Title page

Title: The efficacy of learning analytics interventions in higher education: A systematic review.

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Abstract

Educational institutions are increasingly turning to learning analytics to identify and intervene with students at risk of underperformance or discontinuation. However, the extent to which the current evidence base supports this investment is currently unclear, and particularly so in relation to the effectiveness of interventions based on predictive models. The aim of the present paper was to conduct a systematic review and quality assessment of studies on the use of learning analytics in higher education, focusing specifically on intervention studies. Search terms identified 689 articles, but only 11 studies evaluated the effectiveness of interventions based on learning analytics. These studies highlighted the potential of such interventions, but the general quality of the research was moderate, and left several important questions unanswered. The key recommendation based on this review is that more research into the implementation and evaluation of scientifically driven learning analytics is needed to build a solid evidence base for the feasibility, effectiveness, and generalizability of such interventions. This is particularly relevant when considering the increasing tendency of educational institutions around the world to implement learning analytics interventions with only little evidence of their effectiveness.

Keywords: Learning analytics, learning analytics interventions, educational data mining, student attrition, higher education.

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Introduction

At present, there are nearly 20 million tertiary students engaged in full- or part-time study in the European Union. Of these, approximately seven million (36%) will never complete their degree (Vossensteyn et al., 2015). Similarly, in the US, almost eight million (39%) of approximately 20.5 million university students will discontinue their studies before graduation (Shapiro et al., 2016). Other countries report similar discontinuation statistics, including, for example, Australia and New Zealand (20%), Israel (25%), and Brazil (52%) (OECD, 2016). Further, within this group of people who discontinue study, particular sub-groups are over-represented. In the UK, students classified as mature-age at point of entry (i.e., over 21 years) are more likely than those who enter university directly from high school to drop out after their first year (11.8% vs. 7.2%, respectively). And in the US, only 50.1% of ethnic minority university students graduate compared to 62.4% of White students (Higher Education Statistics Agency [HESA], 2013; Shapiro et al., 2016). Additionally, universities vary in discontinuation rates, with some universities recording dropout levels as high as 43% in the EU and 64% in the US (HESA, 2013). This suggests that there is ample room and opportunity to improve retention in the sector by active intervention. One way to do this that has received increased attention in recent years is by using learning analytics (LA).

LA integrates various types of data (e.g., learning and teaching behavior, academic performance, socio-economic status (SES)), statistical analysis, and predictive modelling to inform interventions in the way that students learn, instructors teach, and educational institutions design their curriculum (Na & Tasir, 2017; Williams, 2014). For example, achieving success in a particular course or educational program may be linked in some way with certain student characteristics and behavior. Students with limited access to computers and IT technology – for example students from lower SES brackets – may be more likely to be less computer savvy and therefore might find it harder to engage with an online course environment than their higher SES counterparts. This, in turn, may affect their performance and chances of graduation. Similarly, students with a low high school grade-point average (GPA) may be more likely to perform poorly at university than individuals graduating high school with top grades. Indeed, past research has found that a range of SES and academic history factors predict student success and retention with considerable accuracy (Fancsali, Zheng, Tan, Ritter, Berman, & Galyardt, 2018; Papamitsiou & Economides, 2016; Williams, 2014). These variables underpin LA predictive models, assisting teaching faculty in identifying and intervening with those students at risk of underperformance and/or discontinuation. The use of and interest in this methodology has increased in recent years, generating a steady stream of research on LA design, implementation, and effectiveness. For example, the EU Learning Analytics Community Exchange (LACE) project focuses exclusively on the use of LA in education and has organized a large database with up-to-date findings to support educators and institutions.

Early LA models typically relied on fixed factors to generate a single set of predictions within a specific timeframe. That is, these types of models incorporated, for instance, high school GPA, socio-economic status (SES), and scholastic aptitude test (SAT) scores in an algorithm to forecast student success or retention at a designated future time – such as at the end of a course in the first year of university (e.g. Agnihotri & Ott, 2014; Cochran, Campbell, Baker, & Leeds, 2013; Dekker, Pechenizkiy, & Vleeschouwers, 2009; Green, Plant, & Chan, 2016; Guruler, Istanbullu, & Karahasan, 2010; Harrak, Bouchet, Luengo, & Gillois, 2018; Kotsiantis, Pierrakeas, & Pintelas, 2003; Morris, Wu, & Finnegan, 2007; Tsai, Tsai, Hung, & Hwang, 2011; Yasmin, 2013; Yukselturk, Ozekes, & Türel, 2014). Traditional LA models thus included a relatively simple combination of student characteristics at one time-point to predict later academic performance (Williams, 2014). While these LA models are useful and relatively accurate in predicting student success or risk (prediction accuracy is typically in the 70-87% range; e.g., Yukselturk et al., 2014), their value is somewhat limited when it comes to ongoing assessments of student risk factors and interventions (Williams, 2014). That is, while traditional models are able to gauge, for example, student retention with reasonable precision, most of these predictions are based on one-shot assessments of rather static factors (GPA, SAT scores, SES etc.). Such models thus only allow an initial forecast – for instance at the start of a school year or semester. In other words, the value of these types of models in terms of intervention is presumably limited as they are unable to incorporate more fine-grained and shifting information in their predictions.

In response to this limitation – and in light of the surge in online virtual learning environments (VLE) – recent research into LA has focused on more dynamic models that incorporate predictions based on fluid online data (e.g. student behavior in and engagement with VLEs over time). This format affords more comprehensive forecasts with comparable precision and better opportunity for proactive and timely interventions that can be tailored to specific situations as they arise (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-Garcia, 2014; Freitas, Gibson, Du Plessis, Halloran, Williams, Ambrose, ... & Arnab, 2015; Joksimovic, Gasevic, Loughin, Kovanovic, & Hatala, 2015; Lykourentzou, Giannoukos, Nikolopoulos, Mpardis, & Loumos, 2009; Macfadyen & Dawson, 2010; Tempelaar, Rienties, & Giesbers, 2015; Whitmer, 2010). Thus, the added value of LA resides in its potential to identify and retain subgroups of the student population that are at increased risk of underperforming and/or dropping out. Indeed, most LA interventions are predicated on the notion that identifying the at-risk population and making these students aware of their high-risk status will motivate them and their teachers to proactively address these problems before it is too late (bin Mat, Buniyamin, Arsad, & Kassim, 2013; Williams, 2014).

