JOURNAL OF LEARNING ANALYTICS

SoLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Volume 5(3), 198–221. http://dx.doi.org/10.18608/jla.2018.53.13

What Constitutes an "Actionable Insight" in Learning Analytics?

Rasmus Leth Jørnø[1], Karsten Gynther[2]

ABSTRACT

The possibilities of Learning Analytics as a tool for empowering teachers and educators have created a steep interest in how to provide so-called actionable insights. However, the literature offers little in the way of defining or discussing what the term "actionable insight" means. This selective literature review provides a look into the use of the term in current literature. The review points to a dominant perspective in the literature that assumes the perspective of a rational actor, where actionable insights are treated as insights mined from data and subsequently acted upon. It also finds evidence of other perspectives and discusses the need for clarification of the term in order to establish a more precise and fruitful use of the term.

Notes for Practice

- At the time of this review, we only found a single source in the literature that discusses the definition of "actionable insights." All other sources task the reader to infer the meaning of the concept from its use.
- This paper provides a selective overview of learning analytics literature that sheds light on the use of the concept and its equivalents.
- We identify a widely used perspective taken in learning analytics, which we dub "data-informed decision-making." This perspective is characterized by an insistence of the perspective of a rational actor and the use of learning analytics for the institutional goal of increasing retention.
- We contend that "actionable insights" should be interpreted as data that allows a corrective procedure, or feedback loop, to be established for a set of actions.
- We argue that the field of learning analytics would benefit from greater attention to the role of perspective and action capabilities in determining what "actionable insights" are.
- The implications of these findings are that the perspective of data-informed decision-making is challenged, and with it, the idea that the presence of data alone provides the basis for determining insights. Instead, it charges any learning analytics researcher to map out the workflow of actions, the end goals of the actors involved, and the relevant couplings between them.

Keywords

Actionable insights, learning analytics, data-informed decision-making

Submitted: 26.01.2018— **Accepted:** 03.06.2018 — **Published:** 11.12.2018

Corresponding author [1]Email: ralj@pha.dk Address: University College Absalon, Trekroner Forskerpark 4, 3000 Roskilde, Denmark
[2]Email:kgy@pha.dk Address: University College Absalon, Trekroner Forskerpark 4, 3000 Roskilde, Denmark

1. Introduction

The current literature on learning analytics exhibits a wide consensus among researchers that the success of LA rests on data providing "actionable insights" (Clow, 2012, 2013, 2014; Colvin et al., 2016; Gašević, Dawson, & Pardo, 2016; Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017; Wise, 2014). Despite this stated importance, there is limited clarity on what is to be understood by "actionable insights" and the term's equivalents. The concept, on the face of it, promises to marry the practitioner's need for a concrete focus on how to utilize LA with the researcher's ambition to operationalize theory. However, the meaning of the term is mostly left for the reader to discern from its use. While the community agrees that data is abundant (Greller & Drachsler, 2012; HM Government, 2013; Macfadyen, Dawson, Pardo, & Gašević, 2014; Sclater, Web, & Danson, 2016; Shacklock, 2016; Swan, 2012; Wagner & Ice, 2012), there is also a clear conviction that data in itself (or "raw" data) does not provide any guidance for action (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012; Nguyen, Rienties, & Toetenel, 2017; Sclater, Web, & Danson, 2016). In order for researchers and practitioners alike to carve out a direction for this joint ambition, this selective literature review examines the research question: What constitutes an actionable insight in learning analytics?

For reasons of manageability, results concerning MOOCs have been excluded, focusing the review on papers related to campus-based learning. In addition, the authors' focus on learning design and support structures limits the applicability of the conclusions arrived at in this paper.

1.1. Background

Analytics is the creation and use of data, statistical analysis, and explanatory and predictive models. It lies at the core of overarching global trends in data use, often referred to as Big Data, Business Intelligence (BI), Business Analytics, Web Analytics, Data-driven Decision Making, or Data Mining (Macfadyen & Dawson, 2012). Analytics draws from and develops theories and methodologies concurrently with fields such as statistics, computer science, artificial intelligence (AI), and machine learning.1 The ambition of analytics proper is to procure insights and act on complex issues based on the number-crunching capabilities of computers. Avella, Kebritchi, Nunn, and Kanai (2016) call analytics "the scientific process that examines data to formulate conclusions and to present paths to make decisions" (p. 14).

In an educational context, the use of analytics has gained a lot of traction. There are, at this point, quite a number of directions that vie for attention in this space: personalized or adaptive learning (Atkinson, 2015; Bartle, 2015), analytics for pathway planning (Sclater, Peasgood & Mullan, 2016), educational data mining (Baker & Yacef, 2009), analytics for e-learning (Ice, Stephens-Helm, & Powell, 2011), academic analytics (Campbell, DeBlois, & Oblinger, 2007), and institutional analytics (Piety, Hickey, & Bishop, 2014), to mention only a few.

Learning analytics (LA) then is "the application of analytics in an educational context" (Sclater, Web & Danson, 2016, par. 6). An abundance of overview and introductory articles (Avella et al., 2016; Clow, 2013; Sclater, Peasgood, & Mullan, 2016; Ferguson et al., 2016; Haythornthwaite, de Laat, & Dawson, 2013; Pardo, Dawson, Gašević, & Steigler-Peters, 2016; Sundorph & Mosseri-Marlio, 2016; Swan, 2012) and literature reviews (Ferguson, 2012b; Moissa, Gasparini, & Kemczinski, 2015; Sclater, Peasgood, & Mullan, 2016; Sergis & Sampson, 2017) attempt to get a handle on this exponentially growing field, its key concepts, potentials, and limitations, as well as on strategies for its implementation and adoption.

The enormous interest in analytics in an educational context has a number of driving factors (Avella et al., 2016; Bichsel, 2012; Ferguson, 2012a; Gašević et al., 2016; Johnson et al., 2013). These consist of general factors, such as the copious amounts of data and the ever-widening and -deepening penetration of spheres from which data is generated, the rapid development in technology that processes this data, and the hype generated by the increasing number of arenas applying analytics to their processes (sports, medicine, law, education, etc.). Specific to educational matters, there is increased pressure on funding, coupled with a focus on quality and accountability (Macfadyen & Dawson, 2012) and an influx of non-traditional students who expect a different focus on the development of their skills and competencies (e.g., 21st century skills) and maintain life-long relations to learning institutions (Gašević et al., 2016). As an expression of how these tendencies can be seen as a fundamental shift in education, the now-ubiquitous adoption of educational technologies, such as Learning Management Systems (LMSs; Brown, Dehoney, & Millichap, 2015), has, in combination with LA capabilities, been referred to as the third wave in educational technology (Brown, 2011; Jacobson, 2016), echoing Alvin Toffler's (1980) foretelling of the information age.

1.2. Tracing the Concept of "Actionable Insight"

As can be expected from any emerging field, LA exhibits many attempts to seize the power of definition by naming the field (e.g., Goldstein & Katz, 2005), coining terms, defining central concepts, and outlining possible future directions. Such a conceptual turmoil is predictably followed by calls for clarification and the establishment of a common language by researchers (van Barneveld, Arnold, & Campbell, 2012). This review naturally agrees with such an ambition, but is itself only focused on the concept of "actionable insight." The purpose of this review is therefore not to investigate or discuss the definition of LA.2 However, a few remarks are in order to contextualize the use of the term "actionable insights."

In a comprehensive review, many terms overlapping with LA would have been examined. Also, the many attempts to clarify competing definitions and taxonomies would be subject to scrutiny. Already, LA seems either to occupy a place as an umbrella term or to have several siblings working in parallel. As the purpose of this selective review is only to provide an

[1] For an introduction to the general history of analytics, see Cooper (2012a).
[2] See Cooper (2012b) and Elias (2011) for a discussion of this sort.

overall indication of how actionable insights are conceptualized and operationalized, such terms have neither been specifically included in nor excluded from the search.

