns based on the potential variations caused by suffixes.

Table 1. Search terms for systematic review.

Primary	Secondary	Tertiary
Learn* Analytics Education* Data Mining Education Big Data Academic Analytics Educational Analytics	Outcomes OR Retention OR Progression OR Achievement OR Performance OR Engagement OR Intervention OR Teaching OR Active OR Predict OR Satisfaction OR Learning OR Attainment OR Adaptive	Student OR higher education OR Universit* OR HE OR Data Science OR Data Analytics

Table 2. Databases searched during systematic review.

Platform	Database
EBSCO	British Education Index
EBSCO	Education Abstracts
EBSCO	Education Administration Abstracts
EBSCO	Education Resources Information Center
EBSCO	Business Source Premier
EBSCO	Library, Information Science & Technology Abstracts
EBSCO	Teacher Reference Center
Proquest	Australian Education Index
Scopus	All

Separate searches were conducted for each of the five primary terms; only literature which included the primary search term in their abstract were included. The results of the primary search terms were refined by the use of secondary and tertiary search terms; literature had to include at least one secondary and one tertiary search term in its main text to be included. After agreeing the inclusion criteria and search terms, nine databases serviced by three platforms, were chosen based on their applicability to higher education. These are detailed in Table 2.

Whilst EBSCO provides the functionality to search selected databases simultaneously, the reviewers chose to search individually and record the results by database. This proved useful when sifting for duplicate records and quality assuring the search during later stages; assuring the quality of the search process at this stage involved searching a selection of databases again to ensure the same amount of results were obtained. Logging the results individually also facilitated a meta-analysis of the databases to understand which yielded the most relevant results. The search was carried out in three stages. Learning and academic analysis was carried out between 2017 and 2018, and the search into learner analytics was carried out in 2018. In 2018 an additional search was carried out to ensure that recent research literature has been identified. This will be used to inform future systematic reviews in this subject area.

Sifting

Due to the large volume of initial results, the sift activity was carried out in three phases. Phase one involved the automatic exclusion of literature in accordance with the agreed criteria based on document type and publication date. This phase also included the removal of duplicate results and literature not written in the English language. Phase two involved excluding articles based on the content of their abstract; articles were categorised as either:

- excluded – not higher education
- excluded – not primary research
- excluded – research criteria
- progressed to sift stage three.

The category 'excluded – research criteria' was used only where the abstract clearly did not meet the following clause of the inclusion criteria; 'literature on the deployment and effectiveness of learning analytics, learner analytics and academic analytics methods to improve student outcomes by enabling targeted academic and professional support interventions'. Quality assurance in phase three involved a second review of all articles in this category to ensure a consistent interpretation of the inclusion criteria plus a random 10% of all other excluded material. If the abstract was mutually agreed to be inconclusive it was progressed for full text review.

Recording

As with the searching stage, there is a critical precursor to the recording stage of a systematic review which is the formulation of the research questions. Where the inclusion criteria set out what is relevant to the review, the questions structure the presentation of the results. The research questions should operate in harmony with the search criteria to avoid any conflict in scope. They should also inform what is captured during the recording stage to facilitate an efficient and critical analysis. The research questions in this systematic review are as follows;

RQ1: Where, how, and in what ways, have educational analytics been deployed in the studies progressed?

RQ2: How effective are educational analytics in improving student outcomes?

RQ3: What methodologies are used to evidence and report the effectiveness of educational analytics and how valid and reliable are they?

Templates were used to record the detail of the remaining literature and were populated for all material which passed stages one and two of the sifting process. The use of the template as part of the sift stage was effective as it helped to maintain a consistent application of both the inclusion criteria and research questions. If the literature was found to meet the inclusion criteria the article was classed as 'progressed' and the remaining two sections were completed. Section two captured additional detail required to inform a critical discussion of the papers and section three logged any additional references which had not been captured in the database search. These papers then went through the same three stage process of review as other materials.

Assessment

We approached the systematic review task as critical realists (Bhaskar 1975; Danermark et al. 1997) interested in ensuring that we were able to tease out the salient critical issues, challenges and opportunities for discussion and future research. Critical realism enables an assessment of the underlying logic or theory of change of the research presented in the articles to be undertaken by asking questions of whether the underlying connection between what is reported as inputs, outcomes and benefits is examined and reported on (Pawson 2013). That is, it ensures that questions are asked of specificity. In addition, critical realism allows for an assessment of the context within which the research study was undertaken, and the voices of those involved as subjects and thus those that matter – in this case the student and or academic staff member.

Results

The full search returned 3427 citations in total; an initial sift to remove duplicates and ensure the criteria defined in the methodology meant that 2010 abstracts were left to review. 125 articles were progressed for a full text review of which 34 were found to wholly meet the criteria of primary research on the effectiveness of educational analytics methods to improve student outcomes in higher education. The most dominant objective of the abstracts we reviewed was mining the data to uncover trends and behavioural patterns; we did however identify that there is an increasing trend (Figure 1) towards reporting the use of these outputs for intervention.

