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O4 – Literature review: tutoring/ study advising

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RESPONSIBLE PARTNER:
ARTTEVELDE UNIVERSITY OF APPLIED SCIENCES

PARTICIPATING PARTNERS:
UMC UTRECHT
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Output 4 – Literature review: tutoring/ study advising

A1. Each researcher will take an area agreed by the project team and will conduct a literature review.

A2. Final editing and publication to the project website will be led by Artevelde University of Applied Sciences.

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Making data effective – advice on shaping support based on data

The current literature review aims to provide guidance for the project Onwards from Learning Analytics (OfLA). The literature review looks at current good practices on using learning analytics in combination with tutoring/study advising to support student success. The good practices will be used as inspiration for the pilot studies in this project.

After an introduction on the goals and the approach, an overview is given of the selection process for the articles and cases used. Next is a collection of advice. After a conclusion, we end with notes and suggestions for further reading.

1. Introduction

The current literature review aims to provide guidance for the project Onwards from Learning Analytics (OfLA). OfLA investigates how learning analytics can support student success using a three stage model: prompts, communication and actions or intervention. The focus is on the instructional scaffolding that is required to act effectively on insights from data. Practical advice and guidance at each of these stages are vital to effectively transfer the latest research outputs from learning analytics into education. The project aims to answer questions like: How do we use existing institutional data to develop early warning prompts to identify students in need of help? How do we communicate most effectively with these students so that we can increase the likelihood of them making contact with an adviser or tutor? How do we improve the quality of the conversation and subsequent support?

This literature review focuses on approaches to offering advice to students according to the flow of prompts, communication and intervention.

Note that semantics from the articles get in the way. Prompts do not only relate to data (e.g. which data are used to initiate a prompt), but also to communication to the students themselves (e.g. a pop-up informing them how they are doing) and even to communication to the staff (e.g. which students to contact). Therefore, prompts can be defined as some form of communication that aims to invite students to take action, like a change in activity or seeking advice from a counsellor. Similarly, when prompts, for example, inform students that they are not performing so well, they can also be considered an intervention.

2. Selection of the articles

The literature review process started from two recent literature reviews: Wong (2017) and Viberg, Hatakka, Bälter, & Mavroudi (2018). Both systematic reviews map the current scientific knowledge about the application of learning analytics in higher education, both in face-to-face and distance learning. Although their focus was on the research approaches, methods and the evidence for learning analytics, there are explicit and implicit links to supporting students based on the data (e.g. assistance, feedback, communication, intervention).

For this literature review, the two reviews were screened for references to case studies that could be linked to the three stage model. There was either a reference to prompts generated, to how communication of data was conducted with students or how an intervention was shaped. The analysis led to a selection of 39 articles for abstract analysis to verify the links to the three stage model. After abstract analysis, 23 articles reporting on a total of 48 cases were processed. From the 48 cases, 36 were only referenced in one article. 9 cases were mentioned multiple times: one case was mentioned four times, one case three times and seven were mentioned two times. Appendix 1 offers an overview of the cases mentioned more than once.

Advice

For this review, the articles were processed to look for guidance for the OfLA-project according to its three stage model. The literature review reports on this guidance in the form of advice. Each piece of advice will be evidenced with elements from the articles. The advice should lead to a thoughtful use of learning analytics for more efficient and effective support of students. The advice starts with a section on institutional context and pedagogy, and then moves from prompts, over communication to intervention.

3. Institutional context and pedagogy

Advice 1. Frame your intervention in a pedagogical approach/model and the institutional context

The use of learning analytics should be connected to the institution's vision and goals. The choice of what data to collect (Mattingly, Rice, & Berge, 2012) and how to translate this into interventions (Chacon, Spicer, & Valbuena, 2012), should be linked to the strategy of the organization. The institutional context is a determinant for success. Successful interventions are tailored to your student population (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). With a framework, like for example the six guiding principles of Wise and colleagues (Wise, Zhao, & Hausknecht, 2013) or the Learning Analytics Readiness Instrument (Arnold, Lonn, & Pistilli, 2014), institutions can structure and systematize discussion on the implementation in their own context (West, Heath, & Huijser, 2016).