Rationale and aims

Given the nascence of research into LA interventions – and in particular those that incorporate online student behavior and activity – a considerable limitation to the science in this area relates to the fact that there are very few empirically tested LA programs (Rienties et al., 2016). Indeed, the vast majority of the research to date comprises correlational studies focusing on particular variables and their predictive power, typically in terms of student success, retention, and/or experience (Borden & Coates, 2017; Papamitsiou & Economides, 2014; Saunders, Gharaie, Chester, & Leahy, 2017). In recent years, a number of qualitative and systematic review articles have appeared (Bienkowski, Feng, & Means, 2012; Ferguson, 2012; Papamitsiou & Economides, 2014; Romero & Venura, 2013), and a recent meta-analysis of published studies (Papamitsiou & Economides, 2016) has supported the use of LA in educational contexts. However, most previous reviews have not focused specifically on the effectiveness of interventions based on LA. In fact, to our knowledge, only three reviews have been published with this particular focus (Ferguson & Clow, 2018; Ferguson et al., 2016; Viberg, Hatakka, Bälter, & Mavroudi, 2018). These papers provide good insight into the current state of the evidence (particularly Viberg et al., 2018 who review the Learning Analytics Community Exchange (LACE) hub of evidence) and make similar conclusions on this basis – that is, that there is limited empirical evidence to support the effectiveness of LA in higher education in terms of student outcomes. However, neither article includes a complete, detailed review of existing evidence. Critically, past reviews also have not undertaken a quality assessment of the evidence base. As a result, there is a need for a systematic and reflective evaluation of the current state of the field in terms of the effectiveness of deliberate LA interventions in higher education, aimed at increasing student success and/or retention by identifying and intervening with those at risk. Nonetheless, higher education institutions around the world are investing heavily in LA interventions that (given the scarcity of an organized evidence base) often end up being generated from limited and/or outdated evidence. In other words, if individual LA interventions, trialed at particular educational institutions, are to be adapted and implemented on a regional or even national scale, it is imperative to scrutinize and assess the effectiveness of such programs to ascertain which work best and under which conditions. In light of this, it would seem germane to synthesize the empirical knowledge on best practice in terms of LA intervention design and implementation.

In this report we aim to systematically review and appraise the evidence on the efficacy of LA interventions in terms of student retention and/or academic success (i.e., performance and/or achievement). To this end, standard systematic review methodology will be employed. While this field is relatively young, it is quickly expanding in many different directions, with new findings constantly updating and/or complicating past evidence. In light of this, we argue that there is an urgent need for a synthesis and qualitative appraisal of the current knowledge on this topic. By establishing a sound evidence base we hope to focus future research and evaluation of LA interventions and programs. Thus, with the present review of the literature, we will advance state-of-the-art recommendations for current and future LA interventions in terms of methodology, design, and implementation.

Method

Protocol

This review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. PRISMA is a widely used and validated method of conducting systematic reviews on a broad range of topics and disciplines, ranging from clinical medical trials to social sciences, including psychology and education sciences. This review method has been endorsed by several editorial organizations, including Centre for Reviews and Dissemination, Cochrane Collaboration, Council of Science Editors, as well as the World Health Organization. PRISMA has further received endorsements from 100+ high-ranking journals, including The Lancet, the Journal of the American Medical Association, Implementation Science, and Trials. We elected to use PRISMA methodology because of its sound validity and adaptability to various fields of research. Details can be accessed at www.prisma-guidelines.org.

Literature search strategy

Given the wide array of fields in which LA might be developed and/or applied (e.g. medicine, psychology, pedagogy, business, etc.), we examined a diverse range of journals for literature on LA. Specifically, a comprehensive search was conducted of the following EBSCO-host databases: British Education Index; Business Source Complete; Child Development & Adolescent Studies; CINAHL Plus with Full Text; Education Research Complete; Educational Administration Abstracts; E-Journals; ERIC; Library, Information Science & Technology Abstracts; MEDLINE; Psychology and Behavioral Sciences Collection, SCOPUS, Sciencedirect, IEEE Explore, ACM Digital Library, dblp. We also performed a literature search using Web of Science and Google Scholar to identify additional references.

The search terms used comprised the following words and combinations: “Learning analytics intervention”, “learning analytics effectiveness”, “educational analytics intervention”, “educational analytics effectiveness”, “learning analytics program evaluation”, “educational analytics program evaluation”, “learning analytics feedback” “learning analytics remediation”. Reference lists of relevant papers were also manually searched for additional articles.

Studies were selected based on the following inclusion criteria:

i. The article reported studies evaluating the effectiveness of LA interventions in terms of academic retention, achievement, and/or overall student success in higher education institutions.
ii. The full text was available (in the event that an article was unobtainable via database searches, we would send a request directly to the author(s)).
iii. The article was in English.

iv. The article had undergone scientific peer review.

v. The article had been published since 2000.

Articles obtained from the search were reviewed by the researchers in three rounds against the inclusion criteria. In the first round, articles were retained or excluded based on their title. That is, articles that clearly did not pertain to the subject matter were rejected. In the second round, the remaining articles were assessed based on their abstracts. Finally, the papers that were retained after the first two rounds were downloaded and examined in detail by the research team. This final review included an appraisal of the quality of the research. To this end, we used the Quality Assessment Tool for Quantitative Studies (QATQS) (Thomas, Ciliska, Dobbins, & Micucci, 2004). The QATQS assesses research on six characteristics in terms of ‘strong’, ‘moderate’, or ‘weak’. The combination of these appraisals of individual parts of the research study makes up the overall quality evaluation as ‘strong’, ‘moderate’, or ‘weak’. These characteristics include study population selection bias, study design, confounding variables, researcher blinding, data collection methods, and participant withdrawals and attrition. Although this assessment tool was originally designed for use within a public health context, it has often been applied to other research with behavioral outcomes (e.g. Ganann, Fitzpatrick-Lewis, Ciliska, & Peirson, 2012; Peirson et al., 2014, 2015). Given the fact that our review focuses on identification of at-risk students and intervention evaluation in the educational sector, and thus centers on student behavior as the main outcome variable, we found this method of quality assessment suitable for our purposes. All papers were coded independently by the first and third authors. Assessments diverged on only a single paper (94% inter-rater agreement), and this was resolved through discussion and re-examination of the paper. The final quality assessment results for each study included in this review can be seen in Table 1.