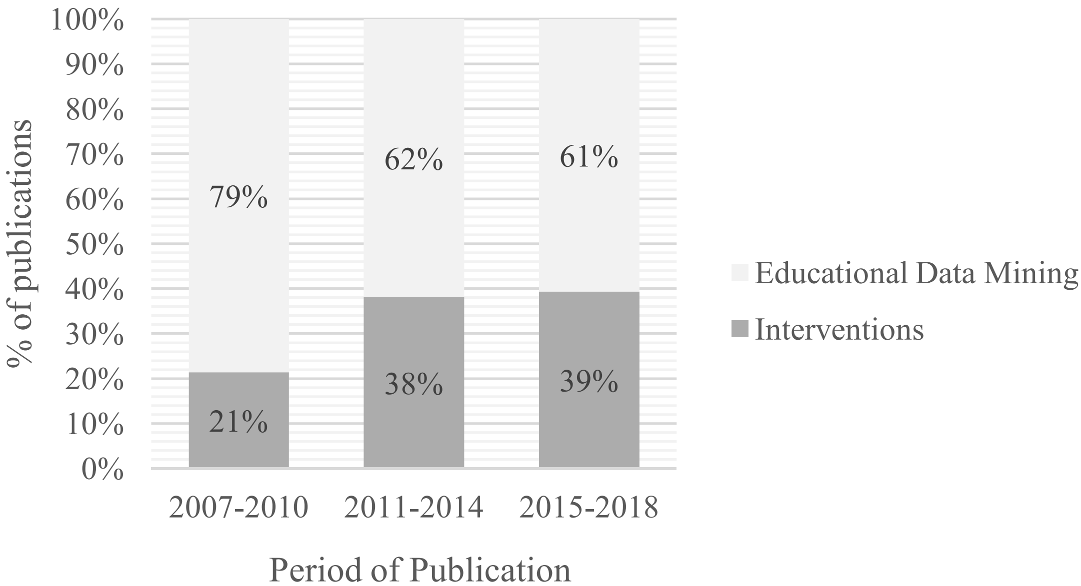

Figure 1. A comparison of themes in the abstracts reviewed.

Table 3. Overview of characteristics of studies.

Characteristic		Studies (n)	Proportion (%)
Period of publication	2007–2010	0	0%
	2011–2014	10	29%
	2015–2018	24	71%
Geographic location	North America	12	35%
	Rest of the World^	8	24%
	Europe	7	21%
	Asia	5	15%
	UK	2	6%
Delivery method	On Campus only	17	50%
	MOOC; Blended or Distance Learning; Flipped Classroom	17	50%

Table 3 gives a breakdown of the studies by characteristics and details the increasing number of publications since 2007 with 71% of studies published in the last four years. Although educational analytics deployments were initially reported in North America, Europe now produces the most scholarly outputs (25% in the last four years; 21% cumulative) with Asia also contributing significantly (21% in the last four years; 15% cumulative). Table 3 also shows that there is an equal amount of literature reporting the use of educational analytics in a traditional on-campus setting and in online or blended environments. The underlying data does show that the increase in on campus deployments has been steady over the period whilst the studies published relating to courses with a compulsory element of online content has increased significantly.

Of the 34 studies, 29% reported that their sole aim was to improve academic performance through the deployment of educational analytics. Learning analytics and academic analytics studies are primarily designed for the improvement of academic performance although some focussed on retention too; results show that learner analytics is, to date, more aligned to improving student engagement. Only two studies sought to improve student retention rates alone however this is a common focus of the campaigns which aim to improve multiple outcomes simultaneously. 13 studies utilised the same analytics tool or intervention method to impact multiple student outcomes. Table 4 summarises the high-level results.

The number of data variables used in the process is found to be dependent on the analytical approach. Some studies tailor the intervention strategies to specific outcomes; others attempt to

Table 4. Student outcomes used to measure impact.

Characteristic		Studies (n)	Proportion (%)
Outcomes measured	Multiple Outcomes	13	38%
	Academic Performance	10	29%
	Engagement	9	26%
	Retention	2	6%

Table 5. Stated effectiveness by student outcomes.

Stated effectiveness	Multiple outcomes	Academic performance	Engagement	Retention	Subtotal
Yes	9 (69%)	7 (70%)	5 (56%)	2 (100%)	23 (68%)
No	1 (8%)	2 (20%)	2 (22%)	–	5 (15%)
Inconclusive	1 (8%)	–	2 (22%)	–	3 (9%)
Partially	2 (15%)	1 (10%)	–	–	3 (9%)
Total articles	13	10	9	2	34

improve multiple outcomes via the same analytics or intervention mechanism. Of the 34 studies, 23 (68%) reported that the use of an analytics tool combined with an intervention strategy had a positive impact on student outcomes. Although the number of studies is too small to do a test of statistical significance, the descriptive statistics in Table 5 show that the studies which framed their objectives relative to the improvement of academic performance were most successful. The studies looking to influence student engagement had a lower success rate with four of the nine studies reporting either no impact or inconclusive results.

The methods utilised to evidence impact are unequivocally in favour of quantitative analysis with only two studies taking a solely qualitative methodology. A further four studies use a mixed methods approach, with the remaining 28 articles using a range of statistical techniques to quantify the change in the metric they are measuring. Learning analytics and academic analytics research studies involve larger sample sizes than student-facing learner analytics (usually greater than 100 participants) with a more quantitative focus and an equal proportion of control methodologies. Learner analytics samples tend to be smaller and control strategies are in the minority. Despite the dominance of quantitative methodologies, very few studies reported adopting advanced sampling and control techniques such as randomised control trials and two-sample hypothesis testing which are often associated with experimental activity that is quantitively measured (Herodotou et al. 2017).