Unfortunately, there is often little mention of pedagogy or of a pedagogical model of intervention (Tarmazdi, Vivian, Szabo, Falkner, & Falkner, 2015). References which were made are to Tinto's model (Arnold & Pistilli, 2012; Chacon et al., 2012; Jayaprakash et al., 2014), Draper's work on motivation (Chacon et al., 2012), Swail's determinants of college retention (Chacon et al., 2012) and Astin's and Cuseo's work on the importance of (instructor) interaction (Jayaprakash et al., 2014).

Similarly, also ethics are barely mentioned. A bare minimum according to Atif and colleagues (Atif, Richards, Bilgin, & Marrone, 2013) is letting learners know they are being tracked, or asking their permission for example through checkboxes (Sclater, Peasgood, & Mullan, 2016). Communicating on learning analytics with students also avoids the idea of 'big brother' and proposes a shared responsibility (Chacon et al., 2012). Assuming most follow legal requirements, one explicit mention is made of a 'Policy for the ethical use of Student Data for Learning Analytics' that goes beyond the legal requirement (Sclater et al., 2016). In the further reading section at the end of this paper, reading material on ethics is suggested.

Advice 2. Involve and train the end-users from the onset to the end

Learning analytics should eventually end up in the hands of students and staff (Rienties et al., 2016). In order to cater to their needs, the end-user should be involved from the beginning and throughout the process (Lonn, Krumm, Waddington, & Teasley, 2012; Sclater et al., 2016). It is especially crucial as business needs, wants and limitations can conflict with the needs and wants of students and academic staff (West et al., 2016). This also increases buy-in (de Freitas et al., 2015) and allows for the institution to build better interventions (Dodge, Whitmer, & Frazee, 2015; Smith, Lange, & Huston, 2012). For students, who are mostly happy with the use of learning analytics (Sclater et al., 2016), it diminishes the idea of big brother (Chacon et al., 2012) and their input on experiences of interventions are valuable (West et al., 2016). In addition to this, students also have a responsibility themselves. Yet, it is often not explicit or even thought-through what obligation or monitoring an institution attaches to this responsibility (Atif et al., 2013; bin Mat, Buniyamin, Arsad, & Kassim, 2013; Karkhanis & Dumbre, 2015).

The efforts should be evaluated for improvement (West et al., 2016). Student and staff appreciation are part of this (Lonn et al., 2012). Looking at what services are recommended and how they are followed up by students to see if they are effective (Karkhanis & Dumbre, 2015; Lonn et al., 2012) as some might also yield unwanted consequences like early, unnecessary withdrawal (Jayaprakash et al., 2014). By following up on interventions, institutions can determine what services help support student success and as such deserve prioritization of resources (Chacon et al., 2012)

At a final stage, training programmes for staff and students should be implemented (Chacon et al., 2012; Sclater et al., 2016; West et al., 2016). This has been identified before as a gap (West et al., 2016). Even with motivated teachers who voluntarily agreed to work with learning analytics engagement was low, usage very different and difficulties were noticed for providing actions and support (Herodotou et al., 2017). Trained and knowledgeable support staff are a critical support factor (Sclater et al., 2016).

4. Prompts

Prompts are automatically generated messages that inform or encourage action. They are generated based on metrics or data institutions gather. In order to provide valid prompts, metrics or data should be identified that are meaningful, measurable, and monitored (Mattingly et al., 2012).

Advice 3. Use a combination of data including at least actionable and recent data

Data can have static (unchangeable like prior academic history) and dynamic (changeable like making deadlines) attributes. Although some argue for the use of as much data as possible (bin Mat et al., 2013), it is important to use a combination of (current) data (Arnold & Pistilli, 2012; Sclater et al., 2016) of which dynamic, recent behaviour should be viewed with more significance (Sclater et al., 2016; Smith et al., 2012) as it is actionable.

References to static data include demographic information, information of the admission application, financial situation, administrative aspects of academic performance, registration data, scores on placement tests, academic ability and history (concurrent credit load, total sum of credits successfully completed and total sum of credits attempted but not successfully completed) (Karkhanis & Dumbre, 2015; Sclater et al., 2016; Smith et al., 2012). References to dynamic attributes, like data on performance and effort, include student (online) activity data (e.g. total hits or number of quizzes taken on the learning management system, deadlines (not) met) (Arnold & Pistilli, 2012; de Freitas et al., 2015; Fidalgo-Blanco, Sein-Echaluce, García-Peñalvo, & Conde, 2015; Sclater et al., 2016; Smith et al., 2012; Tarmazdi et al., 2015), current academic performances (Arnold & Pistilli, 2012; Atif et al., 2013; Lonn et al., 2012; Sclater et al., 2016; Smith et al., 2012) and interaction/group work data (Atif et al., 2013; de Freitas et al., 2015; Fidalgo-Blanco et al., 2015).