Results

Literature search results

The literature search identified an initial set of 689 articles based on the search terms. Of these, 577 were related to LA-predictor variables, and 41 articles focused on analytics interventions. The vast majority of these papers were excluded due to one or more of the following reasons: The paper introduced a novel analytics concept or approach, but was exploratory in nature with no evaluation; the paper did not cite empirical research (i.e., editorial, comment); the paper focused on analytics strategies that were not relevant in an academic context; the paper focused on elementary school or high school rather than higher education institutions; the paper dealt with special populations such as people with learning disabilities; the paper reported insufficient statistical detail for evaluation; or a combination of these issues. Ultimately, a total of 11 peer-reviewed articles was retained for the review (see Figure 1 and Table 1). In the following sections, we critically review the evidence in terms of the efficacy of LA-based interventions targeting academic underperformance and drop-out rates.

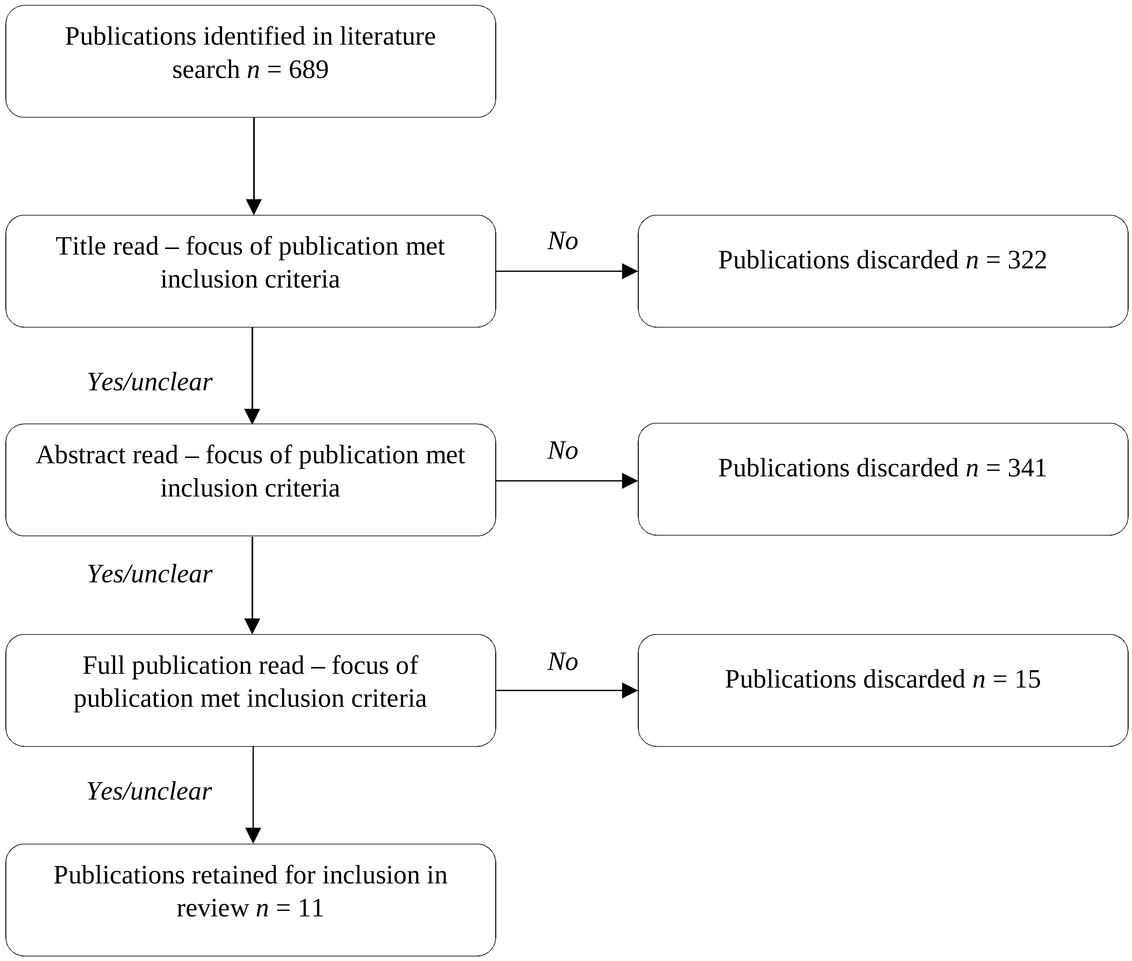

Figure 1: Publication screening flowchart

Table 1

A summary of the effectiveness of LA interventions on student retention and performance

Author	Country	Study design	Study population (N)	LA intervention	Predictor variables	Intervention design	Results	Research quality
Arnold & Pistilli (2012)	USA	Correlational	Undergraduates (26652)	Course Signals	• Academic performance (pts earned in course) • Interaction with LMS relative to peers • Academic history • High school GPA • SAT scores • Residency • Age • Credits attempted	Based on the results of the student success algorithm, a traffic light signal indicating the likelihood of success is displayed on student's homepage. Instructors may also take action.	The Course Signals program predicted 10% increases in A and B grades and a 6% decrease in D and F grades. Further, there was a positive and linear relationship between student retention and number of CS courses taken. Specifically, CS courses consistently retained approximately 10% to 25% more students than courses not using the program.	Moderate
Cambruzzi et al. (2015)	Brazil	Quasi-experimental	Undergraduates	Multitrail	• Academic history VLE activity	Based on individual assessment, individual students were engaged by instructors online to design a proactive plan for improvement.	The Multitrail approach to represent and manipulate data predicted student dropout rates with average of 87% accuracy. The intervention reduced dropout rates by 11%.	Moderate
Chen et al. (2008)	Taiwan	Experimental	Undergraduate (52)	Ubiquitous Learning Environment (ULE) Information Aware System	• ULE vs. desktop computer access to learning materials. •	The ULE makes learning resources available to students across all devices (computer, tablet, cell phone, etc.) at all times, allowing students to engage with material when and where they want. The VLE is based on three modules: Learning status awareness, schedule	Relative to the control group, use of ULE did not impact on student academic performance on weekly quizzes. It did, however, increase task completion rates by 16.65% and logins to the VLE by approx. 50%. 84.8% of students further agreed that the mentor arrangement module was helpful and effective.	Weak

