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A review of learning analytics intervention in higher education (2011–2018)

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Abstract Intervention has long been practised in higher education to provide assistance for at-risk or underachieving learners. With the development of learning analytics, the delivery of intervention has been informed by data-driven approaches to identify learners' problems and provide them with just-in-time and personalised support. However, intervention has been claimed to be the greatest challenge in learning analytics and has yet to be widely implemented. This paper reviews 24 case studies of learning analytics intervention in higher education. The cases were categorised and summarised according to their objectives, the data used, the intervention methods, the outcomes obtained and the challenges encountered. The results show that intervention practices have focused most frequently on increasing students' study performance, offering personalised feedback and improving student retention. The frequent types of data involved students' online learning behaviours, study performance, demographics and course selection information. The most commonly used intervention methods involved offering personalised recommendations and visualising learning data. The interventions have led to outcomes such as enhancing study performance, retention and course registration, as well as productivity and effectiveness in learning and teaching. The challenges covered a wide range of aspects, including the scalability of intervention, conditions for implementing intervention, limitations of the channels for delivering intervention and the evaluation of intervention effectiveness. The results suggest that learning analytics intervention has the potential to further extend its scope of practices to serve a wider range of purposes, but more studies on the empirical evidence, even with null or negative results, are needed to support its long-term effectiveness and sustainability.

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Introduction

Learning analytics refers to "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens 2012). Given the massive amount of data available about learners and learning, it has been regarded as having great potential for offering learners a better learning experience that focuses on their individual preferences, strengths and needs (Clow 2013; Siemens 2012).

One major objective of learning analytics is to discover early those students who are likely to fail in their studies and provide them with just-in-time and personalised support (Sclater et al. 2016; Wong et al. 2018). Khalil and Ebner (2015) proposed a life cycle of learning analytics which consisted of four stages: (1) data generation—usually from learning platforms, such as massive open online courses, learning management systems (LMS) and virtual learning environments; (2) tracking—traceable data of learners on the learning platforms; (3) analysis—to generate patterns and retrieve information from the data and (4) action—which may include prediction, intervention and personalisation.

As the final stage of the learning analytics cycle, intervention has been claimed to be the biggest challenge in learning analytics (Rienties et al. 2017). Although the idea of making learning analytics data meaningful and available to learners has been promoted in recent years, most research still puts an emphasis on developing an accurate prediction model and few studies have addressed the intervention strategies (Clow 2012; Corrin et al. 2016; Rienties et al. 2016). Rienties et al. (2017) state that, despite there being an increasing amount of research on small-scale, experimental implementation of intervention, there is not yet a comprehensive model supported by a strong evidence base for instructors to make effective interventions.

This paper aims to review the case studies of learning analytics intervention in higher education. Within the limited availability of empirical studies on this topic, it provides a categorisation of the intervention methods and the data used for analysis, and identifies the outcomes and challenges as shown in the intervention practices. The results offer insights into the formulation of intervention strategies for higher education institutions which practise learning analytics.

Literature review

Within the scope of academic or instructional areas, interventions refer to the provision of assistance to learners who are at risk or underachieving when compared to an existing standard (Fuchs et al. 2003). They aim to prevent learners' academic failure by monitoring their progress, providing additional instruction or support that matches learners' needs and influencing their physical, intellectual and moral development.

With the support of learning analytics, interventions usually target improving undesirable situations such as a dropping retention rate or an unsatisfactory pass rate, which are informed by data on the learning progress of students. Their potential advantages have been recognised in literature. For example, students who are less likely to attain the learning objectives of a course can obtain support to improve their performance (Beattie et al. 2014; Sclater and Bailey 2015). Instructors can take the opportunity to consolidate their relationship with students, reflect on their teaching performance and adjust the teaching or course contents accordingly (Rienties et al. 2016). Also, faculty or school administrators can enhance course modules or make better use of resources and information technology infrastructure through resource re-allocation and collaboration across departments (Molinaro et al. 2016; Wong and Lavrencic 2016).