1.2.1. From Academic Analytics to Learning Analytics

According to van Harmelen and Workman (2012), a push of publications from EDUCAUSE sparked widespread interest in analytics for educational purposes in 2007. One of these publications was an oft-quoted text by Campbell and Oblinger (2007) that identified itself as "Academic Analytics" (AA) without using the term LA — which came into broad use shortly after. The text states that "The goal of any analytics project is to enable an institution to act based on predictions and probabilities" (Campbell & Oblinger, 2007, p. 7, our emphasis). This frames AA primarily as an analytics project that happens to have learning as its subject area and, importantly, as one that operates on an institutional level. Such a phrasing is perhaps not surprising, given a strong early influence on the field from Business Analytics. Businesses operate on markets and have well-defined objectives (e.g., to maximize profit and optimize business models). Decisions informed by data are made at a strategic and institutional level (Davenport, 2006), as, for instance, in data-driven decision-making (Sclater, Web, & Danson, 2016). In Business Analytics, the term "actionable intelligence" thus signifies (secret) information (as in "military intelligence") that can be used to gain a favourable position, and it is used much in this sense in the early literature on AA (Campbell et al., 2007; Siemens & Long, 2011).3 For example, "information can ... be summarized in reports and displays that provide intelligence for making better-informed decisions to shift patterns of behaviors in desirable ways" (Wagner & Ice, 2012, p. 38). The implication is, although not explicitly stated, that an actor ultimately responsible for making decisions based on information acts rationally, in the sense of a Homo Œconomicus; that is, aiming to optimize the outcome of her decisions. "Economic decisions count as optimizations, whether or not they turn out badly, because the decision-maker can always claim — no doubt truthfully — that the decisions were intended to optimize results" (Heilbroner, 1995, p. 890).

This rational perspective is echoed four years later in an often-quoted definition of LA provided in the call to the first international conference on Learning Analytics and Knowledge in 2011: "The measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and *optimizing* learning and the environments in which it occurs" (LAK, 2011, our emphasis). Emphasizing this phrasing is not intended to suggest that the organizers arranged the conference or their approach to analytics with a view to furthering business perspectives in education. Rather, the intent is to draw out how the phrase, regardless of the reasons for its employment, implies that situations are "optimizable"; i.e., possible to reduce to a single or small set of objectives and fully transparent alternative courses of action. Situations of learning would likely otherwise be recognized as multifaceted and many-purposedg, involving many actors with multiple, often conflicting interests, and incommensurable interpretations of the situation. Aside from the problems associated with models based on rational decision making (Simon, 1957), such a framing ignores the multiple actors involved in education, who work at different levels of granularity, who have different motives and aims, and who work in different contexts — all of which affects what is interpreted as optimal and actionable in a given situation. The idea of optimization thus threatens to reduce the heterogeneity of multiple viewpoints into a single point of view. When combined with the specific goal of increasing retention rates, there is a strong sense that the perspective taken operates on an institutional level. This does not preclude other audiences — for instance, instructors, students, and the public — but it does place them in the situation of assessing information relative to this end.

Later that same year, Siemens and Long (2011) advocated a distinction between AA and LA that reserves the use of AA for the "institutional, regional, and international level" (p. 34), but retains the LAK '11 definition for LA. The definition, as well as Siemens and Long's article, emphasizes a commitment to learners and learning issues. Siemens and Long write: "Academic analytics reflects the role of data analysis at an institutional level, whereas learning analytics centres on the learning process (which includes analyzing the relationship between learner, content, institution, and educator)" (p. 34). This forking partly remedies the above problem. However, Siemens and Long's article retains the perspective of a rational decision maker making sense of data about learners and learning, as it reiterates the purpose of LA to be about "optimization." In a table presenting different levels of analysis, Siemens and Long put LA at "course-level" and "departmental." There is no mention of a group or individual level for learning. In other words, the data may be about the learning process, but it is still obtained for the purpose of making strategic decisions that benefit the overall goals of an educational institution.

A year later, the JISC series on analytics for learning and teaching provides a definition of LA that brings us closer to an actual learning situation. It states: "Learning analytics is the application of analytic techniques to analyze educational data, including data about learner and teacher *activities*, to identify patterns of *behaviour* and provide *actionable information* to *improve learning* and learning-related *activities*" (van Harmelen & Workman, 2012, p. 5, our emphasis). What stands out is the specification that data is about learner and teacher activities and behaviour and that the purpose is to "improve learning" rather than to optimize it. What is more, the definition also provides us with the term "actionable information" as opposed to "actionable intelligence." Any hint of an implied institutional perspective seems removed with these changes. This aligns with

[3] See also http://www.businessdictionary.com/definition/actionable-intelligence.html

recent speciations of LA that argue for approaches that take didactical and pedagogical concerns much more into consideration, as well as obtain much more fine-grained data on learning situations, e.g., social learning analytics (Ferguson & Buckingham Shum, 2012), learning process analytics (Schneider, Class, Benetos, & Lange, 2012), multimodal learning analytics (Blikstein, 2013), teaching analytics (Prieto, Sharma, Dillenbourg, & Jesús, 2016), insight and action analytics (Miliron, Malcom, & Kil, 2014), and dispositional learning analytics (Tempelaar, Rienties, & Nguyen, 2017). However, as we shall see, many efforts still seem to retain a default view on data and on what constitutes an actionable insight that frames the deliberation of data as a rational decision-making process ultimately focused on increasing retention. This brings us to the subject of this review.

1.3. Definition of Actionable Insight

Articles discussing, or even cursorily defining, the meaning of "actionable insights" are few and far between. Mostly, as this review reveals, the meaning of the term has to be inferred from its use. The only discussion we have identified is found in Adam Cooper's (2012b) article "What is analytics? Definition and essential characteristics." Cooper writes, as an answer to the question "What are 'actionable insights'?":

> "Actionable" indicates that analytics is concerned with the potential for practical action rather than either theoretical description or mere reporting. It implies that the conclusion of the analytics process may lead a rational person to follow different courses of action according to their values and factors not accounted for in the analysis (e.g., for which data is missing or unobtainable). It also implies that conclusions are qualified with measures of their validity or reliability — such as statistical significance or confidence level, an acknowledgement of limitations or bias, etc. — since these are necessary to judge whether action is warranted or not. Too frequently, management reports fail to provide this level of clarity and leave actionable insights as missed opportunities. (p. 4, our emphasis)

Cooper goes on to give two examples. The first one is in website design, where statistical data is used to decide which design to use between competing alternatives. The second is a recommendation system, used by call-centre employees, that provides tailored offers to customers in order to incentivize them to retain or renew their contract. Both examples stay within the market analogy. He subsequently emphasizes the importance of adopting a "scientific attitude of analytics" (Cooper, 2012b, p. 4) whereby real-life problems can be translated into statistical questions and ultimately data-processing decisions. We interpret Cooper's discussion as stating that LA is a perspective or "frame of mind" that is:

1. **Pragmatic**: Primarily oriented towards what to do, rather than towards explaining or understanding.
2. **Contingent**: Any action taken will be deliberate and reflective; data does not prescribe, as much as it informs.
3. **Substantiated qualitatively and quantitatively**,: Information is presented in a way that makes decision makers able to gauge its relative importance.