Analysis

It is clear that the measurement of outcomes varies in research on educational analytics methods. Studies looking to improve academic performance may judge success either through the impact on the class average or by counting students who improved their grades and this may be compared to a baseline from a different academic cohort or to the students' future predicted outcomes. As such it is pertinent to present the studies here in detail before a discussion of the implications of such disparate approaches to improving outcomes through analytics informed interventions. The studies are grouped by the impact that they tried to achieve on student outcomes – retention, academic performance, engagement, with a final section covering those studies which measured the impact of educational analytics using multiple outcomes metrics. The following subsections are supported by a number of abridged tables for reference; unabridged versions can be found online.

Retention

Reduced dropout rates amongst students receiving an educational analytics intervention was the primary outcome of two studies examined (see Table 6).

Table 6. Key findings from the research on educational analytics for improved retentioner.

Authors	Tool/Intervention	Methodology/Sample Size	Summary findings reported
Burgos et al. (2018)	Predictive model. Tutoring action plan sets out interventions delivered to students at risk of dropping out	Quantitative Nonprobability >100 (without a control group)	Retention improved by 14% Grades also improved by 6%
Cambruzzi et al. (2015)	'Multitrail'. Teachers alerted to students with low performance and possible dropout. Teachers respond with personalised actions and interaction.	Quantitative Nonprobability >100 (without a control group)	A positive impact of 23% and 6% for classes within the same discipline.

Both studies describe the development and testing of a predictive EDM alongside the deployment of academic interventions to improve retention amongst particular identified 'at risk' students. Both report improvements in retention for those students receiving an intervention, although the measurement of success reported in each study differs. Burgos et al. (2018) compared the retention of those receiving an intervention against a previous year's cohort that did not receive any intervention, using activity grades to predict students at risk of dropout. They report a 14% reduction in drop out. Cambruzzi et al. (2015) measure success by comparing the retention rates for classes who received some form of intervention versus those that did not within the same academic year. They report an 11% reduction in dropout rates. The academic tutor interventions included a 'special-purpose tutoring action plan' (Burgos et al. 2018, 2) involving targeted email and other forms of personalised student contact including tutor recommendations, and a set of preventative pedagogical actions – tutors interacting with students identified as having low performance profiles and therefore potentially 'at risk' studying at a distance (Cambruzzi et al. 2015). Whilst both studies report improvements in retention rates as a consequence of the academic interventions implemented, Cambruzzi et al. (2015) acknowledge that multiple factors might well be responsible for the dropout phenomena, including course design, although unfortunately their study does not go on to account for the potential impact these may have had on the overall results. In addition, the study identifies the specific opportunities that distance education offers in monitoring and evaluating student interactions.

Academic performance

The most common aim of the studies reviewed was to improve academic performance (see Table 7). Where most studies in this category look at grades at the cohort level, Rahal and Zainuba (2016) use data from previous academic students as the baseline against which to measure the grades of their individual dashboard users. They theorised that engaging students in self-monitoring and self-regulation would drive achievement, however the study presents mixed results. Rahal and Zainuba report an improvement of 4.7% on the average final examination score and an increase in the percentage of students achieving As, Bs and Cs. Despite this, the failure rate of the cohort overall was not improved which highlights the relative dichotomy of student level attainment and cohort level progression. Although the dashboard helped to improve the grades of students from Cs to Bs and Bs to As, it did not help the students at the lower end of the academic performance scale to meet the objective of passing the course.

Herodotou et al. (2017) used predictive data to identify students at risk of not attending the final examination. Their interventions therefore aimed to reduce the failure rate which addresses attainment through a model of failure rather than achievement. Brouwer et al. (2016) also reported success relative to the proportion of students obtaining a grade, rather than improvement in the grade itself. Brouwer et al.'s hypothesis is that accessing the dashboard enables learners to explore and reflect upon relationships between their current study behaviour and future predicted results. By visualising

Table 7. Key findings from the research on educational analytics for improved academic performance.