Learning analytics interventions can take different forms, ranging from various kinds of communication, such as emails or phone calls, to the imposition of additional assessment. Choi et al. (2018) summarise the common intervention approaches, viz. emails, phone calls, instant messaging, posts and news on LMS, group consultation, face-to-face consultation, video recording, peer review and e-tutorials. However, these involve different costs—for instance, for instructors, face-to-face consultation is much more costly than emails, although it may be a more effective approach.

Rienties et al. (2017) argue that the greatest challenge is the uncertain impact of different types of intervention on learners' attitude, behaviour and cognition. It has been found that students and instructors may also find intervention challenging. Wise (2014) asserts that at-risk students may be weak at interpreting the learning analytics data and taking action according to them which requires strong metacognitive skills and self-regulation. Instructors face the problem of the cost of time, especially those who have larger courses, as insufficient time and inadequate availability of resources may restrict them from taking proactive intervention (Corrin et al. 2016). Also, for education institutions, Lonn et al. (2015) found that the main challenge of scaling up a learning analytics intervention comes from technological barriers. These challenges are one factor which has led to the limited practice of learning analytics intervention reported so far.

The limited practice of learning analytics interventions has been shown in previous reviews. For example, Si Na and Tasir (2017) reviewed the learning analytics interventions in 2012–2016 and found 13 relevant articles, among which only six reported empirical intervention practices. Sønderlund et al. (2018) found that only 11 articles on learning analytics interventions evaluated their effectiveness, which was generally limited by factors such as simple evaluation designs, convenience sampling and small study populations. Also, Sclater (2017) described interventions as an emerging area, while relatively undocumented, in learning analytics. In view of the limited coverage of previous reviews, the current status of learning analytics interventions has yet to be fully revealed and a wider review is needed.

Method

This paper reviews the case studies on learning analytics intervention. Case studies reporting learning analytics intervention were first collected via Scopus and the Web of Science using the key terms ("learning analytics" AND "intervention") for the period

Table 1 Country/region of the institutions practising learning analytics interventions

Country/region	Frequency
USA	13
Australia	1
Hong Kong	1
Spain	1
Taiwan	1

Seven cases did not specify the location of the institutions

2011–2018.[1] In addition, more relevant articles were collected from the proceedings of the International Learning Analytics & Knowledge Conferences for the same period of time. The articles were chosen based on the following criteria:

1. They reported at least one empirical case of intervention in a higher education institution or an online education platform.
2. They contained the rationale for the intervention strategy, a description of the practice and the outcomes.
3. They illustrated how the intervention strategy was informed by data analysis in learning analytics.

Following these criteria, a total of 24 practices of learning analytics were selected. The details of the intervention practices, including the institution, objective, data used, intervention method, outcome and challenge, were then identified and summarised.

Findings

Overview of the interventions

The 24 case studies of learning analytics interventions are summarised in the Appendix. In terms of geographical locations, Table 1 shows the country/region of the institutions where the interventions were practised. Just over half the interventions took place in the United States, with the others being in Australia, Hong Kong, Taiwan and Spain—together with seven cases which did not specify the locations.

Objectives of the interventions

Table 2 summarises the objectives of the learning analytics interventions. The most frequent type of objective was related to improving students' study performance, covering remedial actions taken to help those who were at risk of failure or encountering learning difficulties. Offering personalised feedback was another frequent type

[1] Relevant articles were found on Scopus and the Web of Science starting from 2011.