In this frame of mind, "actionable insights" means (pertinent) information that a rational actor may or may not feel compelled to act upon. The definition of "actionable insight" aligns with the above definitions of LA (LAK, 2011; Siemens & Long, 2011) that posit a rational decision maker whose decisions are informed by data. There is, of course, no necessary connection between a rational perspective and the adoption of institutional goals such as increasing retention rates. However, when confronted with the question "to what end?" they cultivate data about student behaviour. Educators and educational researchers, who take the positions of rational decision makers, may find themselves referring, by default, to what lies at the end of an educational path. The trouble is that learning may have an academic degree as its strategic institutional goal, but learning as an activity in itself, first and foremost, serves its own purpose. Although the two are intertwined, understanding what leads to one does not necessarily lead to achieving the other, and vice versa. As such, a diploma may be a consequence of learning behaviour, but not its purpose, per se.

In an AA perspective, this is not relevant, since the problem being solved resembles "business conditions." For instance, the problem of enrollment for higher education resembles a market situation, with competing actors and different strategic decisions to be made. Such a perspective makes the perspective of rational decision making perfectly natural:

> Actions might range from "information" to "invention." For example, an analytics project might provide students with information in the form of an educational progress dashboard where they can view their progress toward a degree, comparisons with their peers, and possibly suggestions on how to improve. At the other end of the spectrum, if the model predicts that a student could be at risk of dropping out of school, analytics might trigger an intervention designed to change student behavior and improve learning. That intervention could be an automated, technology-mediated contact or a personal phone call or e-mail from an advisor about study skills and resources, such as help sessions or office hours.

> Institutions should create mechanisms for measuring impact, such as whether students actually came to office hours when invited. (Campbell & Oblinger, 2007, p. 7, our emphasis)

Note how "insights" pertain to ways of improving behaviour or steering clear of risk behaviours. The insights are "actionable," because there are measures available to influence student behaviour. The behaviour in question may very well be learning behaviour, but it is being monitored with the express purpose of directing students toward a degree, which makes the perspective institutional in consequence. Any activity is easily reframed as a means to an (institutional) end in this way. In an LA perspective, such a reframing ought to be conspicuous, but it seems to go unnoticed. For instance, Pardo, Mirriahi et al. (2016) write:

> A likely reason for the low influence on instructional practice can be attributed to the lack of actionable insight these models provide. Although the traffic light metaphor used in Signals is intuitive, there is insufficient transparency related to the reasons why and how certain predictions are made. This transparency in risk calculations is essential in order for instructors and students to understand how best to act upon the predictions. (p. 475)

The use of concepts such as "risk calculations" and "predictions," without specifying to which end they are applied, allows the data collection to be tacitly tied to an institutional goal. Other terms such as "dispositional indicators" and "performance indicators" perform the same job. The problem is, to reiterate, that there is no *necessary* connection between student behaviour that leads to a degree and student behaviour that leads to learning, although the argument can be made that the two overlap. For instance, Waddington and Nam (2014) analyze data from a chemistry course to show that students who use exam preparation or lecture resources more than their peers are more likely to receive an A or B as a final grade. Given that LA is concerned with "improving learning and learning-related activities" (van Harmelen & Workman, 2012, p. 5), can we say that the use of this information to identify students who do not use these resources or to proactively steer students towards using them constitutes an insight on learning? And, if students, warned by the system, emulate the beneficial behaviour and go on to receive higher grades; can we say that we have improved learning? We may argue that the above constitute insights on learning-related activities and that we, in fact, have improved the students' learning behaviour, but the point is that we have set up a correlation between observable behaviour and desired end result that effectively "black-boxes" what goes on in terms of learning, as Strader and Thille (2012) put it.

The question of what constitutes an actionable insight thus forms part of the more general question of what goals we are pursuing. What are we trying to accomplish by translating learning situations into data? Ferguson et al. (2016) provide a recent overview and synthesis of international research that analyzes implementations of learning analytics as falling into two broad groups:

1. Universities that "treated analytics as a way to enhance existing practices" and "focused on performance measurement and retention interventions."
2. Universities that "viewed retention as an important proxy for student engagement" and "focused more deeply on learning as a pursuit of understanding." (p. 21)

Or, more to the point, some universities see retention as the final goal of LA, where others see student learning as the final goal, with retention as a necessary, but not sufficient, condition (Ferguson, 2016). This divide can be taken as an expression of researchers and educators attempting to resolve the conundrum that the entire field of LA faces: how to merge data and learning perspectives. But the divide also sets up a false dichotomy that partly obscures the insight that there are not two (teacher and administrator) but multiple audiences for whom the data collected has to serve many competing goals. Examining how actionable insights are conceptualized and operationalized is, apart from clarifying the usage of the term, a way of mapping the decisive importance of what perspective is taken in relation to data.

2. Methodology

This selective literature review follows the accepted methodology of Kitchenham and Charters (2007). This includes the analysis framework consisting of the review's research questions, the inclusion and exclusion criteria, and the literature search strategy.

The following questions were defined in order to collect insights on the current literature in the field of Learning Analytics on the important issue of actionable insights. The initial questions were based on extensive reading in general in the literature on learning analytics and related fields. The first question we posed was:

Q1. What constitutes an "actionable insight" in learning analytics?

This research question was directed at evidence or traces of conceptualizations and operationalizations of both terms, preferably in conjunction. It focuses on descriptions of events, research designs, and applications of LA that involve a transition from analysis of data or conversion of data to an initiation of events, processes, interventions, or actions. The following sub-questions were used as guiding posts in the search process, but not in a systematic or exhaustive manner:

Collection
- What data is created?
- What are the data sources?

Purpose
- For whom is the data created?
- Why is the data being collected?

Interpretation
- How is the data presented?
- Who is supposed to act relative to the actionable insight?
- How is the action performed?

Outcome
- What is the (perceived) benefit of acting?
- Who benefits?

These questions are not attended to directly in the following. In parallel with the initial search for papers, a taxonomy of different themes or categories of topics were established. This likely influenced the coding of the search.

A set of criteria were devised for the paper selection process:

Inclusion criteria:
- Publications containing original, peer-reviewed research that specifically mentioned or identified its subject as Learning Analytics.
- Reviews, editorials, and grey literature of high quality were included. Where quality was indicated by sufficient bibliographical information, international organizations, research labs, and academic research institutions were also included.

Exclusion criteria:
- Research before 2007 was not included in the search. However, literature from before 2007 that was already known to the authors informed the initial search for a focus and is included in the references.
- Only publications written in English were considered.
- Updated versions of a publication were only considered once.
- Posters and books were excluded.

The online digital databases used for the literature research included:
- Google Scholar
- Academic Search Premier
- Education Resource Information Center (ERIC)
- Teacher Reference Center
- Scopus

The search for literature proceeded in three stages. For the first stage, the following protocol in terms of search terms was used. The search term "learning analytics" was set as required, in combination with one of the following terms: "actionable insights," "actionable data," "actionable intelligence," "actionable knowledge," "actionable information," "actionable steps," "actionable value," "actionable measures," "actionable strategies," "actionable feedback," "actionable interventions," "intervention design," "intervention model," "intervention engine," or "intervention strategies."[4]

Only the Boolean search operator "AND" was used in order to keep the number of results down. The search terms used are selective and have not been crosschecked in different databases or in terms of their equivalents in database thesauruses. The inclusion of results containing the word "intervention" was decided upon as it was interpreted to signify the

[4] As already mentioned, a comprehensive study would include search terms of competing names for the field.

implementation or conversion of actionable insights into action. A decision was made not to search in fields that could be considered adjacent to "learning analytics," such as "academic analytics" and "serious games analytics." In order to keep the number of results down, more general combinations using Boolean logic, such as "learning analytics" AND "interventions," were not included. In order to keep the number of results down in Google Scholar, results containing the search terms "games" and "MOOC" were excluded from the search. The results were filtered for relevance and duplicated twice (see Appendix I), ending with 353 articles.