Advice 4. Data should lead to action

Gathering data merely for the sake of data will not impact course completion, student success, retention rates or anything else. In order to lead to results, data should lead to action, either on the side of the student, the staff or the institution (de Freitas et al., 2015; Gray & Perkins, 2019; Jayaprakash et al., 2014; Karkhanis & Dumbre, 2015; Lonn et al., 2012; Sclater et al., 2016; West et al., 2016). The range of action varies widely. Data can be used to inform staff or students, but can also lead to or be part of an action (Chacon et al., 2012; de Freitas et al., 2015; Lonn et al., 2012; Mattingly et al., 2012; West et al., 2016) preferably framed in a carefully designed pedagogical model of intervention (Wise et al., 2013) (see also advice 1). The bare minimum, making students aware, might already be the most efficient at motivating them to seek help (Jayaprakash et al., 2014; Sclater et al., 2016).

Despite that informing students seems to be enough in some cases, it should be more than just offering the data. Access to data does not automatically lead to improvements (Lonn et al., 2012). Learners should be helped with its interpretation (even as an integral course activity) (Wise et al., 2013) for example through mentors (Lonn et al., 2012) or setting up an action plan with support staff (Sclater et al., 2016). Visually clear representations might also be of service (see advice 5).

Actions, be it communication or interventions (see advices below) can be targeted (Dodge et al., 2015; Jayaprakash et al., 2014; Karkhanis & Dumbre, 2015) and/or customized (Atif et al., 2013; Mattingly et al., 2012; Smith et al., 2012). Although effects have been seen on all students (Taylor & McAleese, 2012), interventions tend to target or prioritize at-risk students or students not doing so well (Dodge et al., 2015; Taylor & McAleese, 2012).

Advice 5. Data should be easily, visually, and continuously accessible for all stakeholders

One aspect of translating data into action is offering this data to students and supporting them with the interpretation. The visualization should make the data easy-to-interpret (Lonn et al., 2012). Both are best achieved through always accessible (de Freitas et al., 2015; Fidalgo-Blanco et al., 2015), (near-)real time (Arnold & Pistilli, 2012; de Freitas et al., 2015) visual representation for the use by students but also as a tool for support staff, lecturers, instructional designers, or even administrative staff (Atif et al., 2013; de Freitas et al., 2015; Fidalgo-Blanco et al., 2015; Mattingly et al., 2012; Sclater et al., 2016; Smith et al., 2012; Tarmazdi et al., 2015; G. K. W. Wong & Li, 2016). These visualization often (1) map the results onto, for example, warning levels (Arnold & Pistilli, 2012; Smith et al., 2012), (2) sometimes go further by laying bare hidden patterns (Wong & Li, 2016) or (3) are used to engage in or improve the conversation with mentor (de Freitas et al., 2015; Jayaprakash et al., 2014; Lonn et al., 2012; Millecamp, Gutiérrez, Charleer, Verbert, & De Laet, 2018).

5. Communication

Just presenting the data to students, even with a visually accessible dashboard, does not always suffice. As a result, staff should consider contacting students to encourage, explore, and engage (Lonn et al., 2012). They can do this for example through email messages inviting student to come and see academic advisors (Arnold & Pistilli, 2012; Jayaprakash et al., 2014; Karkhanis & Dumbre, 2015). The communication should supplement, rather than replace staff (Lonn et al., 2012).

Advice 6. Make the advice (seem) customized through staff-involvement

For students not to feel like a number and for the communication to sink in more, one should avoid making the communication appear obviously automated. Preferably the communication is personal or customized, or, for the sake of still being workable, should come across as personal or customized (Arnold & Pistilli, 2012; Lonn et al., 2012). Ways to achieve this include addressing the student by name, sending the communication on behalf of the faculty (Dodge et al., 2015; Star & Collette, 2010), including the information about their current performance (Arnold & Pistilli, 2012) and including why a teacher is contacting a student (Herodotou et al., 2017). Next to impact, this also helps students to not get lost and drop into anonymity (Chacon et al., 2012).