Table 2 Objectives of the learning analytics interventions

Type of objective	Frequency
Increase study performance	6
Offer personalised feedback to students	5
Improve student retention	4
Help students to make informed academic decisions	3
Enhance students' self-awareness/self-reflection/self-regulation	3
Increase the effectiveness of tracking students' learning process/performance	2
Promote collaborative learning	1
Support academic advisors' just-in-time decision-making	1
Improve student engagement	1

An intervention may have more than one type of objective

of objective, where students' specific profiles were often analysed or categorised for tailoring feedback to cope with their needs. Other types of objectives focused on the student perspective, which included improving student retention; helping students to make academic decisions such as course selection; enhancing their self-awareness, self-reflection and self-regulation; promoting collaborative learning and improving student engagement. In addition, some interventions aimed to support the work of staff, such as tracking students' learning process and performance, and helping them to make just-in-time decisions.

Data collected for the interventions

Table 3 presents the data used to support the learning analytics interventions. The data related to students' online learning behaviours were most frequently used, which usually involved students' actions on LMS or platforms specifically developed for learning analytics (e.g. login, access to materials, participation in discussion and collaborative activities). This was followed by students' study performance (e.g. assignment/exam scores, course grades and GPA), demographic information (e.g. gender, age, ethnicity and socio-economic status) and course selection. Some types of data were used relatively infrequently, including students' academic history (e.g. prior studies and study modes), perceptions/emotions (e.g. perceived task difficulty, interest in a course and daily emotion) and in-class feedback (e.g. votes and qualitative responses). There were also a few types of data which were used only in one practice, including students' study progress, learning goals and teachers' observations of students, where manual labelling and coding may be required to process the data.

Intervention methods

Table 4 shows the intervention methods applied in the case studies. Offering personalised recommendations was the most frequent method, with the areas covered including course selection, online/in-person services, learning resources and tailored programmes. The recommendations were delivered through various channels such

Table 3 Data used for the learning analytics interventions

Type of data	Frequency
Students' online learning behaviours	14
Students' study performance	11
Students' demographics	8
Students' course selection	7
Students' academic history	3
Students' perceptions/emotions	3
Students' in-class feedback	2
Students' study progress	1
Students' learning goals	1
Teachers' observations on students	1

An intervention may use more than one type of data

Table 4 Methods for the learning analytics interventions

Type of intervention method	Frequency
Personalised recommendation	12
Visualisation of learning data	7
Personalised report on study progress/performance	5
Personalised assignments/assessments	2
Social contact	2
Recommended actions for academic advisors	1
Visualisation of students' feedback	1

An intervention may involve more than one type of method

as emails, SMS, voice messages, social media and face-to-face meetings. Visualisation of learning data was the second most frequent type of method, with diverse applications such as helping students to get a better understanding of their own or peers' learning behaviours in order to adjust learning strategies; facilitating teachers to easily interpret student learning progress for determining remedial actions and highlighting key points made in online discussion for teachers to deepen and broaden the discussion. The third most frequent type of method was providing personalised reports through emails or the dashboard on students' study progress or performance, based on which students or teachers could take timely action on the situations.

Several intervention methods were used only in one or two cases. For students, personalised assignments or assessments were provided based on students' knowledge levels or development needs for specific skills, and informal social contact was made with students such as welcoming emails, phone calls and reminder emails for assignments and quizzes. For teachers/academic advisors, recommended actions were shown for their reference (e.g. encouraging students to keep doing well, exploring their progress in detail and engaging them in accessing possible difficulties), and students' in-class live feedback was visualised for the teachers to evaluate students' knowledge or perceptions and make adjustments in teaching.

Table 5 Outcomes of the learning analytics interventions

Type of outcome	Frequency
Improved study performance	8
Higher retention/registration rate	4
Enhanced productivity/effectiveness in learning and teaching	4
Facilitated understanding of progress/performance	3
Increased participation/engagement in learning	2
Positive perceptions of students	2
Found suitable courses for students	1

An intervention may have more than one type of outcome

Outcomes of the interventions

Table 5 summarises the outcomes of the interventions. Improvement in students' study performance (e.g. course grades, pass rate in exams and mastery of knowledge) was most frequently reported. This was followed by a higher retention/registration rate; higher productivity/effectiveness in learning and teaching (in areas such as students' self-regulation, collaborative learning and teachers' readiness to react to students' situations) and better and easier understanding of study progress and performance (e.g. assessment of students' competency against teachers' expectations and identification of students who needed help).