For the second stage, these articles were categorized by title and abstract (see Appendix II) under 20 different headlines. These were mainly informed by the paper's fields of application, its intended audiences, the focus of the sstudy (what produced the data and what was its purpose?), and the specific technology used in the setting or used for analysis. The annotations were sorted using thematic analysis (Braun & Clarke, 2006), which further sorted the papers into four overall categories. These four categories were arrived at relative to their perceived granularity of data (see Appendix II). The categories were as follows:

A. Data mining and prediction (institutional level; 67)
B. Learning design and support structure (learning design level; 39)
C. Prediction and social analysis (student behaviour; 115)
D. Specific technology (other; 95)

Category B articles were selected for reading (39 articles). This review is therefore selective, in that identified, relevant literature was excluded in the latter half of the review process for reasons of manageability. Including either category A or C or both in the reading would have significantly improved the validity of the review. However, the chosen research questions were directed at generating an overview, not precise definitions, and the initial categorization confirmed the impression from general readings that a large part of the literature has adopted the framework and perspective of focusing on student risk behaviours and prediction models. It was, therefore, deemed appropriate to single out category B for reading, as this category encapsulates the task of coupling learning issues with data capabilities. There is, of course, a risk of confirmation bias in this strategy.

For the third stage, the selected literature was further evaluated for compliance with the above criteria. Three documents were eliminated after closer reading. Several documents were unavailable at the time of the review. The final review consisted of reading through and annotating 26 documents. Specifically, the papers were read to identify any suggestions on how the concept of "actionable insight" or its equivalents were perceived or used. The results form the basis of the following analysis.

3. Results and Analysis

3.1. A Simplified Story

More than half of the texts found in the first search were categorized as having to do with prediction and student retention. These texts were identified by terms such as "at-risk students," "prediction," "predictors," "indicators," "early-warning systems," and the like (e.g., Brown, 2012; Essa & Ayad, 2012). Several authors (Clow, 2013; Colvin et al., 2016) point out that LA, early on, mainly focused on retention, student attrition, and drop-out prevention through developing early-warning systems and prediction models (Liu, Taylor, Bridgman, Bartimote-Aufflick, & Pardo, 2016) and many still see this as LA's primary objective (Gašević et al., 2016). We reserve the term "data-informed decision-making" for this approach to LA. Outward signs of the approach are as follows:

- The institutional objective of reducing student attrition: "The primary issue confronting online and distance education providers is how to reduce student attrition whilst maintaining course quality" (Dawson, Macfadyen, & Lockyer, 2009, p. 185).
    - The ambition of developing early-warning systems or prediction models.
    - A direct or indirect focus on student behaviour in relation to student success — perceived as retention.
    - The division of work with data into distinct activities, for example "sense making" and "decision-making":: "The process of using analytics to inform teaching and learning is comprised of two central activities: making sense of the information presented in the analytics and taking action based on this information" (Wise, Vytasek, Hausknecht, & Zhao, 2016, p. 3).

In this data-informed decision-making approach, all other issues (technologies, processes, implementation, design, ethics, etc.) relate to the above in some way. For instance, summing up the state of LA, Gašević et al. (2016) name three major emerging themes:

1. Predictors and indicators (prediction models and early warning systems)

2. Visualizations (e.g., dashboards in which faculty, students, and advisors are alerted when intervention is needed)d
3. Interventions (devising precise actions to "shape the learning environment") (p. 5)

However, it is easy to be caught up in a particular taxonomy, the specifics of a project, or one article's perspective. Data can derive from different sources or technologies, like Learning Management Systems (LMS); Digital Learning Environments (DLE); MOOCs (Moissa, Gasparini, & Kemczinski, 2015); and social networks, web tools, or student information systems (SIS); as well as from surveys, course evaluations, or self-reporting. Data can be about students interacting with other students, mentors, teachers, learning materials, and even learning environments (location, temporal data; Avella et al., 2016). It can also be about teachers, support staff, or administration. It can follow different processes (discussion forums, access of video material, teaching sessions, mentoring programs, etc.). It can be "about" learning (student trace data or digital footprints, e.g., clicks and log-ins), as well as present in-depth data on student products (e.g., essays and forum posts). It can be affected by the culture, traditions, and sector from which it is gathered. The data can be about different stages of an educational career, different settings (e.g., Virtual Worlds; Fernandez-Gallego, Lama, Vidal, & Mucientes, 2013), and settings wherein informal learning takes place (de Laat & Schreurs, 2013). The data collection can serve all sorts of purposes, such as analyzing skills development, student behaviour, learning patterns, instructor performance, course recommendations, course development, etc. And, not least, the data can be created specifically for students, mentors, teachers, administrators, or other educational stakeholders (parents, governmental agencies, educational technology firms, or researchers) to assess and act upon. What we have found is what really ties data-informed decision-making together is its insistence on the perspective of a rational decision maker. Regardless of the configuration of the above variables, the situation boils down to an object (data, behaviour, a dashboard) and a subject presented with the object for purposes of rational deliberation (awareness of a problem, reflection on different courses of action, evaluation of data/designs, assessment of performance, decision-making, intervention, design, etc.; Dyckhoff et al., 2012; Krumm, Waddington, Lonn, & Teasley, 2012; Liu et al., 2016; Valkanova, Cukurova, Berner, Avramides, & Mavrikis, 2016; Wise et al., 2016). This means that a system designed to set up a reflective practice cycle for students and encourage them to actively engage in self-regulated learning (Wise et al., 2016) shares a perspective with a redesign process of an LMS undertaken by a faculty member based on click-stream data (Farrel, 2017). Their shared perspective lies not in their findings or purpose, but in how the situation is framed. First, the data gathered about an object is contemplated. Second, the data is acted upon. For the student, it just so happens that the object of the data gathering is herself. When acting upon this data, she is behaving as a rational actor in the same way as the teacher redesigning his course based on LMS data.

Given this similarity, a clear pattern emerges across the articles we have reviewed. We contend that the data-informed decision-making perspective is commonplace; that its primary focus is to "create insights" by gathering (primarily comparative) data on student behaviour — often centred on identifying dispositional and background predictors, assessing student activity performance indicators (Brown, 2012), or establishing a prediction model or learner profiles. "Taking action" is thus understood in terms of measures taken to influence student behaviour. We have consistently found terminology and phrasings that emulate this pattern. For instance, Rienties, Boroowa, Cross, Kubiak, Mayles, and Murphy (2016) set up a model for translating insights into actionable interventions:

> The A4AEF distinguishes six different key phases that teachers and institutions will need to go through in order to translate the insights from learning analytics into actionable interventions that can then be effectively evaluated for their impact: 1. Reviewing key learning analytics metrics; 2. Implementing response actions; 3. Determining protocols; 4. Outcome analysis and evaluation; 5. Sharing evidence; 6. Building strategic insight. (p. 8, our emphasis)

The first two phases correspond to "creating insights" and "taking action." Similarly, Clow (2012) sets up a "learning analytics cycle" consisting of four steps. The first step consists of the learners themselves. The second step is "the generation and capture of **data** about or by the learners" (p. 34, author's emphasis). The third step is "the processing of this data in to **metrics or analytics**, which provide some insight into the learning process" (author's emphasis). And the cycle ends with what Clow calls "closing the feedback loop" since "the cycle is not complete until these metrics are used to drive one or more **interventions** that have some effect on learners" (author's emphasis). Here, steps 3 and 4 correlate with the above pattern. Note that the model Rienties et al. (2016) set up is addressed to teachers and institutions, while Clow's cycle considers learners and teachers as audiences for analytics. Particularly, Clow's idea is that the cycle only closes when feedback reaches the learners in question. While both models place a rational actor at their centres, and they agree on capturing data on learners, they differ markedly in the agency they assign to the actor. This is depicted in Figure 1, below. The x-axis holds different possible actors for whom the analytics can be constructed. The y-axis depicts the level of impact a decision may have on student behaviour, ranging from real-time adjustments made in a classroom, over day-to-day or week-by-week interventions, to reconfigurations of course loads or complete redesigns of courses.