						reminder, and mentor arrangement.		
Fritz (2011)	USA	Correlational	Undergraduates (2567)	Check My Activity (CMA)	Activity (hits, clicks, or access) on online system, Check my Activity	CMA allowed students to assess own activity relative to peers in real time	Students receiving Ds and Fs used CMA 39% less than students receiving Cs and above.	Weak
Huberth et al. (2015)	USA		Undergraduates (2234)	E^2Coach	• GPA. • Demographics. • Class grades. • In-class performance scores. • Homework scores. • Exam scores. • Frequency of access to E^2Coach. • Length of activity on E^2Coach	Based on student information, they received a profile of strengths and milestones, personalized grade predictions, norm-based information about comparable past students' study behavior.	Student performance increased with their use of E^2Coach at a statistically significant level.	Moderate
Jayaprakash et al. (2014)	USA	RCT	Undergraduates (1739)	Open Academic Analytics Initiative (OAAI)	• Gender • Age • High school GPA • Number of assignments/tests submitted Activity on university VLE	Awareness (notification of risk). OASE (peer-to-peer support community)	The intervention groups achieved 6% higher grades than the control. Further, 23.3% of students in the intervention groups withdrew whereas only 13.5% of students in the control group withdrew.	Strong
Kim et al. (2016)	South Korea	Experimental	Undergraduates and graduates (151)	Learning Analytics Dashboard (LAD)	• LAD usage frequency • LAD satisfaction	Students had access to their own as well as their peers' online activity (total log-in time, log-in frequency, frequency of LAD use, time spent on LAD, frequency of LAD resource use).	The experimental group scored 4.02 (p<.01) points higher on the final test than the control.	Moderate
Krumm et al. (2014)	USA	Quasi-experimental	Undergraduates (Phase I: 150, Phase II: 200)	Student Explorer	• Course progress uploaded weekly to the VLE. • VLE activity	Students and teachers were alerted to student progress and performance in terms of traffic light colors. For green-lit students teachers	Participating sophomores recorded significant increases in ACT scores following the implementation of Student Explorer.	Moderate

						would be prompted to recognize their progress. For yellow-lit students, teachers were asked to explore further. For red-lit students, teachers were encouraged to engage with them in a consultation.		
Lonn et al. (2015)	USA	Longitudinal	Undergraduates (213)	Student Explorer	• Course progress uploaded daily to the VLE. • VLE activity	Same as Krumm et al. (2014).	There were no significant differences between pre- and post-intervention self-reported course performance. There was a significant decrease in self-reported course mastery.	Moderate
Lu et al. (2017)	Taiwan	Experimental	Undergraduates (102)	N/A	• Level of engagement with course material (video). • Level of engagement in course discussion. • Self-regulation (attention planning ahead, content management, organization, checking/correcting, planning during writing, self-evaluation)	Instructors notified at-risk students of their risk status by email and arranged face-to-face discussions if needed.	Post intervention, the experimental group was significantly more likely to engage with course materials and contribute to discussion. These students also improved in terms of self-regulation. Ultimately, these outcomes resulted in 17.4% higher test scores for the experimental group relative to the control.	Moderate
Milliron et al. (2014)	USA	Experimental	Undergraduates & Postgraduates (161500 across three studies)	Illume Inspire	• High school GPA. • Degree program. • Live GPA slope. • Days enrolled before term. • Terms completed • ACT writing score • Average SD GPA points per term. • Credits earned. • Duckworth Grit Score • …	Illume Inspire identified the at-risk population and determined why they were at risk. Instructors would then intervene via email with students.	Post intervention, experimental groups across the three studies recorded statistically significant increases in course completion (3%) and persistence (3.21-7.62%) compared to the controls.	Strong

Note. All papers are peer reviewed. All but two have been published in international journals. Arnold & Pistilli (2012) is a conference papers. Krumm et al. (2014) was published as a book chapter. See reference list for full details.

LA intervention effectiveness

While past research clearly supports the predictive power of LA models, an important question relates to how this knowledge is translated into interventions, and whether these interventions are effective. A key assumption driving LA interventions is that such models enable the identification of at-risk students based on individual risk factors, and that the dissemination of students' risk status to both students and teachers increases awareness of specific learning issues, and guides the direction of intervention to address these issues. The current review identified 11 studies that evaluated the effectiveness of LA interventions (see Table 1).

In a Brazilian study on the predictive power of a tracking system, MultiTrails, which longitudinally recorded student behaviors and characteristics to identify potential dropouts, Cambruzzi, Rigo, and Barbosa (2015) were able to forecast dropout rates with 83.6% to 87% accuracy. The MultiTrails application allowed for simultaneous and longitudinal assessment of multiple variables – in this case, these related mainly to student academic history and performance (GPA, extracurricular activities), student activity in the university VLE (participation in online discussion forums), as well as the nature of this engagement (content analysis and keyword flagging of student exchanges in the VLE). A central component of the MultiTrails system also centered on the extent to which the accurate identification of low performing and/or dropout students could facilitate effective pedagogical interventions. Specifically, teachers were alerted to students deemed at risk of discontinuing study, and by virtue of the nature of his or her risk assessment provided by the MultiTrails system, the specific problem was pinpointed and appropriate and tailored action decided upon. Cambruzzi et al. (2015) identified several common reasons for dropout. These pertained to lack of student purpose and motivation in the given course, trouble with the distance learning format, insufficient student activity (e.g. due to lack of comprehension of the material following a poor evaluation, or failure to see the importance in the course training), and disagreement with the teacher or his/her methods. The MultiTrails system for intervention was associated with an 11% reduction in student dropout.