There were also a few types of outcomes which showed in one or two cases only. For example, the interventions by Wise et al. (2014) and Lu et al. (2017) helped students to monitor, reflect on and participate in learning activities such as online discussion. Students' perceptions of learning analytics were also improved, which encouraged them to make use of the analytics results (Kimberly and Pistilli 2012). Students were also helped to find alternative and suitable courses when their preferred courses were full (Bramucci and Gaston 2012).

Challenges encountered

Table 6 shows the challenges reported in the case studies regarding the intervention practices. It is notable that the challenges covered a wide range of aspects where each type involved at most only two cases. In general, there were challenges in the scalability of intervention (e.g. too many requests for help from students, and complexity of variable combinations); conditions for implementing the interventions (e.g. students' contribution of data, teachers' experience, being able to reach at-risk students and coordination of variable groups of professionals); limitations of the channels for interventions (e.g. email and visualisation); as well as evaluation of intervention effectiveness (e.g. difficulties in evaluation and generalisation of intervention results).

These challenges are possible factors leading to the limited number of empirically tested learning analytics programmes (Sønderlund et al. 2018). As a consequence, some other challenges were encountered in the intervention practices, such as a lack of benchmarking of information and best practices of learning analytics interventions, and uncertainty about the long-term effectiveness of the interventions.

Table 6 Challenges for the learning analytics interventions

Type of challenge	Frequency
Intervention not sustainable at scale	2
Reliance on students' contribution of data	2
Too many variables and their combinations	2
Difficulty in reaching at-risk students	1
Difficulty in coordinating different groups of professionals working together	1
Difficulty in evaluating the effectiveness of intervention	1
Difficulty in generalising the results of intervention	1
Distraction for students	1
Lack of benchmarking information	1
Lack of best practices	1
Limited effectiveness for students at a low knowledge level	1
Limited impact of emails	1
Reliance on teachers' experience	1
Unknown long-term effectiveness	1

An intervention may have more than one type of challenge

Discussion

This paper has presented an overview of learning analytics interventions, covering the types of data used, methods applied, outcomes obtained and challenges encountered. The results contribute to addressing a gap in literature as existing intervention practices have yet to be comprehensively reviewed. The findings also provide empirical evidence for researchers and practitioners about implementing learning analytics interventions.

In terms of the geographical locations, the results of this review show that the learning analytics interventions were mainly implemented in the USA. Contrary to the results of Wong et al. (2018) that learning analytics has in general been practised in an increasingly wider range of countries, the findings of this review suggest that—at least from the published literature—learning analytics interventions have yet to be widely practised in various parts of the globe. Sønderlund et al. (2018) suggest that the actual use of learning analytics interventions might be higher than is reported in the literature, with some not published due to null effects or being seen as commercially sensitive. Nonetheless, the 24 intervention practices found in literature and included in this review exceed that in previous reviews [i.e. 13 in Si Na and Tasir (2017) and 11 in Sønderlund et al. (2018)], showing that intervention—while being seen as the biggest challenge in learning analytics (Rienties et al. 2017)—has been gradually put into practice.

Among the intervention practices reviewed, their objectives were broader than those usually stated in literature which focus on providing remedial actions for students underperformed or at risk of dropping out (Si Na and Tasir 2017; Sønderlund et al. 2018). The interventions covered not only dealing with students encountering problems but also enhancing student success in general. For example, the work of McNely et al. (2012) aimed to promote collaborative learning for students participating in online collaborative writing activities by facilitating their formative assessment of peer-to-peer interaction and feedback during writing. Santos et al. (2013) enhanced students' self-awareness, self-reflection and sense-making in learning through deepening their understanding of their own and peers' learning behaviours. In this sense, future practices of learning analytics could be devised with a more proactive approach. Rather than early detection or prediction of students' problems for remediation, aiming to improve students' effectiveness in learning through personalised support may benefit a wider range of students and reduce the occurrence of learning problems at the beginning.