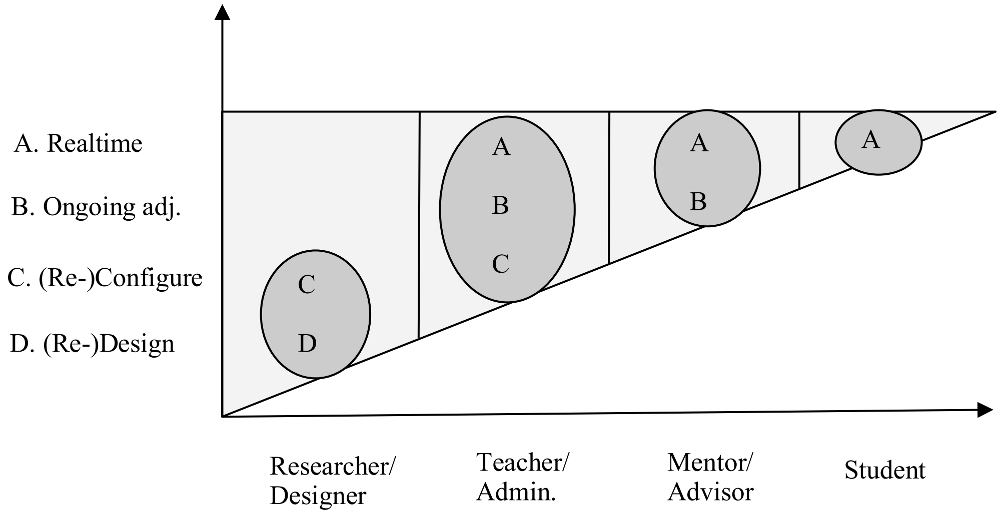

Figure 1. Agency assigned to different actors relative to level of impact of a decision.

The light grey sections in the triangle thus illustrate the impact of actions taken by the actor in question. For instance, if a teacher reconfigures the workload of a course, it could affect real-time participation in the classroom, as well as the need for ongoing adjustments. The dark grey circles represent the influence the actors are allowed. For instance, a mentor or advisor is not in a position to take actions that reconfigure a course. And although a researcher may make design decisions that affect day-to-day interactions, they are seldom allowed to take action in the classroom, as such. This hierarchical structure has not gone unnoticed. Chen and Zhang (2016) write that

> In a traditional learning analytic scenario, the learners reside at the bottom of a hierarchy, being treated as "data objects" to be interpreted by "data clients" performed by teachers, institutions, and governmental agencies (Greller & Drachsler, 2012). For example, institutional data are fed into algorithms to predict student success, with resulting predictions delivered to the teacher on demand to trigger intervention (Arnold & Pistilli, 2012). (p. 145)

But the point is not simply to bring attention to this built-in hierarchy, but rather to follow how the perception of what constitutes an insight or an action is affected by this pattern. In the following, we trace how the data-informed decision-making perspective is translated for each of the different groups of actors.

3.1.1. Actionable insight translates into changing student behaviour

For the students, the data cycle starts and ends with their own behaviours, punctuated by an opportunity to reflect on the adequacy of their performances. Wise et al. (2016), in an attempt to establish a framework for self-directed learning, note that the framework gives "students the opportunity to engage with analytics as a tool to inform their actions" (p. 168), and Xie, Zhang, Nourian, Pallant, and Bailey (2014) remark that in their classroom study they "required students to take notes diligently as this practice would give them opportunity to reflect on their own design" (p. 764). Similarly, Souza (2013) describes a student who appears to be doing well:

> After reviewing her longitudinal report, we saw that on questions spanning all coursework involving calculations she earned a 70% average. She now knows where to direct her efforts prior to taking the North American Pharmacist Licensure Examination. After students are presented with their longitudinal reports, they are required to write a reflection on their performance and briefly describe steps they will take to address areas of concern. In this way, we are encouraging students to take responsibility for their learning. (p. 4)

The student's position as a rational actor with data concerning his own (and his peers') behaviour naturally aligns with Schön's (1983) image of the reflective practitioner, which Wise et al. (2016) indeed refer to. At no point is the possibility considered that the student could be responding to data about the teacher, the learning design of the course, or some other

ISSN 1929-7750 (online).

variable: "*Action* is when learners engage in behaviours to realize their goals. These behaviours also generate the data from which the analytics will be created" (Wise et al., 2016, p. 162, their emphasis).

The same motif is repeated for mentors in Krumm et al. (2012), who work from the following research question: "How did mentors use the EWS to inform their support activities with students?" (p. 3). Mentors work with students in order to change student behaviour. Krumm et al. (2012) describe four so-called "activity systems" based on activity theory in this manner:

> (1) A mentor receives a data display and examines students' performances. The outcome of this engagement is some form of communication with a student, which leads to another activity system (2) where mentors engage students and a recommendation is made. If a student acts on the recommendation, then he or she engages in another activity system, (3) such as a study group, whereby the outcomes may include some increased knowledge. And lastly, (4) a student engages a subsequent course assessment with new insights gained from activity system #3, and a plausible outcome is a better than expected score on this assessment. (p. 7)

The insight is on the student's performance. The action is the engagement and recommendation made to the student. The student closes the loop by acting on the recommendation. But note that the insight has now shifted to the student (increased knowledge) in conjunction with the student's action (joining the study group), and the outcome is a better test score.

In the case of teachers and administrators, the range of interventions is greater, but the general structure is the same. A teacher may be in need of live data informing her of progression in a classroom or alerting her to groups in need of support (Dimitriadis & Goodyear, 2013; Valkanova et al., 2016; van Leeuwen, van Wermeskerken, Erkens, & Rummel, 2017); day-to-day data on the effects of her teaching practice; which students are accessing contents or tools; posts on discussion forums; or patterns of participation and learning behaviour (Bakharia et al., 2016; Dyckhoff et al., 2012). These examples stay within the regular boundaries of the primary task of teaching. A teacher may also use data for purposes of classroom management or orchestration (Dimitriadis & Goodyear, 2013; van Leeuwen et al., 2017), for instance to look across courses and schedules to adjust workloads for students according to other activities (Nguyen et al., 2017). We can note that the insights mentioned here are on student behaviour and the actions taken are intended to correct student behaviour. This area of focus is probably what most stakeholders have in mind when they think about LA. It gives the teacher insights into areas that are otherwise off-limits, such as student behaviour out of class or what goes on inside students' heads. Van Leeuwen et al. (2017) speak of teachers "driving blind," referring to the "near impossibility of keeping up with the activity and progress of all groups of students in the classroom at the same time" (p. 44). Their idea is to "arm" teachers with information, thus providing them with more "vision." This could be done, for example by setting "alerts that are triggered when a student's performance level, activity level (accessing the course), or involvement level (participation in various discussion fora, completion of various evaluative components) fall below certain pre-set threshold values" (Buerck & Mudigonda, 2014, p. 134).

Besides focusing on students, teachers have the possibility of "dropping down" into a designer's or researcher's position in order improve their own teaching, reflect on and evaluate their practice, and apply their findings to redesigning their courses (Bakharia et al., 2016; Farrel, 2017; Knight, Brozina, & Novoselich, 2016; Morse, 2014; Nguyen et al., 2017). Once the data is about themselves, though, they find themselves in the same situation as the students, and they have to assume the frame of mind of a reflective practitioner. Nguyen et al. (2017) write, "By visualizing how learning design changed over time, teachers can explicitly reflect on their practice as well as compare and contrast with others" (p. 178). It can be noted that what we are directing attention to is not that students and teachers are put in a position of reflecting when confronted with data about their own behaviour. It is that, for a large percentage of the articles, the "rational decision maker" is the default perspective with which LA is conceptualized and its future prospects imagined.