Fritz (2011) adopted a similar approach at the University of Baltimore in Maryland, USA. Here, a relationship between student grades and activity on the university's online course management system was hypothesized and tested. Results indicated a positive association between grades and online activity, with students receiving Ds and Fs using the online system approximately 39% less than students receiving Cs and above. This inspired the development of an online tool – Check My Activity (CMA) – that allowed students to assess their own online activity relative to their peers in real time throughout the semester. CMA thus represented a type of compass to allow students to gauge their own efforts and to keep them on track throughout the semester. An evaluation of CMA showed that 91.5% of students used CMA at least once, and compared to students who did not use the tool throughout the semester, these students were 1.92 times more likely to earn a C or above (Fritz, 2011). Thus, the observed significant increase in grades was connected not only to their online activity, but also to their awareness of their own online activity compared to their peers.

Akin to Fritz's intervention (2011), Chen, Chang, and Wang (2008) created a so-called Ubiquitous Learning Environment (ULE) designed to make the university's VLE available to students across a range of devices in addition to computers (cell phone, tablet, PDAs). The ULE incorporated extra features into the existing VLE, including task reminder notifications (deadlines, assignments, etc.), dynamic student learning targets and progress reports (based on VLE activity), and mentor appointment scheduling – all delivered directly to students' cell phones by SMS. As such, the ULE relied on the notion that tailoring learning objectives (through progress reports) to individual students based on their ULE activity, reminding students of tasks and deadlines by SMS, and scaffolding their learning environment with a mentor scheme, would increase their academic performance. Testing this hypothesis in an experimental intervention study, Chen et al. (2008) found no difference between the intervention and control groups in terms of academic performance on weekly tests. Students receiving the intervention, however, did log onto the VLE twice as often as the control group, and increased their task completion rate by 16.65% relative to the control. Further, 84.8% of students also agreed that mentorship assisted them in their learning.

In another study relatively similar to that of Chen et al. (2008), Lu, Huang, Huang, and Yang (2017) used LA analysis on student engagement (interaction with study materials, and contribution to online discussions) and seven self-regulation parameters (e.g. attention, planning ahead, organization) in an online course to identify the at-risk population. Teachers were then tasked with notifying the relevant students of their risk status and arranging for face-to-face consultation if needed. Results indicated that the experimental group achieved a 17.4% higher final test score than the control group. In terms of self-regulation, the experimental group similarly outperformed the control group on every one of the seven parameters at a statistically significant level.

In a slightly different approach, Kim, Jo, and Park (2016), tested the effectiveness of the Learning Analytics Dashboard (LAD) – an educational system designed to allow students to review their own as well as their peers' learning accomplishments and activities. Specifically, the LAD provided access to information about their own as well as other students' log-in time and frequency, and use of online resources. The authors hypothesized that because students were graded on a relative scale, information about other students' level of course engagement would represent a significant motivator for participation and learning. Results indicated a statistically significant 4.02 difference in learning performance favoring the intervention group.

The E^{2}Coach intervention (Huberth, Chen, Tritz, & McKay, 2015) is somewhat comparable to that implemented by Kim et al. (2016). Here, an online tool – the E^{2}Coach – was developed to provide individually tailored support to students in STEM courses. Specifically, the tool focuses on improving study habits and techniques, encouraging student activity and engagement when appropriate, and providing peer advice. In an evaluation study, students received a digital profile based on their student record (grades, courses) and their current performance as defined by regularly updated homework scores, exam scores, and in-class activity scores. Students also completed surveys on the E^2Coach platform throughout the semester, and results were used to further tailor their profile. These surveys included questions about student background, test scores, planned approaches for exam preparation, what grade they were working towards and how likely they were to achieve it. Based on their ongoing assessment, students received messages at key moments throughout the semester. The messages highlighted strengths and weaknesses of student progress and provided customized graphics displaying norm-based information about past and current peer study habits and grades. The messages also included a grade prediction based on the student's semester activity. Evaluations of the intervention revealed that student activity on the E^2Coach platform correlated positively and significantly with student performance, with high usage improving students' GPA by an average of 0.18 points on a standard four-point scale.

Another promising LA intervention is the Illume program (Milliron, Malcolm, & Kil, 2014). This program predicts student performance and risk of discontinuing by assessing student characteristics, including (but not limited to) demographics, high school GPA, course GPA, enrollment details, financial aid status, and activity in VLEs. Illume predictive modeling takes an iterative approach, constantly updating its models with new information (e.g. census data, application data, etc.). In an evaluation study (Milliron et al., 2014), individual students' risk profiles were made available to academic program administrators who alerted at-risk students to their risk status by telephone or email and offered further support. This approach was tested at three higher education institutions in the US. Results indicated that across three semesters at each institution, students who received the intervention scored higher in course persistence (i.e. remain enrolled) by 3.21-7.62%, and successfully completed the course at a higher rate (3%) than the control. The study also found that the predictive models generated at each institution diverged in content to achieve comparable accuracy. Based on this, the authors concluded that there is no one-size-fits-all predictive model of student success. Models need to be tailored to institutions. Finally and importantly, this study also tested the effectiveness of different outreach methods. These results indicated that phone calls were most effective for certain student segments (early-term students) while email communication was more effective for others (students with 10+ terms at the institution).