The data used for the interventions covered both online and face-to-face learning contexts. In addition to the types of data which usually existed in an institution's LMS/VLE/SIS (e.g. students' demographics, online learning behaviours and study performance), there were also types of data collected specifically for the learning analytics practices (e.g. students' perceptions, emotions and learning goals). The current state of data collection for intervention shows that a major issue in learning analytics lies in sourcing the required data (Gašević et al. 2017), but this has been progressively tackled, with institutions attempting to use creative ways for collecting the data which enable them to address the questions they are interested in. However, some types of data (e.g. teachers' observations of students) were shown to be more costly in terms of data collection and processing. To allow learning analytics intervention to be sustainable at scale—one of the major challenges reported in the studies reviewed—more cost-effective ways to source the data which do not commonly exist in an institution's data warehouse for learning analytics should be explored.

The various types of intervention methods covered visualising learning data, offering personalised reports, recommendations, assignments or assessments and social contact—which students or teachers could react to and take corresponding actions. The methods in general involved a change in student behaviours in order to have an effect. It is thus important to give enough time and information for students to reflect on and take action on the feedback provided. This is also emphasised in the paper by Li et al. (2018), which surveyed the views of academics and administrators in higher education institutions on the areas that should be addressed in learning analytics practices. In addition, it is notable that the interventions did not at all follow only a pathway to enhance student success and retention. There were also a few practices which targeted improving teaching. For example, Rivera-Pelayo et al. (2013) gathered and visualised students' in-class live feedback for lecturers to evaluate students' knowledge or perceptions and make adjustments in teaching. While existing learning analytics interventions have focused mainly on student learning, the areas other than learning, such as teaching and course administration, have been rarely addressed and therefore should receive more attention.

The challenges faced by interventions were mainly encountered during the implementation process (e.g. difficulties in reaching at-risk students and evaluating effectiveness). This differs from the results of Li et al. (2018) which showed the obstacles for some institutions in starting to implement learning analytics, such as the lack of institutional support and a negative perception of institutional management on learning analytics. However, the current review has shown that many of these obstacles had been resolved in existing intervention practices. As regards the challenge on sustaining intervention at scale, the problems mainly lie in the limited time of instructors for handling students' problems. Strategies have been proposed in Choi et al. (2018) for using different intervention methods according to the significance and urgency of student problems, so that less costly but scalable methods (e.g. email reminders) can be used for students without significant difficulties, while methods which are costly and not scalable (e.g. face-to-face consultation) are used only for students in need.

Conclusion

This review study shows that learning analytics interventions have enabled students' learning to be enhanced, their problems to be identified early and timely personalised support to be offered. The cases of interventions reviewed also suggest that they have the potential to further extend the scope of practices to serve a wider range of purposes. They demonstrate how the data available in institutions can be utilised to support various kinds of learning analytics practices, which could be applicable to diverse educational contexts ranging from face-to-face to blended and online learning. As emphasised by Gašević et al. (2017), it is important to build up a data-informed culture so that academic decisions and early reactions on issues identified are based on empirical evidence. While the case studies revealed a lack of empirical evidence to support the long-term effectiveness of learning analytics interventions, more studies on empirical experience, even with null or negative results, should be reported to serve as examples for future intervention practices.

The cases of intervention highlighted the importance of personalised feedback to address students' specific problems: as Gašević et al. (2016) stressed, learning analytics should not aim to be a one-size-fits-all solution but interventions should be geared to students' particular situations and personal needs. It is noted that, among the limited studies on learning analytics interventions, very few have reported quantitative analyses data (Wong 2017). As the effectiveness of interventions may vary among groups in different settings, future research should address the contextual diversity.