Authors	Tool/Intervention	Methodology/ Sample Size	Summary findings reported
Brouwer et al. (2016)	Coach 2 Data for both current study behaviour and predicted outcomes are displayed to learners via a dashboard within the VLE.	Quantitative Nonprobability n not stated (with a control group)	A statistically significant higher chance of successfully graduating for a course (79% for dashboard learners) than 67% of learners without dashboard access. More than half the learners with no dashboard failed the course; 68% of learners with a dashboard passed the course.
Chen et al. (2017)	WebIntera-classroom. Used by instructors to improve supervision with students and by students to improve their interaction with VLE and their instructors.	Mixed methods Nonprobability >100 (without a control group)	There was an improvement in academic performance for students using the tool but this is not tested for significance. Student survey satisfaction results are presented, however the findings of the interviews are not presented in depth.
Choi et al. (2018)	Predictive model . Preventative proactive advising whereby tutors establish a good rapport with students and contact them.	Quantitative Nonprobability >100 (without a control group)	The study found that the pass rate for students receiving an intervention was significantly higher than for the rest of the course
Corrigan et al. (2015b)	PredictED Students received engagement and attainment data for the modules they were studying. Academic staff monitored student engagement through a dashboard.	Quantitative Nonprobability >100 (without a control group)	A 2.8% improvement (58.4% to 61.2%) on exam performance for those students who opted in to the programme. Significant performance improvement in 3 modules and improved performance in 5 additional modules.
DeMonbrun and Brown (2017)	Student Explorer. Students directed to engage with E2Coach - a digital coaching system to deliver tailored advice and study support to students.	Quantitative Nonprobability >100 (without a control group)	The study identified that engagement in the online digital tools reduced risk levels of students in the sample.
Dodge et al. (2015)	A model utilising engagement (VLE logins) and academic (grades) data and trigger events. Targeted interventions in the form of email nudges sent to students via the VLE suggesting ways to improve their performance.	Quantitative Nonprobability >100 (with a control group)	There was no significant difference between the experimental and control groups on course achievement. Interventions were associated with a higher final grade in one course, but only for a particular demographic group
Herodotou et al. (2017)	Predictive model. Email from the Student Support Team; outbound call from Learner Support; and email to the students' Associate Lecturer informing them that the student had not picked their end of term exam date	Quantitative Nonprobability <100 (with a control group)	No significant differences between the three intervention types and control conditions were reported in relation to students' end-of-module performance. There was also no significant impact on the number of students taking the end of module exam.
Rahal and Zainuba (2016)	Students access two predictive tools in a spreadsheet to forecast their performance and get real time feedback. Students self-regulate their class engagement which includes seeking help from an instructor	Quantitative Nonprobability n not stated (without a control group)	Students receiving the intervention outperformed those not receiving the intervention suggesting the innovation significantly improved students performance. No significant improvement of at-risk students was observed.
Van Horne et al. (2018)	Elements of Success. Dashboard allows for the summarisation of student performance and personalised feedback suggests appropriate resources.	Quantitative Nonprobability >100 (without a control group)	High and moderate users are reported as achieving significantly higher course grades than the low or non users. Although the study reports that learners benefited from regularly accessing the feedback but extreme amounts of usage were not necessary to achieve a positive result.
Wright et al. (2014)	E2Coach. Tailored advice and study support to students.	Quantitative Nonprobability >100 (without a control group)	Students using E2Coach significantly performed better than expected on GPA performance. Students using E2Coach infrequently or not at all showed no significant difference.

comparative study behaviour it was expected that the tool would be used for 'mirroring', defined by the authors as 'the idea that learners see themselves operating in the context of their peers' (Brouwer et al. 2016: 363). DeMonbrun and Brown (2017) also took a predictive approach by comparing students' movement through academic risk profiles. They found that the students who engaged with E2Coach entered the risk categories far less often.

Due to the quantitative nature of the academic performance metrics chosen by the researchers, such as average grades and failure rates, it is unsurprising that all the studies in this category took a quantitative approach to their methodology. Chen et al. (2017) did conduct a student survey, however their survey findings are not presented in depth and do not ratify or contextualise their quantitative findings.

Engagement

Engagement is used to describe studies whose primary research aims are to improve student awareness, reflection, participation, involvement and motivation through the deployment of an educational analytics intervention. Interventions that aim to bring about changes to student engagement are often referred to as self-regulated learning interventions. The nine studies detailed in Table 8 report the effects that visualising student data has on student engagement in learning, as measured by changes in: student access to an assessment tool anytime and anywhere, along with its usefulness and impact on peer interaction (Aljohani and Davis 2013); students' awareness of their course progress through badges and through collaborative interaction (Charleer et al. 2013); students' self-reflection, metacognition, mastery, sense making and motivational orientations (McNely et al. 2012; Lonn et al. 2015; Kitto et al. 2017; Mejia et al. 2017; Silva et al. 2018); students participation in online discussions in real time learning environments (Wise et al. 2014); and instructors delivery of real time learning interventions (Shimada et al. 2017). The majority of studies presented data in the form of a dashboard.

While success is reported in the majority of studies, given the measurement methodologies deployed (mixed methodologies including interviews, self-report surveys, diaries and assessment of student posts (blogs etc)), it is perhaps unsurprising that the presentation of findings appear complex. Charleer et al. (2013) report favourably that the formative assessment feedback delivered through personal and collaborative dashboards enabled greater student awareness of their progress, and about the tasks and goals required to successfully complete the course, but with some variation amongst the approaches. Kitto et al. (2017) report that the use of dashboards improved student awareness of their learning processes and how to improve them; while Wise et al. (2014) examined the visualisation of discussion posts using embedded and extracted analytics on students' real time learning, and reported the impact was often to allow students to reflect upon their engagement and regulate their performance.

In Shimada et al. (2017), the visualisation of student data was primarily for the benefit of the tutor, who was able to view student engagement in lectures, and change speed or topic in order to maximise student engagement. In Lonn et al. (2015), a data visualisation dashboard was developed primarily for academic tutors to use in conversation with their students, although the study does not report if students looked at the data view with the advisor, but it was possible to do so. Lonn et al. (2015) report the intervention, which involves a visualisation dashboard for tutors to use when delivering face to face student support, may 'moderately decrease students' mastery goal orientations'. The authors explain that 'we were surprised to learn that showing students their own data within the context of the Student Explorer early warning system (EWS) may have contributed to this decrease' (Lonn et al. 2015: 95).