The role of staff in this should not be neglected. They know the student, the course and programme the best. Involve instructors to identify students at risk and set up the communication (bin Mat et al., 2013; Dodge et al., 2015; Mattingly et al., 2012) and allow them the final say about whether or not to send a message (for example leaving out students in special circumstances like illness) (Jayaprakash et al., 2014; Star & Collette, 2010). Based on the issue, different types of support staff should be able to contact the student (Chacon et al., 2012).

As the instructor seems crucial for success of the intervention, you have to avoid it becoming overly burdensome (Jayaprakash et al., 2014; Tarmazdi et al., 2015). There is much gain in student success and staff time and energy to be made by automating processes in learning analytics for example by automatically alerting staff on students at risk (bin Mat et al., 2013; Chacon et al., 2012; Karkhanis & Dumbre, 2015; Smith et al., 2012; Tarmazdi et al., 2015; Taylor & McAleese, 2012) or sending communication to students (bin Mat et al., 2013; Chacon et al., 2012; Karkhanis & Dumbre, 2015; Smith et al., 2012; Tarmazdi et al., 2015; Taylor & McAleese, 2012).

Advice 7. Communication should allow or lead to relevant action

Even when discussing prompts, communication should try and do more than just inform. It should lead to action that can improve performance, like a reference to (online) support or support staff (bin Mat et al., 2013; Dodge et al., 2015; Jayaprakash et al., 2014; Lonn et al., 2012; Mattingly et al., 2012; Millecamp et al., 2018; Star & Collette, 2010).

Advice 8. Avoid too invasive communication

Email seems to make the most sense to communicate with students. It is workable and an accustomed method of communication with students (Dodge et al., 2015; Smith et al., 2012; Star & Collette, 2010). Efforts with other media like telephone (Sclater et al., 2016) have also not yielded expected results. Although students who were contacted directly succeeded more, two-thirds of the calls made lead to non-direct (e.g. voicemail) or no (e.g. wrong number, no response) contact at all (Smith et al., 2012). Also, overpenetration with too directive intervention risks impediment of learner's development of metacognitive and self-regulatory skills as you build dependency (Arnold & Pistilli, 2012; Wise et al., 2013). There is evidence that some students don't improve regardless the number of communications (Jayaprakash et al., 2014; Sclater et al., 2016).

6. Intervention

When students have responded to the communication and contact an academic advisor, an intervention can take place. Academic performance, retention, and graduation rates have been positively affected by increasing instructor-student interactions and improving support personnel interventions (Star & Collette, 2010).

Advice 9. Timing is important

For an intervention to be successful, timing is of importance. Often, 'early' interventions are recommended in view of offering students enough time to change behaviour (Arnold & Pistilli, 2012; Jayaprakash et al., 2014; Taylor & McAleese, 2012). Thanks to learning analytics, educators do not need to wait to the end of the first semester to tell a student that they are not performing well (Chacon et al., 2012; Mattingly et al., 2012; Sclater et al., 2016). Yet, due to the different milestones depending on the type of intervention, timely is also a good word to use (Fidalgo-Blanco et al., 2015; Tarmazdi et al., 2015). A more timely intervention can take place at any relevant point (Smith et al., 2012) or crucial time of the year (Millecamp et al., 2018; Taylor & McAleese, 2012). This timeliness is important as the time window to effectively support students at risk seems relatively short (between 2-4 weeks) (Herodotou et al., 2017).

Advice 10. Use the data to start a dialogue

A valuable intervention that surfaces is positive staff-student interaction. Initial results strongly support the value of student-teacher dialogue (Star & Collette, 2010; Wise et al., 2013) preferably in a dynamic interaction on their data supported by visual analytics (Arnold & Pistilli, 2012; de Freitas et al., 2015; Smith et al., 2012). These are used to generate and support conversations, mostly at the beginning, to start from factual insights (de Freitas et al., 2015; Lonn et al., 2012; Millecamp et al., 2018; Sclater et al., 2016). The data can also boost the quality of the conversation as staff can be better informed (Jayaprakash et al., 2014; Lonn et al., 2012).