The practice of intervention, as the final stage of the learning analytics cycle (Khalil and Ebner 2015), relies on the input from the previous stages for identifying specific problems to be tackled. The choice of intervention methods also depends on factors such as the capacity of the infrastructure (e.g. the availability of a data visualisation function on LMS) and human resources, as well as the nature and urgency of the problems. Future work should therefore also examine the interrelationships between the various factors to identify how effective intervention methods can be devised.

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Appendix

See Table 7.

Table 7 Summary of learning analytics interventions

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Bramucci and Gaston (2012)	South Orange County Community College District	Provide personalised recommendations to assist students in making better-informed academic decisions	Student profiles as data source; rules created by subject matter experts to determine the conditions for sending out recommendations	Personalised recommendations were provided covering course selection, study information and online services, in multimodal formats (e.g. email, SMS, voice message or social media) and based on various triggers (e.g. time, event or location)	The system helped students who were closed out of a class to find a suitable alternative class; and it was integrated with the learning management system to provide personalised announcements	NA
Kimberly and Pistilli (2012)	Purdue University	Increase student success	Students' grades; students' demographic characteristics and past academic history; students' actions on LMS	Personalised emails as well as 'traffic signals' indicating how each student is doing were sent to students by faculty members	There was about a 10% point increase in Grade A & B by students, and a significantly higher retention rate. Positive perceptions were given by both students and faculty members on the system	There were too many emails from concerned students to faculty seeking help and there was a lack of best practices in using the system

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
McKay et al. (2012)	University of Michigan	Offer personalised academic coaching for students	Information about students' progress in the course concerned, and performance in other courses; advice from students and faculty members	Personalised advice was delivered to students, covering their study habits, assignments for practice, feedback on progress, predictions for final grade and encouragement for them	NA	NA
McNely et al. (2012)	A mid-size public research university in Midwestern USA	Foster students' metacognition and promote collaborative learning	Data on collaborative writing activities recorded by Google Docs	Visualisations were generated from document revision history to help users gain a better sense of ongoing text development as a collaborative writing activity	Using the system, participants collaborated on complex knowledge work projects in creative and productive ways	Learners' individual contributions to collaborative writing work can be captured only when they produced part of the writing
Smith et al. (2012)	Rio Salado College	Improve students' retention	Data on online student activities (e.g. logged into course selection page, viewed assessment feedback and opened a lesson), assignment grades and enrolments, which were collected from LMS and SIS	Students were labelled as Low, Moderate and High according to their warning levels identified by the predictive models. Direct and informal contact (e.g. phone calls) was made and welcome emails were sent to the students	There was a 40% decrease in dropout rate compared to the control group	Interventions designed by faculty members did not generate significant improvements in success rates, possibly because of the difficulty for instructors to reach students by phone calls

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Lonn et al. (2013)	A university in USA	Provide early warning on student academic performance to support academic advisors' just-in-time decision-making	Grade information, student demographic and course history information stored in the LMS	Recommended actions were shown for advisors' reference, including—'encourage' students to keep doing well, 'explore' students' progress in more detail or 'engage' students immediately to assess possible academic difficulties	NA	Technical, cultural and process-oriented challenges may be unavoidable as different groups of professionals work together
Rivera-Pelayo et al. (2013)	NA	Provide live feedback from students to lecturers, and improve the students' attitude, attention and concentration during classes	User-input feedback such as vote	Students' live feedback was openly gathered, aggregated and visualised, for lecturers to evaluate students' knowledge or perceptions and make timely adjustments	The effectiveness relied on motivating students to use the app and the readiness of lecturers to react on feedback retrospectively	There was a potential distraction for students concentrating on the app instead of the class, and there were concerns regarding the voluntarily participation in giving feedback
Santos et al. (2013)	NA	Enhance students' self-awareness, self-reflection and sense-making through the use of a learning analytics dashboard	Learning traces of students, such as time spent on a course, resource use (e.g. wiki and blog) and social media use (e.g. Twitter)	Different learning traces were visualised for students' self-awareness and reflection, and understanding about peer behaviours	The tool had a potentially higher impact for students working in groups on the same topic than for students working individually on different topics	Students may not know whether they were doing well or needed to change their learning behaviours, even when the learning traces were given