What is evident from studies on engagement is the importance of the student voice in determining study design and evaluation, alongside measuring success and impact. Often evidence of success or impact is measured through the use of student self-report data and/or the quality

Table 8. Key findings from the research on educational analytics for improved engagement.

Authors	Tool/Intervention	Measurement/ Sample Size	Summary findings reported
Aljohani and Davis (2013)	Quiz My Class Understanding (QMCU). Through the dashboard students engage with formative assessment in order to receive immediate feedback.	Mixed method Nonprobability <100 (without a control group)	70% of students reported that the mobile dashboard was useful and motivated them to use QMCU.
Charleer et al. (2013)	Navi Badgeboard and Navi Surface. Visualisation of student learning and social media activity is used to impact on student reflection, sensemaking and motivation. Badges are used.	Quantitative Nonprobability <100 (without a control group)	Navi Badgeboard did improve students' awareness of the goals and tasks. Students did not think that Navi Surface improved their awareness of their progression within the class.
Kitto et al. (2017)	Connected Learning Analytics (CLA). CLA toolkit provides instructors and students with reports on engagement and participation in learning activities and communities.	Qualitative. Nonprobability <100 (without a control group)	Trial One: Hypothesised to be 'minimal' due to lack of alignment with assessment. Trial Two: Suggested positive impact on the quality of students reflection and engagement. Trial Three: No evidence from student comments however staff reported it had increased engagement with the online community (not quantified).
Lonn et al. (2015)	Student Explorer. Face-to-face student support by academics with the aim of improving motivation and goal orientation using Achievement Goal Theory.	Quantitative Nonprobability >100 (without a control group)	A statistically significant decrease in students' reported mastery scores between pre and post bridge programme. The intervention of showing students their dashboard and data may have led to this decrease.
McNely et al. (2012)	Uatu. Students see their edits compared to the group derived from document revision history data on asyncronous collaborative writing tasks in Google Docs	Qualitative Nonprobability <100 (without a control group)	General implications for the datafication and analysis of collaborative writing tasks however several students who used Uatu gave positive feedback that it made them more metacognitive.
Mejia et al. (2017)	PADA. Visualisation of students' individual 'learning model' aims to make students aware of their 'strengths' (their learning styles) and their 'weaknesses' (their reading skills and cognitive traits).	Quantitative Nonprobability <100 (without a control group)	Whilst 61.5% of students felt that the tool could always or almost always encourage self-regulated learning, statistically there was no improvement for dyslexic students using PADA. Some small scale qualitative feedback suggests it had a positive impact however it is not disclosed whether this applies to the independent variable of dyslexia.
Shimada et al. (2017)	A tool to collect data from digital resources and provide real time information to the teacher about classroom engagement Academic tutors monitor engagement and adapt delivery to support students' engagement.	Quantitative Nonprobability >100 (without a control group)	The synchronisation ratio of the experimental group was significantly better than the comparator group (77% to 60%). Students who received the interventions were better engaged with the online resources.
Silva et al. (2018)	A dashboard which includes information on attendance, academic performance and online engagement factors. Students in the experimental group were sent the bulletin after each learning unit and encouraged to reflect on the four components	Quantitative Nonprobability <100 (with a control group)	The bulletin was successful in improving students' help-seeking and self-evaluation scores. There was also a significant difference between the experimental group and the control group who did not receive the bulletin.
Wise et al. (2014)	Starburst. Additionally learner summary reports are produced for the student to view. Students provided with real time feedback on their activity. Accompanying intervention in the form of guidance on how to interpret the information presented.	Mixed Methods Nonprobability <100 (without a control group)	Students reported the use of Starburst positively impacted their behaviour and improved their strategic engagement with discussion posts. Reactions to the extracted analytics varied with some perceived usefulness alongside feeling 'wronged' or 'ashamed' by the metrics (2014:60). The introduction of extracted analytics did quantifiably increase the amount of posts read.

and volume of student written work (blogs, posts etc). Thus qualitative rather than quantitative assessment of success is described. Of interest also is that in one or two instances, studies focus on students' learning abilities, such as dyslexia (see for example Mejia et al. 2017). In this study, the impact of PADA (acronym for the Spanish name Panel de Analiticas deAprendizaje deDislexia en Adultos), in assisting students with particular learning difficulties to achieve awareness and thus improve reflection and self-regulation as part of the learning process was measured, with Mejia et al. (2017: 64) reporting 'All in all, based on the empirical case study results, we believe that PADA was well-received, and it could be used to facilitate the learning process of students with dyslexia or reading difficulties'.