Another LA intervention, *Course Signals* (CS), is an LA software product developed and implemented at Purdue University in 2007. CS aims to increase student success through the use of an algorithm that takes into account several different predictors (Arnold & Pistilli, 2012). Specifically, the software forecasts student success by incorporating four central components in a risk assessment. These include *performance* (percentage of points earned in course to date), *effort* (as indicated by interaction with the online learning system, Blackboard Vista), *academic history* (GPA, SAT scores), and *student characteristics* (residency, age, credits attempted). Based on a weighted assessment of each of these factors, individual current performance and risk assessment reports are generated for students to peruse. The reports contain detailed information about the particular issues that might have been identified as well as what the student can do to improve. The overall result of this report, however, is conveyed to students in the simple form of a traffic light (i.e., green/yellow/red light in their VLE profile). Thus, the CS software provides an assessment based not only on a single factor or two. Rather, it gauges student performance in real time based on multiple static and dynamic indicators, and feeds this information back to the students in an easily accessible, practical, and understandable fashion. Evaluations of the CS program have shown 10%

increases in A and B grades and a 6% decrease in D and F grades in courses where CS was employed. Further, retention data suggests a positive and linear relationship between student retention and number of CS courses taken. Specifically, CS courses consistently retained approximately 10% to 25% more students than courses not using the program.

The CS program was expanded in a study by Jayaprakash, Moody, Lauría, Regan, and Baron (2014) where they similarly predicted at-risk students based on VLE activity, academic history, and demographics. The study involved 3176 participants at four different educational institutions in the USA. The researchers added to the CS notifications system by incorporating a student support portal (the Online Academic Support Environment; OASE) in the VLE. This support included increasing awareness of student assistance services, promoting peer-to-peer engagement, provision of self-assessment tools, as well as educational scaffolding content. Overall, the program successfully identified between 74.5% and 84.5% of at-risk students over the time span of six months. The central aim of the study, however, was to assess whether adding the OASE component would enhance the standard CS program in terms of student success and withdrawal rates. Results indicated that this was the case, but only for some outcome variables. Overall evaluations generated further support for the original CS intervention by indicating that among students identified as being at risk on the basis of CS predictor variables, the intervention (with or without the OASE component) lead to a 6% increase in grades compared to the control group. Similarly, for students designated as at-risk due specifically to their lower socio-economic status, a 7% increase in grades was observed. In terms of withdrawal rates, however, results indicated that 25.6% of students receiving the intervention dropped out compared to only 14.1% of the control group. The researchers speculated that this result might have been due to students opting to discontinue their studies rather than failing at the end of semester.

Finally, two studies reported on an LA intervention – Student Explorer – that is similar to the CS program in goal, style, and operation. Student Explorer is based on student VLE activity and course progress reports uploaded to the VLE on a regular basis. Both teachers and students are alerted to student progress and performance in terms of traffic light colors. For green-lit students teachers are encouraged to recognize and reinforce the student's progress. For yellow-lit students, teachers are prompted to explore the given student's performance and activity further to identify any potential issues or problems that may account for the yellow rating. For red-lit students, teachers are implored to engage with the student in a direct student-teacher consultation. Evaluating the efficacy of this approach to improve student performance (as defined by their GPA), Krumm, Waddington, Teasley, and Lonn (2014) conducted a pre/post analysis of student performance in a STEM course before implementation of Student Explorer (2008-2009 and 2009-2010 academic years), and after (2010-2011 and 2011-2012 academic years). They found significant increases in GPAs for post-intervention students relative to the pre-intervention cohort. These results held up when accounting for incoming students' ACT scores.

A subsequent assessment of Student Explorer did not generate comparable results, however. Lonn, Aguilar, and Teasley (2015) examined the effectiveness of the Student Explorer program in improving pre-college, remedial students' self-reported course mastery and motivation. While they recorded no significant differences in pre- and post-intervention motivation scores, they did find an overall significant *decrease* in course-mastery scores from pre- to post-intervention. This result appeared to be driven by the unexpected finding that the number of times that teachers showed students their Student Explorer data predicted lower student self-reported mastery scores.

Discussion

In this paper, our aim was to systematically review the evidence on the efficacy of LA interventions in higher education. At face value, the findings from the 11 studies are promising, with results indicating 6% increases in overall grades (Jayaprakash et al., 2014), 10% increases in top grades (As and Bs) (Arnold & Pistelli, 2012), and a nearly two-fold increase in the likelihood of students achieving C-grades or above (Fritz, 2010). In addition, these studies also found between 11% (Cambruzzi et al., 2015) to 25% higher retention (Arnold & Pistelli, 2012) from pre- to post-intervention. Thus, while limited, the current evidence base suggests the potential effectiveness of LA interventions in terms of student success and retention.

In consolidating the main points made in the literature concerning tried and tested LA interventions, however, several themes and variations emerged. Of the papers that assessed LA interventions in terms of student academic success (Arnold & Pistelli, 2012; Cambruzzi et al., 2015; Chen et al., 2008; Fritz, 2010; Huberth et al., 2015; Jayaprakash et al., 2014; Kim et al., 2016; Krumm et al., 2014; Lonn et al., 2015; Lu et al. 2017; Milliron et al., 2014), all but one (Lonn et al., 2015) reported significant post-intervention increases in grades and/or course activity (see Table 1). While generally positive, the results on student withdrawal rates, however, varied somewhat. Arnold and Pistilli (2012) reported increases in retention rates ranging from 10% to 25%, while Milliron et al. (2014) found a 3% increase in course completion, and Cambruzzi et al. (2015) an 11% decrease in withdrawal following their intervention. However, a study on the modified version of Course Signals (CS) found an 11.5% higher likelihood of dropping out for students receiving the intervention compared to the control group (Jayaprakash et al., 2014). This is partially consistent with Arnold and Pistilli's (2012) original CS trial where they initially found an increase in withdrawal rates immediately following the intervention. The authors argued that this might have been due to students deciding (based on intervention feedback) that their chosen course was not right for them, and withdrawing as a result of the feedback. However, this needs to be confirmed with further study.

The overall success of the intervention programs listed above speaks to the validity of their nearly identical approaches. That is, all of the reviewed studies aimed to increase student success and retention along the same pathways: By identifying the at-risk student population through LA, analyzing their individual risk factors, and disseminating this information to students and their teachers. This, in turn, was then expected to increase awareness of potential learning issues, and encourage intervention and thus academic success and retention. Nevertheless, there were slight variations in the intervention designs. In Jayaprakash et al. (2014), Cambruzzi et al. (2015), Chen et al. (2008), Huberth et al. (2015), Lu et al. (2017), and Milliron et al. (2014), the basic approach of feeding back risk-assessment results to students was coupled with practical advice on exactly *how* the student could improve and/or an offer of academic consultation and support. In this way, these studies specifically incorporated tailored, well-defined, and practical student support into their respective intervention designs. Intuitively, this should increase the impact of such interventions; however, such comparative effects have yet to be evaluated.