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Cerezo et al. (2014)	University of Oviedo	Improve the effectiveness of tracking students' learning process in LMSs	Log files of LMSs (e.g. content view, task submission, forum view and participation)	The student learning process was visualised for easy and intuitive interpretation by teachers	The tool enabled and facilitated the interpretation of each student's activities and performance in the LMS	NA
Grann and Bushway (2014)	Capella University	Visually indicate a student's performance level relative to specific competencies	Assignments graded according to specific competency requirements, expected course competencies and programme outcomes	Students' performance levels in relation to specific competencies were visualised using various colours	The use of the tool helped students to understand their competency performance in relation to the faculty's expectations, and improved the course registration rate	NA
Jayaprakash and Lauría (2014)	Marist College	Improve student retention rates in colleges	Data from SIS (i.e. student demographic and aptitude data, course grades and course related data) and LMS (i.e. student interaction data generated in courses, students' scores on gradebook items like assignments and exams)	Students at academic risk were identified based on a predictive model developed using the data, for faculty members to follow with suitable intervention strategies	NA	NA

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Nam et al. (2014)	A large American Midwestern university	Determine the optimal term-by-term course selections for students	Students' academic history and demographic data, such as course enrolment information, course grade, GPA, ACT/SAT sources, number of years taken to graduate and kind of degree obtained	Advice on course selection was given based on students' scholastic characteristics and concurrent course enrolment	NA	The large number of variables and their combinations made it difficult to analyse the suitable sequence of course-taking for different students
Wise et al. (2014)	NA	Provide pedagogical intervention based on students' participation in online discussion	Log files and posts in the discussion forum (e.g. actions such as viewing/creating/editing/deleting posts, time and date, ID of users performing the actions, ID and length of posts being acted on)	Analytics results were provided to learners for framing their interpretation of online discussion as an integral course activity with clear goals and expectations	The analytics helped students to monitor and reflect on discussion participation, and encouraged dialogue between students and instructors	The one-on-one dialogue between the instructor and each student was not sustainable at scale
Dodge et al. (2015)	San Diego State University	Identify at-risk students and take remedial actions	Students' demographics (e.g. race/ethnicity, socio-economic status and grade level) and learning activities on LMS (e.g. logins, exam and quiz grades and clicker points)	Email messages were sent to students, suggesting online and in-person resources that could help them to improve their course performance	The interventions were associated with a higher final grade, especially for the students with a lower socio-economic status	The email interventions had only a limited impact on student achievements

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Miller et al. (2015)	High schools in Texas and West Virginia	Distinguish different types of student online and offline learning behaviours to support teachers' proactive remediation	Field observations of students collected during class (e.g. engaged/disengaged behaviours using the learning system) and log data from the system	Proactive remediation was provided by teachers on topics that students needed to learn but were not currently struggling with	NA	NA
van Leeuwen et al. (2015)	NA	Identify collaborative writing groups that experience problems and provide suggestions	Online chat messages of student groups, covering the information such as topics, relevant concepts, number of words	The topics, relevant concepts and progress revealed from the discussion were identified and visualised. Teachers can give suggestions to deepen and broaden the discussion	Teachers were enabled to attend to groups which needed help, and to address the problem issues	The amount of teaching experience may affect teachers' interpretation of data, and the amount and effectiveness of interventions
Xiong et al. (2015)	NA	Improve students' long-term mastery of skills	Results of retention tests (based on the percentage of the number of questions answered correctly), and the speed to master relevant skills	Provision of personalised retention test schedules based on students' knowledge levels, and relearning assignments if the students fail in the retention tests	Students showed a better long-term retention performance	The effectiveness of the interventions was small for students at a low knowledge level
Grawemeyer et al. (2016)	NA	Provide tailored feedback to students based on their affective state	Interaction with the learning platform (e.g. actions completed for learning tasks), students' perceived task difficulty and the students' spoken words (collected using speech recognition software)	Students' affective states were detected, based on which instructive feedback, problem-solving feedback and reflective prompts were provided	Students showed a better learning performance after the interventions	NA