Multiple outcomes

13 studies sought to improve multiple student outcomes as part of the same study (see Table 9). This category provides the most diversity in terms of the approaches to both the analytics tools and the subsequent interventions. The most common combination was the improvement of academic performance and engagement, with eight of the 13 studies taking this approach. The majority reported success in both outcomes such as Corrigan et al. (2015a, 2015b), Davis et al. (2016) and Lu et al. (2017). Two studies (Beheshitha et al. 2016; Khan and Pardo 2016) presented more inconclusive evidence of their impact on students' academic performance and engagement. Beheshitha et al. (2016) trialled three different student-facing dashboards and reported both positive and negative effects on student outcomes. This paper reported that the dashboard that located students' performance relative to their class average had a negative impact on both the quantity (engagement) and quality (academic performance) of their blog posts relative to certain personal goal characteristics. This was not the case when students were given sight of their performance relative to the top contributors. Khan and Pardo (2016) also did not find a correlation between students' use of their dashboard and students' academic performance. The remaining five studies looked to increase academic performance and retention; three reported successfully improving both.

Discussion

One of the challenges of any systematic review is the synthesis of themes to facilitate critical comparison across the evidence base (Boland et al. 2013); this is something we encountered when analysing the impact of educational analytics on student outcomes. Despite clear review criteria we found little consensus on the definitions of retention, academic performance and engagement in the 34 studies. As such addressing research question 2 'how effective are educational analytics in improving student outcomes?' is not as simple as analysing the ratio of effective, ineffective and indeterminate reports. Furthermore, as we critically unpacked the results of each study, we found that the lack of consistent definition for student outcomes both compounds, and is compounded by, disparate measurement methods, an overreliance on quantitative methodologies and underdeveloped theories of change underpinning the research. Whilst academic performance, engagement and retention are not mutually exclusive outcomes, few studies articulated their objectives with recognition of the relationship. This is clearly an issue for evaluation in this field: i.e. how we operationally define performance, engagement, attainment etc. This posed further challenges for us as researchers to address RQ3 'what methodologies are used to evidence and report the effectiveness of educational analytics and how valid and reliable are they?'

The impact of educational analytics on retention rates was the simplest outcome to consider due to the binary measurement of student desistence/persistence. Only one study, Jayaprakash et al. (2014), reported no impact on retention, although it did report improved academic

Table 9. Key findings from the research on educational analytics for improving multiple student outcomes.

Authors	Tool/Intervention	Measurement/ Sample Size	Summary findings reported
Arnold and Pistilli (2012)	Course Signals. Personalised interventions made by instructors.	Quantitative Nonprobability >100 (without a control group)	A 10.37 % point increase in A's and B's and a 6.41 % point decrease in D's, F's and withdrawals. Surveys and focus groups support evidence of a positive impact on student attitude and behaviour.
Beheshitha et al. (2016)	Student-facing dashboards. Students given the option to engage with one of the dashboards.	Quantitative Nonprobability: >100 (without a control group)	Some positive and some negative effects on both the quantity (interpreted here as engagement) and quality (interpreted here as academic performance) of students' posts relative to goal orientations.
Corrigan et al. (2015a)	PredictED. Students received engagement data and predictions weekly. Academic staff monitored engagement through a dashboard.	Mixed Methods Nonprobability >100 (without a control group)	There was an increase in 2.9% in the final grade average. Student feedback indicated that 33% of them had changed their engagement with the VLE
Davis et al. (2016)	'Learning Tracker' visualises various engagement metrics and compares the student to previous successful cohorts providing relative feedback on engagement.	Quantitative Nonprobability >100 (with a control group)	Academic performance was better for those receiving the intervention (13.17% vs 11.35%) and two of six engagement proxies improved.
Grant (2012)	VLE tracking data coupled with student and staff feedback. Instructors meet with technology specialists to improve course design.	Quantitative Nonprobability > 100 (without a control group)	The drop rate is reduced for the courses where academic analytics was applied however this is not tested for significance or qualified.
Jayaprakash et al. (2014)	Academic Alert Reports (AARs). One of two intervention strategies. Students sent an "awareness" message indicating their risk status with prescribed remedial actions or were invited to participate in the Online Academic Support Environment (OASE).	Quantitative Unknown sampling >100 (with a control group)	No significant difference between the intervention methods. Receiving an intervention of either type improved final grade by 6%. Students in the treatment groups had higher withdrawal rates. Hypothesised that communicating 'at-risk' predictions had a negative impact on retention.
Khan and Pardo (2016)	Student-facing dashboard visualising engagement with online resources and real time feedback.	Quantitative Nonprobability: >100 (without a control group)	The effectiveness of the dashboard in improving engagement with online resources is not reported but does evidence students adapting their engagement as they progress throughout the course.
Liu et al. (2016)	The Student Relationship Engagement System (SRES) - several datasets centralised for instructors to access and deliver interventions (emails or phone calls)	Quantitative Nonprobability > 100 (without a control group)	Improvement in both the retention rate and students' overall academic performance is stated but not investigated or discussed.
Lu et al. (2017)	Instructors receive a monthly list of students at risk of low engagement. The experimental group received adaptive learning interventions (online, email and face to face).	Quantitative Nonprobability	The intervention had a positive impact. Students adjusted their learning behaviours. As the self-regulated ability

(*continued*)

Table 9. Continued.