Another point worth noting in this context, relates to the negative impact of the Student Explorer intervention on remedial students' self-reported course mastery scores, reported in Lonn et al. (2015). Here, the number of times that teachers alerted red-lit students to their progress reports negatively predicted students' self-reported mastery scores. The authors were unable to make any definitive conclusions explaining this effect. However, they recommended that future research exercise caution when implementing similar interventions as their results indicate that LA data may impact student performance negatively.

Limitations and recommendations for future research

There are several limitations that should be noted. First, we identified only 11 studies that assessed intervention effectiveness. Using the QATQS assessment tool, two of these were categorized as ‘weak’ (Chen et al., 2008; Fritz, 2011) in terms of their methodology, five as ‘moderate’ (Arnold & Pistilli, 2012; Cambruzzi et al., 2015; Huberth et al., 2015; Lu et al. 2017; Lom et al., 2015; Kim et al. 2016; Krumm et al., 2014), and two as ‘strong’ (Jayaprakash et al., 2015; Milliron et al., 2014). These somewhat low average ratings are due to several factors, including a tendency to rely on simple pre/post-intervention designs, convenience sampling, small study populations, as well as a general lack of accounting for potentially confounding variables (e.g. ethnicity, gender, etc.). In fact, only a single article (Jayaprakash et al., 2014) explicitly considered the potential impact of study population characteristics (e.g. SES) on the effectiveness of the intervention.

In other words, the evidence is somewhat tenuous in terms of the sheer number of studies as well as its overall quality. Further, it is reasonable to assume that other studies have found null effects, but not been published due to publication bias. For these reasons, the evidence reported here should be interpreted with caution. This is particularly relevant in the current context where universities around the world are increasingly turning to LA to identify and intervene with at-risk students (e.g., Sclater et al., 2016; Sclater & Mullan, 2016). That is, the current demand for LA in the higher education sector may be based on scant empirical evidence to its effectiveness (Papamitsiou & Economides, 2016). Moreover, the results of many interventions cannot be scrutinized fully as they remain unpublished due to the fact that they are seen as commercially sensitive (Ferguson et al., 2016; Sclater & Mullan, 2016). Thus, in order to maximize academic outcomes and student success, as well as return on investment, this review makes the key recommendation that more research into the implementation and evaluation of scientifically-driven

LA interventions is needed to build a solid evidence base on the effectiveness and feasibility of LA initiatives.

Although it is true that the LA interventions that have been assessed to date show promising results, there is very little evidence for the generalizability of these effects. That is, will the success of, for example, the MultiTrails system readily adapt to another educational institution? Preliminary results on the transferability of the modified Course Signals system to three separate universities are promising with almost identical impact across universities (Jayaprakash et al., 2014; Lauría, Moody, Jayaprakash, Jonnalagadda, & Baron, 2013). On the other hand, Milliron et al. (2014) found considerable discrepancies in effectiveness and feasibility across institutions, and advance the key point that LA interventions (in terms of the predictive algorithm used to identify the at-risk population as well as the intervention) need to be tailored to the specific institutional context. Ultimately, it would seem that the determining which LA interventions – or which components of LA interventions – are scalable and adaptable, needs to be investigated further and in greater detail (e.g. internationally). Indeed, program adaptability and replicability (cf. Krumm et al., 2014 and Lom et al., 2015) should be incorporated into any LA-intervention evaluation as a standard measure (Harackiewicz & Priniski, 2018).

In terms of the specific mechanisms that underlie the effectiveness (or lack of effectiveness) of LA interventions, more research is also needed into the design and delivery of the actual intervention (Sneyers & De Witte, 2018; Vivian, 2005). That is, while the most accurate predictor variables of retention and student success can be identified through relatively straightforward statistical analysis of the increasingly comprehensive data banks on student behavior, characteristics, and background, it is more difficult to establish the best way of intervening with at-risk students. This conundrum is reflected in the largely speculative interpretations of intervention mechanisms and effects in the reviewed studies. Indeed, only one of the papers included in our review (Milliron et al., 2014) empirically tested the efficacy of student outreach and intervention delivery and ascertained significant differences in effectiveness between email and telephone communications dependent on student seniority. One way to achieve more elaborate and detailed such insight could be through more qualitative approaches, including interviews and focus groups with teachers and students.

Still, in the context of intervention processes, it is worth noting that a central theme that emerged from our review concerns the burden of behavior change that interventions prescribed to either students or faculty/institution. In particular, five of the 11 interventions reviewed here (Arnold & Pistilli, 2012; Chen et al., 2008; Fritz, 2011; Huberth et al., 2015; Kim et al., 2016) put the onus primarily on the student to change behavior when prompted (e.g. by traffic light warning systems) rather than on the educational institution to make systemic changes for a more inclusive approach to student care and service. Optimal intervention effectiveness may be better achieved if both student and institution (including teachers) are expected to react to negative student forecasts, such as in the studies conducted by Jayaprakash et al. (2014), Cambruzzi et al. (2015), Lu et al. (2017), Krumm et al. (2014), Lom et al. (2015), and Milliron et al. (2014).

Unpublished research on student performance and retention confirms the need to consider the interplay between the student and the institution in interventions. For example, Day (2015) found positive correlations between student retention and course engagement (i.e. VLE activity, library use, and attendance), and reasoned that if students and teachers were made aware in real time of such decreases in student activity, they could better anticipate issues in learning and course completion and intervene in time. This insight led to the creation of an online portal – the NTU dashboard – containing information on student background, their most recent course engagement (e.g. VLE use), and their overall course activity compared to other students in the same course. This information was made available to both students and teachers in a regularly updated report, flagging students at risk. As with Jayaprakash et al. (2014), both teachers and students could initiate consultation to improve course engagement and functioning. Evaluation revealed that 27% of students reported changing their behavior in response to the dashboard information and teacher consultation (e.g., increasing their campus presence, using the VLE more). Teachers reported that the dashboard allowed them to better tailor and target their individual interventions, with negligible bearing on their workload.