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Siadaty et al. (2016a, 2016b)	Two European organisations	Improve self-regulated learning through technological scaffolding interventions	Users' socio-demographic data, their learning goals, their activities within the learning environment and their organisation's learning requirements	The intervention involved (i) Providing usage information about available resources (ii) Providing the latest updates on users' learning goals and resources, as well as colleagues' learning activities (iii) Showing users' progress in achieving learning goals (iv) Recommending learning goals to colleagues by the users (v) Informing users of the learning objectives and requirements of their organisation (vi) Recommending learning paths and learning activities to users (vii) Showing users' profiles of knowledge sharing	The interventions were perceived as enhancing users' self-regulated learning, in terms of areas such as recommending useful information, learning paths and activities	Self-regulated learning is affected by many factors and scaffolding is only one of them

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Lu et al. (2017)	A university in Taiwan	Improve students' learning outcomes and level of engagement	Log files of the edX LMS, which stored course information (e.g. number of students and course syllabus) and recorded students' interactions with the LMS (e.g. video access and discussion posts) and students' clickstream data collected from a web-based collaborative programming environment for measuring students' levels of engagement	Email messages were sent and face-to-face discussions were held with students	Students' levels of engagement were enhanced in video watching, discussion and collaborative programming activities. Their learning outcomes also improved	NA
Choi et al. (2018)	A university in Hong Kong	Identify at-risk students and implement proactive strategies	Students' demographic data, prior academic results, assignment/quiz scores in current courses, degree of interest in the course and in-class feedback collected using a student response system	Systematic interventions took place at various stages of a course, which included welcoming emails, follow-up phone calls, reminders for assignment/quiz/exam on LMS and face-to-face consultation	There was a 7% higher pass rate in the exam for the students receiving interventions	More rigorous and objective evaluation of the effectiveness of interventions is necessary

Table 7 (continued)

Source	Institution	Objective	Data	Intervention method	Outcome	Challenge
Espinoza and Genna (2018)	University of El Paso	Identify at-risk students and provide immediate feedback	Scores on an assessment (e.g. quiz, assignment and exam) administered early in a term and recorded in the LMS	Students received messages from instructors on their assessment results and feedback (e.g. encouragement and concern) on their level of performance	Students (especially those classified as high risk) benefitted from the intervention in terms of both achievement (i.e. getting a higher course grade) and persistence (i.e. course withdrawal)	The long-term effectiveness of the interventions providing formative feedback to students is not known
Villano et al. (2018)	University of New England	Improve student retention	Students' demographic information (e.g. gender and age), institutional variables (e.g. prior studies, study mode and course type), study performance and workload, daily emotion, online activities, etc.	Email messages were sent which outlined support options, tailored student support programme and teacher enabling course for developing skills for employment	NA	NA
van Horne et al. (2018)	A research-intensive university in Midwest USA	Provide feedback to students through dashboard as an intervention tool	Students' performance in courses	Feedback was provided to students via the dashboard (e.g. current performance, average performance of peers, estimate of students' final grade and suggested resources)	Students who used the dashboard more frequently tended to get higher course grades	It may be difficult to determine how the results of this particular intervention can be generalised to other learning analytics practices

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