7. Conclusion

This literature review focused on current good practices of using learning analytics in combination with tutoring/study advising to support student success. Based on an analysis of 23 articles reporting on a total of 48 cases, ten pieces of advice were formulated in four categories.

Institutional context and pedagogy	
Advice 1	Frame your intervention in a pedagogical approach/model and the institutional context
Advice 2	Involve and train the end-users from the onset to the end
Prompts	
Advice 3	Use a combination of data including at least actionable and recent data.
Advice 4	Data should lead to action
Advice 5	Data should be easily, visually and continuously accessible for all stakeholders
Communication	
Advice 6	Make the advice (seem) customized through staff-involvement
Advice 7	Communication should allow or lead to relevant action
Advice 8	Avoid too invasive communication
Intervention	
Advice 9	Timing is important
Advice 10	Use the data to start a dialogue

8. Notes and further reading

Notes on peer-to-peer learning

The literature review has initially aimed to cover the topic of peer-to-peer learning. However, in the selection of articles, peer-to-peer learning was not referenced or included as an approach. When peers were referenced, this was often in performance-related comparison (Arnold & Pistilli, 2012; Lonn et al., 2012; Millecamp et al., 2018; Sclater et al., 2016) or peer-to-peer interaction in group work or online (Fidalgo-Blanco et al., 2015; Wise et al., 2013; Wong & Li, 2016). Only one reference is made to a student mentor as peer coach offered as extra support (Jayaprakash et al., 2014). We would direct the interested reader to two pieces of further reading, found outside of the literature review process:

The section (pages 65-76) in the following book provides a definition of peer tutoring, an overview of types of peer tutoring and references to case study examples in the literature, an outline of the reciprocal benefits of peer tutoring and the prerequisites for success, evidence of impact and a discussion on the impact of self-selection in analysing success of peer tutoring initiatives.

> Mayhew, M. J., Rockenbach, A. N., Bowman, N. A., Seifert, T. A., & Wolniak, G. C. (2016). *How college affects students: 21st century evidence that higher education works*. John Wiley & Sons.

The following book chapter describes different types of peer support implemented at Manchester University (UK) since the mid-1990s. It includes a model for peer support that has a ‘learning and enabling’ process at the centre and 6 categories of scheme aims: orientation, community development, social integration, academic content, learning strategies and pastoral. The chapter includes case studies of peer mentoring, peer-assisted study session, higher year discussion groups, ‘special topics’ mentoring, INTO peer engagement, and learning communities in halls.

> Ody, M., & Carey, W. (2013). Peer education. *Student Engagement Handbook: Practice in Higher Education.* Bingley: Emerald Group Publishing Limited, 291-312.

Further reading on ethics

To broaden the scope on ethics, we would advise looking at the following articles for further reading.

> Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology*, *45*(3), 438–450. https://doi.org/10.1111/bjet.12152
>
> Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist*, *57*(10), 1510–1529.

The following paper offers a case study of an Australian university.

> Lawson, C., Beer, C., Rossi, D., Moore, T., & Fleming, J. (2016). Identification of 'at risk' students using learning analytics: the ethical dilemmas of intervention strategies in a higher education institution. *Educational Technology Research and Development*, *64*(5), 957–968. https://doi.org/10.1007/s11423-016-9459-0

General further reading

In addition to the two general reviews from which case studies in the review were drawn (Viberg et al., 2018; B. T. M. Wong, 2017), we would advise the following articles for further reading.

In the article below Wise gives valuable ideas for background knowledge and future work on learning analytics by looking at five questions. She offers insights in the added value of learning analytics, data, analyses and applications in function of improving teaching and learning.

> Wise, A. F. (2019). Learning analytics: Using data-informed decision-making to improve teaching and learning. In O. Adesope & A. G. Rudd (Eds.), *Contemporary technologies in education: maximizing student engagement, motivation, and learning* (pp. 119–143). New York: Palgrave Macmillan. https://doi.org/10.1007/978-3-319-89680-9

In the article below Rienties and colleagues look at implementing interventions to positively impact learners' attitudes, behaviour and cognition. They illustrate their ideas with two case studies with different scenarios. They end by presenting the framework being implemented at their institution.