Other unpublished research has taken a different approach, focusing on student health and well-being rather than academic performance and results. Davis (2015) developed an intervention – the Early Alerts System – aimed at reducing student attrition by predicting and intervening against social isolation and loneliness. This initiative focused on student affect and well-being as a significant predictor of study withdrawal, and thus predicted student behavior and affect by analyzing VLE activity, attendance, and academic history against 34 triggers, each representing different well-being behaviors. This information was consolidated into a daily *wellness* report, informing a student support team whether to take action and offer support to a given student via phone, email, and/or social media. This program accurately identified at-risk students, and ultimately created an environment in which informed, tailored, and proactive intervention could occur. Preliminary results indicate that the Early Alerts system increased retention by 6%.

Conclusion

We have reviewed the evidence on LA intervention effectiveness in terms of student retention and success. While there is plenty of research on the forecasting of student performance and retention, there is very little on the effectiveness of LA interventions. In fact, and as mentioned in the introduction, we have found only three peer-reviewed publications that critically assess the effectiveness of LA interventions in higher education in terms of student success and retention (Ferguson et al., 2016, 2018; Viberg et al., 2018). These reviews provide valuable insight into the state-of-the-art of LA in higher education, including most prominently information about current research foci and gaps in knowledge. However, it should be noted that none of them critically assess all of the available evidence. In fact, collectively they refer to only four (Arnold & Pistilli, 2012; Jayaprakash et al., 2014; Huberth et al., 2015; Milliron et al., 2014) of the 11 studies identified in the present paper. In light of this, we hope that our review serves to (1) summarize the current evidence base on LA intervention effectiveness in higher education, and (2) provide a critical and reflective examination of what works in tried and tested LA interventions. On the basis of this synthesis of current knowledge, we hope to update past reviews on where our current knowledge of LA intervention design and efficacy may fall short, and thus determine appropriate directions for future research. For example, in our treatment of the literature, a fundamental question persists throughout: Once at-risk students have been identified, what is the best way to intervene and help them? The LA interventions that we have identified center on the idea that alerting students to their risk status, and engaging them on this basis, will change their performance for the better. While the evidence generally supports this notion, there are a few important caveats that should be noted. These relate primarily to the dearth of LA intervention evaluation, questions of intervention adaptability to different institutions, and the best method of delivering the intervention to maximum effect. Thus, all things considered, and building explicitly on the valuable contributions of past research in the field, we make the following recommendations for future study into LA interventions:

1. The predictive elements of LA interventions should be evidence-based. As such, forecasts of student retention and/or success should principally rely on student academic history, SES, and engagement with course material (as indicated typically by VLE activity). However, exploring other potential (non-academic, experiential) predictor variables, such as student well-being, should also be a focus.

2. Ideally, and where possible, studies should employ experimental research methods (e.g. randomized control trials, stepped-wedge trials) over correlational and cohort pre/post designs. For practical reasons, most applied research may rely on convenience samples and simple pre/post-intervention designs. However, implementing and evaluating interventions at the level of specific university programs or modules, rather than entire institutions (e.g. Rienties et al., 2016), may make it considerably more feasible to design higher quality research studies, including randomized control trials and factorial designs.
3. All outcomes should be broken down by relevant population characteristics (SES, ethnicity, gender, off-campus vs. on-campus study mode, part-time vs. full-time students, etc.). This will ensure data richness and allow for insight into potential mediators and moderators of the intervention effects as well as provide indications of intervention adaptability.
4. Further, recording student and academic staff experience of the initiative (e.g. the technical aspects of VLE systems), and its benefits and/or pitfalls (e.g. adequacy of support and/or guidance for at-risk students), would be valuable in further developing and tailoring the implemented intervention program delivery for greatest effect. This data could be achieved in representative focus groups and/or individual student and staff interviews and/or survey measures. Including the experiences of students who may have withdrawn from their studies in spite of (or perhaps because of) the intervention (see Jayaprakash et al., 2014) would be of particular value.
5. LA interventions may be most effective if they are based on the idea that to maximize student performance, both student behavior as well as the academic environment in which this behavior occurs may need to be adjusted in order to effect change. In other words,

intervention should target student behavior and activity *as well as* the educational facilities that are in place.

6. Standardized assessments of LA intervention programs should be developed and form a central goal of LA research whenever possible. Most prominently, this may involve frameworks such as RE-AIM, which advances the central components that intervention study should evaluate: **R**each in terms of target population, **E**ffectiveness/efficacy of intervention, **A**doption of the intervention by staff/institution, **I**mplementation feasibility, and **M**aintenance of effects over time (Glasgow, Vogt, & Boles, 1999).
7. Finally, generalizability of LA interventions should be a fundamental focus for future study. While this may prove difficult in individual studies, as access to several institutions is crucial in this respect, replicating past results in new contexts may be the best way forward in validating LA intervention programs.

The case for learning analytics resides in the fact that these systems allow educational institutions to track individual student engagement, attainment, progression, and even well-being in near real-time. This allows for any issues to be flagged to tutors, support staff, and students themselves, facilitating early intervention to reduce the risk of withdrawal or underachievement. Overall, the emerging and increasing evidence base on the topic certainly indicates considerable potential and opportunity for LA interventions as an effective means to improve retention and increase student success and experience. However, this review has identified several unknowns that need to be investigated further to know the full value of LA interventions. One reason for this relates to the failure of many early adopters of LA to publish the results of evaluations of such interventions. We call on more researchers to make their research available for wider scrutiny. Nevertheless, we hope that this paper serves to consolidate the evidence base on LA and to provide guidance for future research to build a robust case for the capacity of LA approaches to help both students and educators in reaching their full potential.

The authors declare no conflict of interest in the work reported here.
As this paper is a systematic review of published evidence, and as such does not involve primary data collection, we have no data to make available for public access. Similarly, as this paper is a review paper, no ethics approval was necessary.

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