The data-informed decision-making perspective is embedded in the way data is perceived and in the way actionable insights are interpreted, but mostly it is identifiable in the emphasis on changing student behaviour. Shacklock (2016) goes as far as to state that "To some extent, changing the way students behave is the entire point of an analytics system" (p. 42). This, once again, raises the specter of Business Intelligence, where analytics "is done to move users/consumers to a desired course of action more quickly" (Wagner & Ice, 2012, p. 34). But the focus also has a different origin. We can take a look at Baker and Siemens's (2014) enumeration of different uses of analytics and data mining:

> One can scan through large datasets to discover patterns that occur in only small numbers of students or only sporadically (cf. Baker, Corbett, & Koedinger, 2004; Sabourin, Rowe, Mott, & Lester, 2011); one can investigate how different students choose to use different learning resources and obtain different outcomes (cf. Beck, Chang, Mostow, & Corbett, 2008); one can conduct fine-grained analysis of phenomena that occur over long periods of time (such as the move toward disengagement over the years of schooling — cf. Bowers, 2010); and one can analyze how the design of learning environments may impact variables of interest through the study of large numbers of exemplars (cf. Baker et al., 2010). (p. 253, our emphasis)

The list aligns with Wise et al.'s (2016) observation that "The set of existing frameworks for learning analytics takes a decidedly researcher/developer viewpoint" (p. 156). From such a perspective, the researcher of course becomes the reflective practitioner par excellence. For the researcher/designer, the behaviour of all of the other actors is available as data. The design process can take as a starting point the position of the teacher as the user of learning designs (Biswam, Segedy, & Bunchongchit, 2016) or it may include the behaviour of the teacher, for instance in feedback used to redesign courses (Morse, 2014). Almost as a self-evident matter, the researcher's behaviour is off-limits. And the researcher's retracted position, from which data is considered and interventions devised, is therefore, obviously, a rational decision maker's perspective.

Going over this list of actors makes a pattern evident. Framing all of these active practitioners as data-informed decision makers steers them towards the single-minded goal of changing student behaviour in order to optimize "learner success." The term "actionable insights," in this perspective, thus means data that allows an actor to achieve such optimization. What constitutes "learner success" (e.g., Gašević, Dawson, & Rogers, 2014) obviously depends on what the success criteria are. Reading through the literature gives the impression that there are two competing ambitions: improving retention rates and enabling students to learn better. If this is the case, then rallying efforts around learning ought to be straightforward, since the mentioned definitions of LA unequivocally state the purpose to be to optimize or improve learning. But the distinction appears to be little more than window dressing. As long as any action towards improving learning ultimately also serves the purpose of improving retention, the two are conflated. Terms such as "performance indicators" and "at-risk students" (Brown, 2012) signify a data-informed decision-making mindset that correlate successful learning behaviour with academic performance. Although correlations can be made convincingly between certain behaviours and academic performances (Gašević et al., 2014), the emphasis that these still only constitute correlations is easily lost. Just because we have data about education does not mean we have data about learning. This concern aligns with a well-known general discussion related to the use of technology in education: whether the use of technology in education is guided by pedagogical and didactical priorities (Greller & Drachsler, 2012; Marzouk et al., 2016). There is a perceived gap between LA and pedagogy (Rangel, Bell, Monroy, & Reid Whitaker, 2015; Bakharia et al., 2016; Nguyen et al., 2017). Gašević, Dawson, and Siemens (2015) urge us, for instance, not to forget that learning analytics are about learning. However, as briefly mentioned, there is a false dichotomy at play here. Learning involves multiple, interwoven, heterogeneous goals for the actors involved. The institutional goal for the student is only the most prominent one. The question of what to do with data is thus eclipsed by the question: "To what end do we do something with data?"

4. Discussion

In order to answer this question, the first thing we might attempt to clarify is who does something. The concept of "actionable insights" implies an agent who has the insights and acts upon them. Cooper (2012c) differentiates between the object, subject, and client of the data analysis, where the "subject" signifies who or what the data is about; the "object" refers to who or what will be acted upon as a consequence of the use of data; and, finally, the "clients" are those who use the results. An example would be log-in data from participants in a specific course (subjects), that indicates the need for changes in the learning materials (object), presented in a visualization to the teacher (client). Cooper's distinctions are useful for clarifying who the data is created for. Aside from providing an immediate measure of transparency to systems that harvest data, it also suggests a skeletal use-scenario, making it possible to consider the workflow from insight to actions taken. However, the distinctions do not shed light on equally important aspects: what the ultimate intended goal of the use of data is, what the level or granularity of data analysis is; or who benefits from its use. These have to be discerned indirectly from the article's language and intended audience. For instance, Gunn et al. (2015) adapt the model below from Davenport, Harris, and Morrison (2010) to provide examples of moving from straightforward use of information in the upper row to actionable insights in the lower row.

Wise et al.'s (2016) observation that LA takes a researcher/developer, and, we might add, an institutional viewpoint applies again here. Modelling, doing experimental designs, acting on recommendations, making predictions, or attempting to optimize and simulate learning are all activities that could be undertaken by a student in an attempt to learn, but are more likely to be undertaken in the work life of an educational decision maker or researcher. We could assume that a teacher in the position of receiving recommendation data is intrinsically concerned with learning; however, we have to differentiate between the different roles of the teacher. If the recommendation data ultimately benefits retention rates, then the client, in this scenario, is primarily the teacher as an institutional employee with an interest in retaining students, not the teacher as a didactical designer. What is more, having identified who the recipient of data is and what their end goal is brings us no nearer to establishing what constitutes an actionable insight.

Part of the problem may be with the concept of "actionable insight" itself. In a data-informed decision-maker mindset, the "who" is not specified as anyone in particular. She is simply assumed to think and act rationally. Data seems to be perceived as something extracted from a learning situation, where the insights and courses of action are not generated until data is analyzed. There is also an expectation that mining data will create useful insights and that it is only rational to look for ways to act upon those insights. If it is not clear what we need to do based on the data, it is tempting to conclude that the data is opaque. But this way of framing the problem might be creating a misdirection. The issue might not be the transparency of the data, but its relation to a system's action capabilities. An initial question would be: "Why would data prescribe a specific action?" For instance, in the Purdue Course Signals program (Arnold & Pistilli, 2012), which uses a traffic light metaphor, if the light switches to yellow due to a drop in attendance by a student, what intervention is naturally called for? It would appear that the only reason that it seems obvious to have a mentor, teacher, or guidance counsellor contact the student is because this is how the system currently deals with attendance issues. This implies that we approach data with certain choices of action in mind (i.e., a particular actor), which contextualize data and create the opportunities to discover insights. Here, "actionable insights" simply means creating a feedback loop. This basic cybernetic idea (Wiener, 1951) tells us that in order for a system to accurately self-correct, the actions being corrected by data would obviously have to be the same as those that produced the data. So, for instance, one uses hits on a shooting target to correct the sight of the rifle or one's aim, not the position of the target.

Table 1. Key Questions Addressed by Analytics (Adapted from Davenport, Harris, & Morrison (2010), p. 7.)