Authors	Tool/Intervention	Measurement/ Sample Size	Summary findings reported
	Students in the control group received interventions based on the instructors' observations.	<100 (with a control group)	improved for the experimental compared with those of the control group.
Brusilovsky et al. (2011)	'QuizMap'. Student-facing visualisation of engagement with self-assessment questions and assessment progress. Students signposted to resources.	Quantitative Nonprobability <100 (without a control group)	QuizMap users had an increased number of attempts at quizzes and statistically higher learning gain however this is presented based on active users vs passive users. The validity of this comparison is questionable
Sharma et al. (2016)	Visual feedback tool for MOOC learners in online video resources. Students are directed to the area of the screen which is currently under discussion if their gaze-based engagement with the video is low.	Quantitative Nonprobability < 100 (with a control group)	Both academic performance and engagement through the immediate impact of real-time feedback improved. The intervention had a long-term impact on students' focus for watching the video as the number of interventions required decreased towards the end of the video.
Smith et al. (2012)	'RioPACE'. An automated welcome email system was also piloted for online students.	Quantitative Probability >100 (with a control group)	Intervention 1- did not have a significant impact on success however success was not defined. Intervention 2 - improved drop rate by 40% but 'drop rate' is not defined
Yen et al. (2015)	Log data from students' VLE usage are communicated to teachers. Instructors responded to the data by changing their instructional strategies with the intention of improving students' cognitive load	Quantitative Nonprobability >100 (without a control group)	Strategies had a positive effect on the quality and level of interaction relative to the asynchronous discussions with learning performance significantly improved.

performance. Some studies blur retention and academic performance by measuring dropouts caused by academic failure (Smith et al. 2012). Even seemingly simple pass/fail rates were measured inconsistently. The majority of studies use the final grade of students post intervention and compare it to students who didn't receive or who didn't engage with the intervention (Wright et al. 2014; Dodge et al. 2015; Chen et al. 2017; Choi et al. 2018; Van Horne et al. 2018); however this gives only a partial picture of effectiveness where the range of impact at the student level is masked by the cohort mean.

For the impact on individual academic performance Brusilovsky et al. (2011) and Sharma et al. (2016) define their own 'learning gain' metric; while Yen et al. (2015) adopt a pre-test/post-test methodology. These three studies all applied analytics methods to improve academic performance within the context of engagement. Engagement was the most difficult outcome to synthesise. The studies defined engagement in perceptive terms by assessing student's metacognition, social navigation and levels of self-reflection and regulation (McNely et al. 2012; Charleer et al. 2013; Kitto et al. 2017; Silva et al. 2018). Where some studies considered engagement relative to the students' interaction with resources which were affected or signposted by the intervention (Wise et al. 2014; Corrigan et al. 2015a; 2015b; Shimada, Mouri, and Ogata 2017), others looked no further than interaction with the intervention itself (Khan and Pardo 2016). As such, one of the key findings to arise from this review is that whilst there are studies that report that educational analytics has been effective in improving student outcomes, there is little opportunity for comparison given the breadth of variation in design, definitions, methodologies, sample sizes and cohorts.

The lack of clarity and consistency extends also to the methodologies of the 34 studies. As educational analytics emerged from the mining of educational data in predominantly online learning settings, it is not surprising that early research studies continued to adopt quantitative, numerical and database approaches. Firstly, the skills to carry out analytics were still localised in computer science and mathematics departments which we found to be the settings for a number of the studies reviewed. Secondly, as advances in data technologies support the mining and processing of ever more granular and personal data there exists a concurrent debate about the ethics of using it within the learning environment (see Broughan and Prinsloo in this special edition). Randomised control trials for student support could be perceived as inequitable in a marketized environment where students are investing in their education.

Thirdly, the use of student trace data within analytical 'black boxes' and platforms can come under scrutiny for intrusion and surveillance as debates on the platform university emerge (Francis and Foster 2019). We find the majority of studies react to these challenges by adopting an opt-in approach; whilst this may be the fairest option it poses challenges within purely quantitative frameworks for sampling, sample sizes, controlling and experimenting. Some studies for example use the opt-out population as a control group without documenting their assurance that selection was not in itself a confounding variable. In our view this raises questions regarding the validity and reliability of the reports especially in those which don't account for the socio-economic factors which can impact student outcomes (Tinto 1975; Morrow and Ackermann 2012).

A further notable finding of this review is that very few studies acknowledge the application of analytics methods to address differential student outcomes for disadvantaged students. There was only one dedicated example from 34 studies which used analytics methods to support students with learning difficulties (Mejia et al. 2017). Other studies do take account of socio-economic disadvantage but only as part of their wider analysis (Jayaprakash et al. 2014; Dodge et al. 2015). Although the interventions for improving engagement were more inclusive, especially those which were student-facing, the studies detailing interventions for academic performance and retention on larger cohort scales were more targeted. We question whether intervention approaches, especially those which draw on demographic variables and predictions, fail to exploit the potential for using data analytics to encourage the transformation of all students' outcomes, including high performers, by over-focussing on risk profiles.

This point brings us to another finding of this review – that the majority of research designs of the 34 studies are limited to quantifying impact as opposed to qualifying it. Little attention is given to articulating why change has happened. Glaser and Strauss (1967: vii) highlight the tendency for many researchers to 'focus on their empirical studies and on their efforts to improve the methodology of verification' which leads to a 'gap from the "theory side"'. This is very much the case in the literature that we have reviewed. Where, for example, the implementation of learning analytics is reported as improving retention or student engagement, the specificity of why this is the case is often unexplored, and certainly not reported nor discussed in detail. Rather most studies assume a relationship. What is lacking is a theory of change; a contextual narrative of how the introduction of educational analytics methods has connected the input measures (data sets, EDM), with the outcomes (better retention, improved academic performance) and outputs (intervention nudges, related packages) via an intervention.