> Rienties, B., Cross, S., & Zdrahal, Z. (2017). Implementing a learning analytics intervention and evaluation framework: What works?. In *Big data and learning analytics in higher education* (pp. 147-166). Springer, Cham.

In the report below Sclater and colleagues look at the use and impact of learning analytics based on 11 case studies, all summarized in the report. The case studies illustrate the validity of predivitve models, that interventions have been succesfull and that there are other benefits to working with learning analytics in higher education. Note that this report was also included in the review of Wong and as such also in this literature review.

> Sclater, N., Peasgood, A., & Mullan, J. (2016). *Learning analytics in higher education*. London: Jisc.

Appendix 1: Case studies of learning analytics mentioned in more than 1 article

Name Learning Analytics tool	Mentioned in
Purdue_Signals	Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270). ACM. bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE. Mattingly, K. D., Rice, M. C., & Berge, Z. L. (2012). Learning analytics as a tool for closing the assessment loop in higher education. *Knowledge Management & E-Learning: An International Journal*, *4*(3), 236–247. Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*
Wollongong_SNAPP	Atif, A., Richards, D., Bilgin, A., & Marrone, M. (2013). A panorama of learning analytics featuring the technologies for the learning and teaching domain. In *Proceedings of the 30th Australasian Society for Computers in Learning in Tertiary Education Conference* (pp. 68–72). bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE. Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*
ECU_C4S	Atif, A., Richards, D., Bilgin, A., & Marrone, M. (2013). A panorama of learning analytics featuring the technologies for the learning and teaching domain. In *Proceedings of the 30th Australasian Society for Computers in Learning in Tertiary Education Conference* (pp. 68–72). Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*

Appendix 1 (continued):

UNE_AWE	Atif, A., Richards, D., Bilgin, A., & Marrone, M. (2013). A panorama of learning analytics featuring the technologies for the learning and teaching domain. In *Proceedings of the 30th Australasian Society for Computers in Learning in Tertiary Education Conference* (pp. 68–72). Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*
OUA_PASS	Atif, A., Richards, D., Bilgin, A., & Marrone, M. (2013). A panorama of learning analytics featuring the technologies for the learning and teaching domain. In *Proceedings of the 30th Australasian Society for Computers in Learning in Tertiary Education Conference* (pp. 68–72). Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*
Michigan E^2 Coach	bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE. Mattingly, K. D., Rice, M. C., & Berge, Z. L. (2012). Learning analytics as a tool for closing the assessment loop in higher education. *Knowledge Management & E-Learning: An International Journal*, *4*(3), 236–247.
Arizona_GPS	bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE. Star, M., & Collette, L. (2010). GPS: shaping student success one conversation at a time. *Educause Quarterly*, *33*(4).
Rio_Pace	bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE. Smith, V. C., Lange, A., & Huston, D. R. (2012). Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of Asynchronous Learning Networks*, *16*(3), 51–61.
Marist_OAAI	Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early alert of

	academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics*, *1*(1), 6–47. Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education. *London: Jisc.*

Bibliography

Arnold, K. E., Lonn, S., & Pistilli, M. D. (2014). An exercise in institutional reflection: The learning analytics readiness instrument (LARI). In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge* (pp. 163–167). ACM.

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 267–270). ACM.

Atif, A., Richards, D., Bilgin, A., & Marrone, M. (2013). A panorama of learning analytics featuring the technologies for the learning and teaching domain. In *Proceedings of the 30th Australasian Society for Computers in Learning in Tertiary Education Conference* (pp. 68–72).

bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *2013 IEEE 5th Conference on Engineering Education (ICEED)* (pp. 126–130). IEEE.

Chacon, F., Spicer, D., & Valbuena, A. (2012). Analytics in support of student retention and success. *Research Bulletin*, *3*, 1–9.

de Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., … Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology*, *46*(6), 1175–1188.

Dodge, B., Whitmer, J., & Frazee, J. P. (2015). Improving undergraduate student achievement in large blended courses through data-driven interventions. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (pp. 412–413). ACM.