	Past (Descriptive)	**Present (Predictive)**	**Future (Prescriptive)**
Information	What happened? (Reporting)	What is happening now? (Alerts)	What will happen? (Extrapolation)
Insight (purpose)	How and why did it happen? (Modelling, experimental design)	What is the next best action? (Recommendation)	What is the best/worst possible outcome? (Prediction, optimization, simulation)

From such a perspective, the term "actionable insight" has been approached from the wrong end. We do not couple discovery of insights with particular actions. Rather, it is from specific action capabilities that insights are engendered. The mentor can assign a "buddy," the student counsellor can contact the student, or the teacher can change his teaching style, learning material, etc., while the learner herself can increase study time, expand her note taking skills, or undertake any other initiative that affects her performance. The important thing is that the situation impacted by the changed practice (or non-practice) is the same as the one that produced the data in the first place. Insights can only be discovered or created when we are conscious of the work arrangement for which the insights are generated. In other words, asking what insights a data set can yield requires that we ask what actions produced the data and, not least, who performed the actions and to what end. This is how the question of "who" and the interrogation of their goals become important. An "insight" then represents an uncovering of a significant potential to alter the outcome of a course of action. They are "actionable" because the concerned actor's actions can be changed directly by themselves or indirectly by others.

So "actionable" here means "belonging to the same set of actions that produce the data," while "insight" means "data that allows a (self-)corrective procedure."

In reference to Cooper's (2012b) distinctions, we might say that in order to set up a feedback loop, the subject, object, and client must always refer to the same set of actions. In the example above, the subject is seemingly student behaviour impacted by learning materials. The object appears to be learning materials impacting student behaviour. But because the client is the teacher, the set of actions to which the insight refers is not student behaviour, but the teacher's initial decision to arrange learning materials in a certain way. This is the only way to establish a feedback loop wherein data leads the teacher to rearrange or redesign his learning materials. The proper subject is, then, teacher behaviour that arranges learning materials designed to impact student behaviour, while the object is learning materials designed by a teacher to impact student behaviour.[5] So, the feedback loop established here can be said to be self-corrective for the teacher, but other-corrective for the student. In this case, the client differs from the subject and object; however, the reference still must be to the same set of actions.

This example illustrates how facilitating the creation of actionable insights requires mapping out existing workflows and finding relevant couplings between actors and their action flows within which to improve action responses or, alternatively, create completely new bifurcations of responses. It also makes evident the need to identify the perspective taken. Who is looking at the system, and what is their current impact on it? The implication is not that analytics have to take a student or

[5] For an example, see Lockyer, Heathcote, and Dawson (2013).

teacher perspective in order to qualify as LA. Neither does LA have to focus on "interventions that have some effect on learners," as Clow (2012, p. 135) would have it, unless we interpret the sentence to say that an intervention eventually has to have some effect on learners. Improving course offerings by developing curricula to improve learning and comprehension (Wong & Lavrencic, 2016) may be just as effective a measure in affecting learning outcomes as designs that have the learner front and centre, such as self-regulated learning (Klug, Ogrin, & Keller, 2011) or DIY analytics (Arndt & Guercio, 2014). What is absolutely essential is that we recognize that the outcome space is tied to the action capabilities of the particular actor in question. A different way of saying this is that the data we produce has to be responsive to how we act, in order to form actionable insights. Xie et al. (2014) use the term "instructional sensitivity" (Polikoff, 2010), by which they mean the ability to discern or trace the effect of an intervention in data. To determine instructional sensitivity, Xie et al. (2014) set up a system capable of measuring the impact of an intervention on student activity. Activity is tracked through logs generated by a CAD program used by the student to solve a design challenge. The point is that the intervention tracked occurs outside the CAD program, but is still traceable in the student's logged activity. Having assessment tools with high instructional sensitivity will, in this case, allow a teacher to accurately gauge and adjust her intervention to maximize student responses.

Our choice of perspective has consequences for what is counted as an insight and what actions are proposed. Particularly, it should be clear that actions undertaken to ensure retention are likely different from actions that impact learning. Contrast two very different examples of phrasings: Jayaprakash, Moody, Lauria, Regan, and Baron (2014) use a medical metaphor when speaking of students who improve after receiving a "treatment" or of students "being immune to treatments," where, by "treatments," the authors mean interventions or actions taken to affect student behaviour (p. 42). Opposite this, Chen and Zhang (2016) speak of "analytics as learning" as opposed to "analytics about, of or for learning" to advocate the use of analytics "to support students' epistemic agency and design-mode thinking" (p. 149). The difference is telling; each choice of words carries much significance. We also see this in an alternative definition of LA given by Lockyer, Heathcote, and Dawson (2013), where LA is considered "the collection, analysis, and reporting of data *associated* with student learning behavior" (p. 1439, our emphasis). This is a subtle but important difference from data *about* student learning behaviour.

5. Conclusion

We have established that actionable insights currently are viewed from what we have dubbed a data-informed decision-making perspective. This is a type of rational decision making with the goal of increasing retention. The perspective does not provide any clues as to how to procure actionable insights. On the contrary, its two-step approach, which charges any investigator to first look at available data in order to extract insights and then tries to couple these with courses of action (Picciano, 2012), is alien to most educators, except in the most abstract sense. Educators tasked with interpreting data and then figuring out what to do, without a statistician or data analyst background, thus fight a losing battle when trying to connect data with their teaching practice. The results are ad hoc interpretations and courses of action (Sergis & Sampson, 2017).

In our discussion, we have argued for greater consideration of the roles of perspective and action. It matters who has acted to produce the data. Insights are a way of creating a feedback loop in a system's or actor's action capabilities. It also matters what the producer's intermediate and ultimate goals are. Insights are "actionable" because it is possible to act upon them as feedback information to promote a better end result. "Actionable insights" can thus be said to be constituted by actions. Assuming a single goal in a multivariate organization with many different actors (i.e., increasing retention) skews the feedback cycle and transforms learning practices that are ends in themselves into means to institutional ends, not unlike the scorned practice of "teaching to the test." Indeed, there are a range of topics that play into this that require further consideration, which have not been considered here due to limitations of space: the importance of granularity of data, the relationships and positions of different audiences for data, and, not least, the role of context (Cukurova, Luckin, & Baines, 2017). We have opted to focus on the importance of the feedback loop between action capabilities, data, and end goals in relation to actionable insights. We adhere to Herbert Simon's (1996) notion that in "many cases whether a particular system will achieve a particular goal or adaptation depends on only a few characteristics of the outer environment" (p. 8). There are also practical aspects of what constitute actionable insights. The concept itself suggests that some insights are not actionable, thus demanding a discussion and further refinement of what it is to be considered "actionable."

We contend that what constitutes "insights" and "actions," not to mention "actionable insights," has not been considered adequately. Given the widespread use of the concept, the LA community should pause to consider its meaning and application. Particularly, the perspective of the data-informed decision maker needs scrutiny. The perspective is not inherently wrong; however, its widespread application and its insistence on homogenizing different audiences into a single viewpoint with a single intent create the illusion that insights can be mined from any dataset by any actor, like gold nuggets. It also implies that insights are somehow tied into behaving and thinking rationally. Both of these tenets can be brought into question. Many aspects of learning can be said to be tacit, and a large number of the decisions made by a human actor are examples of satisficing (Simon, 1967) or docility (Simon, 1993) — and are taken without complete information. What is more, human cognitive capabilities are, in some respects, limited, while the underlying rationale of using data is to procure patterns that are only identifiable when aided by computers. Although these aspects have not been discussed here, the reliance on rational decision-making is somewhat undercut by the promise of LA, which envisions a future where we are able to gain insights and possibilities for action that are outside what we can learn from our normal faculties. Leaving the generation of insights to a reflective process outside the generation of data — only supported by wetware — seems at odds with this ambition.

It must be duly noted that this selective review has severe limitations. It deals with a limited number of articles, results related to MOOCs and games have been left out, and the coding scheme (see Appendix II) used was, early on, influenced by a parallel attempt to create a taxonomy for LA papers. The review thus must be considered non-systemic and non-replicable.