As educational analytics has evolved and more researchers begin to acknowledge the need for a greater understanding of the intervention mechanism (Brouwer et al. 2016; Khan and Pardo 2016), the continued oversight of context in research design and implementation - both individual and institutional - is in our view staggering. Significance testing, in a quantitative study, does not equate to explaining why an impact happened, merely it reports the strength of evidence in favour of the relationship between intervention and outcome. Researching context is important in enabling understanding of other salient local and specific contextual factors that may have impacted upon the students' retention, performance and/or engagement. It can help explain what works, for whom, under what circumstances and why (Pawson and Tilley 1997). Context is central to examining cause and effect. It is here that randomised control trials (RCT) can prove their worth (Herodotou et al. 2017) in allowing for comparative analysis to be made, but even without the use of RCT, the lack of reporting of other factors that may have impacted upon the results reported is, we argue, quite astonishing.

To illustrate this point, it is worth exploring the two studies on retention (Cambruzzi et al. 2015; Burgos et al. 2018). What was it about the tutoring action plan involving emails and personalised student contact in the former study, or staff interactions with at risk low performing students in the latter study, that made the difference? Such questions are particularly apt when Cambruzzi et al. (2015: 43) themselves acknowledge that 'a broad mapping of associated dropout factors is necessary, involving the various sectors or educational institutions, since theoretical models about dropout point to multiple causes'. And we would add that there needs to be better reported understanding as to how interventions are used (Wilson et al. 2018). For example, the virtual learning environment (VLE) forms part of a number of studies but its use can and does vary enormously – from being a repository to an interactive and engaging space for learner interactivity. Yet, this detail, crucial to getting to grips with what worked, why and how, is not articulated. Similarly, there is variation as to what actually constitutes an intervention. For example, in the studies of learner analytics, a number report the adoption of the app in terms of user counts and activities rather than engagement with the associated interventions. It is unclear whether the app itself is the intervention and why it is appropriate. That is, there is an unsubstantiated view that students' adoption of the app is demonstrative of something more for the student; what that may be remains equivocal.

It is our view that there is a gap in the academy's understanding of the efficacy of educational analytics methods when compared to other learning and teaching intervention strategies. The growth of technological innovation, alongside data and its analysis, are all too often taken at face value as offering value in terms of student success, whether in improving engagement or academic performance of students. Yet, what of the relative impact of such measures over, say, increased support staff or lower staff-to-student ratios?

Finally, we expected much greater reported engagement with students in the 34 studies. After all, to understand a change in student outcomes, their voice is crucial in examining cause and effect; that is explaining how an intervention influenced and impacted on their cognition, behaviour or performance. In the reports on student-facing analytics, we do find that student feedback has informed the design, and in some cases the evaluation, of the systems and processes. In contrast, the voice of the student in learning analytics and academic analytics studies is mostly absent. Too infrequently are the results of educational analytics deployments complemented with surveys and interviews with staff and students.

Conclusion

We find evidence in the majority of the 34 studies reviewed that educational analytics is reported to be effective in improving student outcomes. The studies detail the collation and analysing of big data sources and explain the integration of data into staff and student facing tools. The majority, but not all, utilise quantitative methods and methodologies, and we report a distinct lack of qualitative innovation and student voice in the 34 studies reviewed. What it is less clear is the role or purpose of the data in the planned intervention and thus, how the analytics process has directly supported improvement. Causality is assumed and many studies do not critically unpack the relationship between educational analytics and student outcomes with sufficient detail to articulate a theory of change.

The gap between descriptive and explanatory research is not new when it comes to researching and measuring student success. Tinto (1975: 89) could not have put it more starkly when reviewing research on retention; 'Despite the very extensive literature on dropout from higher education, much remains unknown about the nature of the dropout process. In large measure, the failure of past research to delineate more clearly the multiple characteristics of dropout can be traced to two major shortcomings; namely, inadequate attention given to questions of definition and to the development of theoretical models that seek to explain, not simply describe, the processes that bring individuals to leave institutions of higher education'. Despite nearly half a century passing since Tinto's observations, the research reported here continues to lack specificity and theoretical insight, favouring instead a focus on sophisticated empirical analysis.

Yet, the increasing ethical and operational challenges posed by using individuals' data means that the quantitative methodologies which dominate educational analytics research are not always appropriately controlled for or sampled at scale (Broughan and Prinsloo 2019). Furthermore, we have highlighted that the definitions of retention, engagement and achievement are inconsistently applied which causes incomparable and often inconsistent results in the discussion of efficacy.

Finally, too few studies report on the efficacy of applying analytics methods to address differential student outcomes for disadvantaged students. If educational analytics is to support a transformational and inclusive educational experience for all students, research must take into account how data and intervention strategies can be leveraged for both disadvantaged and high performing students. By building on the lessons learned from the targeted risk-based models, this latter group of students can benefit from analytics designed to support thriving student communities powered by adaptive and personalised data analytics.

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