Fidalgo-Blanco, Á., Sein-Echaluce, M. L., García-Peñalvo, F. J., & Conde, M. Á. (2015). Using Learning Analytics to improve teamwork assessment. *Computers in Human Behavior*, *47*, 149–156. https://doi.org/10.1016/j.chb.2014.11.050

Gray, C. C., & Perkins, D. (2019). Utilizing early engagement and machine learning to predict student outcomes. *Computers and Education*, *131*(July 2018), 22–32. https://doi.org/10.1016/j.compedu.2018.12.006

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M., & Naydenova, G. (2017). Implementing predictive learning analytics on a large scale: the teacher's perspective. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 267–271). ACM.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J. M., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics*, *1*(1), 6–47.

Karkhanis, S. P., & Dumbre, S. S. (2015). A study of application of data mining and analytics in education domain. *International Journal of Computer Applications*, *120*(22).

Lawson, C., Beer, C., Rossi, D., Moore, T., & Fleming, J. (2016). Identification of 'at risk' students using learning analytics: the ethical dilemmas of intervention strategies in a higher education institution. *Educational Technology Research and Development, 64(5)*, 957–968. https://doi.org/10.1007/s11423-016-9459-0

Lonn, S., Krumm, A. E., Waddington, R. J., & Teasley, S. D. (2012). Bridging the gap from knowledge to action: Putting analytics in the hands of academic advisors. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 184–187). ACM.

Mattingly, K. D., Rice, M. C., & Berge, Z. L. (2012). Learning analytics as a tool for closing the assessment loop in higher education. *Knowledge Management & E-Learning: An International Journal*, *4*(3), 236–247.

Mayhew, M. J., Rockenbach, A. N., Bowman, N. A., Seifert, T. A., & Wolniak, G. C. (2016). *How college affects students: 21st century evidence that higher education works*. John Wiley & Sons.

Millecamp, M., Gutiérrez, F., Charleer, S., Verbert, K., & De Laet, T. (2018). A qualitative evaluation of a learning dashboard to support advisor-student dialogues. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 56–60). ACM.

Ody, M., & Carey, W. (2013). Peer education. *Student Engagement Handbook: Practice in Higher Education.* Bingley: Emerald Group Publishing Limited, 291-312.

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology,* 45(3), 438–450. https://doi.org/10.1111/bjet.12152

Rienties, B., Boroowa, A., Cross, S., Farrington-Flint, L., Herodotou, C., Prescott, L., … Woodthorpe, J. (2016). Reviewing three case-studies of learning analytics interventions at the open university UK. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 534–535). ACM.

Sclater, N., Peasgood, A., & Mullan, J. (2016). *Learning analytics in higher education*. London: Jisc*. Accessed February*, *8*, 2017.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57(10)*, 1510–1529.

Smith, V. C., Lange, A., & Huston, D. R. (2012). Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of Asynchronous Learning Networks*, *16*(3), 51–61.

Star, M., & Collette, L. (2010). GPS: shaping student success one conversation at a time. *Educause Quarterly*, *33*(4).

Tarmazdi, H., Vivian, R., Szabo, C., Falkner, K., & Falkner, N. (2015). Using learning analytics to visualise computer science teamwork. In *Proceedings of the 2015 ACM Conference on Innovation and Technology in Computer Science Education* (pp. 165–170). ACM.

Taylor, L., & McAleese, V. (2012). Beyond Retention: Using Targeted Analytics to Improve Student Success. *Educause Review*, 1–12. Retrieved from http://www.educause.edu/ero/article/beyond-retention-using-targeted-analytics-improve-student-success

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*(October 2017), 98–110. https://doi.org/10.1016/j.chb.2018.07.027

West, D., Heath, D., & Huijser, H. (2016). Let's Talk Learning Analytics: A Framework for Implementation in Relation to Student Retention. *Online Learning*, *20*(2), 30–50.

Wise, A. F., Zhao, Y., & Hausknecht, S. N. (2013). Learning analytics for online discussions: a pedagogical model for intervention with embedded and extracted analytics. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 48–56). ACM.

Wong, B. T. M. (2017). Learning analytics in higher education: an analysis of case studies. *Asian Association of Open Universities Journal*, *12*(1), 21–40.

Wong, G. K. W., & Li, S. Y. K. (2016). Academic performance prediction using chance discovery from online discussion forums. In *2016 IEEE 40th Annual Computer Software and Applications Conference (COMPSAC)* (Vol. 1, pp. 706–711). IEEE.