There are, undoubtedly, insights to be gained through the implementation of LA in educational systems. And, most assuredly, taking action is essential in a data-saturated environment. The use of data promises to transform personal and organizational sensitivity and responsiveness and give us novel insights and possibilities for understanding what we have done (descriptive analytics); how to respond early, preventively, and facilitatively (predictive analytics); and what to do differently, more, or better (prescriptive analytics). In that process, there are risks to consider that have to do with the culture of education and habits of mind. For instance, there is the risk that LA simply gravitates towards insights that confirm longstanding good practice and insights (Gibbs, 2010; Macfadyen & Dawson, 2012), such as "students tend to ignore optional learning activities … [and] focus on activities that are assessed" (Clow, 2014, p. 51).

For future studies, it makes sense to look for perspectives different from what has been named data-informed decision-making here. In this study, we have found growing (albeit scattered) indications that the dominance of the data-informed decision-making approach is regarded as a major problem. The general reading and review reveals voices that advocate different approaches and perspectives. Across these perspectives, the value of reflection-on-action, deliberation on design interventions, or rational judgment of alternatives is never questioned. What is (implicitly or explicitly) questioned is whether the default frame of mind for which LA produces data should be that of a rational decision maker (Marzouk et al., 2016). Here, it makes sense to ask whether analytics, first and foremost, should be embedded in learning, as opposed to data about learning (Chen & Zhang, 2016). This would create the design challenge of creating a system that delivers actionable insights into action flows without necessarily demanding rational deliberation outside the flow.

If LA is going to allow our learning cultures to evolve into something new, then it has to consider what types of data are going to be created and what personal and systemic action capabilities are "naturally" informed by such data. In that perspective, data-informed decision-making is perhaps already irrelevant. Many important factors in learning-conducive environments do not relate to active, conscious (rational) decision-making (e.g., nudging [Thaler & Sunstein, 2008] and a growth mindset [Dweck, 2006]). Perhaps behaviour should be seen as one dimension of learning events, alongside materials, relations, social constraints, distributed cognition, and algorithms, rather than the ultimate focus of attention. To that end, we should seek ways of assessing progress and learning in new terms (Claxton, 2006; Deakin Crick, 2007; Deakin Crick, Huang, Shafi, & Goldspink, 2015). The question is, What type of data does the LA community need to create in order to capture a learning event? Until such decisions are made, we fear that data will continue to yield insights only reluctantly and haphazardly.

Declaration of Conflict and Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) declared no financial support for the research, authorship, and/or publication of this article.

References

*Entries marked with a star were included in the final part of the review. Documents stricken-through were, on closer consideration, deemed non-compliant.

Arndt, T., & Guercio, A. (2014). DIY analytics for postsecondary students. *Proceedings of the 11th International Conference on Cognition and Exploratory Learning in Digital Age* (CELDA 2014), 25–27 October 2014, Porto, Portugal (pp. 253–256). International Association for Development of the Information Society (IADIS).

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: Using learning analytics to increase student success. In S. Buckingham Shum, D. Gašević, and R. Ferguson (Eds.), *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 267–270). New York: ACM. http://dx.doi.org/10.1145/2330601.2330666

Atkinson, S. P. (2015). Adaptive learning and learning analytics: A new learning design paradigm. Retrieved from http://i.unisa.edu.au/siteassets/staff/tiu/documents/adaptive-learning-and-learning-analytics—a-new-learning-design-

paradigm.pdf
Avella, J. T., Kebritchi, M., Nunn, S. G., & Kanai, T. (2016). Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. *Online Learning Consortium: Special Issue on Learning Analytics*, *20*(2), 13–29. http://dx.doi.org/10.24059/olj.v20i2.790
Baker, R. S. J. D., Corbett, A. T., Gowda, S. M., Wagner, A. Z., MacLaren, B. M., Kauffman, L. R., Mitchell, A. P., & Giguere, S. (2010). Contextual slip and prediction of student performance after use of an intelligent tutor. In P. De Bra, A. Kobsa, & D. Chin (Eds.), *User Modeling, Adaptation, and Personalization* (UMAP 2010). *Lecture Notes in Computer Science, 6075*. Berlin, Heidelberg: Springer. https://dx.doi.org/10.1007/978-3-642-13470-8_7
Baker, R. S. J. D., Corbett, A. T., & Koedinger, K. R. (2004). Detecting student misuse of intelligent tutoring systems. In J. C. Lester, R. M. Vicari, F. Paraguacu (Eds.), *Intelligent Tutoring Systems* (ITS 2004). *Lecture Notes in Computer Science, 3220*. Berlin, Heidelberg: Springer. https://dx.doi.org/10.1007/978-3-540-30139-4_50
Baker, R. S. J. D., & Siemens, G. (2014). Educational data mining and learning analytics. In R. Sawyer (Ed). *The Cambridge handbook of the learning sciences* (pp. 253–272). New York: Cambridge University Press. https://dx.doi.org/10.1007/978-1-4614-3305-7_4
Baker, R. S. J. D., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, *1*(1), 3–16.
*Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., Williams, D., Dawson, S., & Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics. *Proceedings of the 6th International Conference on Learning Analytics & Knowledge* (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 329–338). New York: ACM. http://dx.doi.org/10.1145/2883851.2883944
Bartle, E. (2015). *Personalised learning: An overview*. The Institute for Teaching and Learning Innovation, Queensland University. Retrieved from https://itali.uq.edu.au/filething/get/1865/Personalised_learning_overview_Final_16_Mar_15.pdf
Beck, J. E., Chang, K., Mostow, J., & Corbett, A. T. (2008). Does help help? Introducing the Bayesian evaluation and assessment methodology. In B. P. Woolf, E. Aïmeur, R. Nkambou, S. Lajoie (Eds.), Intelligent Tutoring Systems (ITS 2008). *Lecture Notes in Computer Science, 5091*. Berlin, Heidelberg: Springer. https://dx.doi.org/10.1007/978-3-540-69132-7_42
Bichsel, J. (2012). *Analytics in higher education: Benefits, barriers, progress, and recommendations.* Louisville, CO: EDUCAUSE Center for Applied Research. Retrieved from http://www.educause.edu/ecar.
*Biswam, G., Segedy, J. R., & Bunchongchit, K. (2016). From design to implementation to practice a learning by teaching system: Betty's Brain. *International Journal of Artificial Intelligence in Education*, *26*(1), 350–364. https://dx.doi.org/10.1007/s40593-015-0057-9
*Biswas, G., Segedy, J. R., & Kinnebrew, J. S. (2014). A combined theory- and data-driven approach for interpreting learners' metacognitive behaviors in open-ended tutoring environments. In R. Sottilare, A. Graesser, X. Hu, & B. Goldberg (Eds.), Design recommendations for intelligent tutoring systems (Vol. 2) (pp. 135–150). Orlando, FL: US Army Research Laboratory
Blikstein, P. (2013). Multimodal learning analytics. *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge* (LAK '13), 8–12 April 2013, Leuven, Belgium (pp. 102–106). New York: ACM. http://dx.doi.org/10.1145/2460296.2460316
Bowers, A. J. (2010). Analyzing the longitudinal K–12 grading histories of entire cohorts of students: Grades, data driven decision making, dropping out and hierarchical cluster analysis. *Practical Assessment, Research & Evaluation*, *15*(7), 1–18.
Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*, 77–101.
Brown, M. (2011). Learning analytics: The coming third wave. *EDUCAUSE Learning Initiative Brief.* Retrieved from https://library.educause.edu/~/media/files/library/2011/4/elib1101-pdf.pdf
Brown, M. (2012). Learning analytics: Moving from concept to practice. *EDUCAUSE Learning Initiative Brief.* Retrieved from https://library.educause.edu/~/media/files/library/2012/7/elib1203-pdf.pdf
Brown, M., Dehoney, J., & Millichap, N. (2015). The next generation digital learning environment: A report on research. *EDUCAUSE Learning Initiative Brief.* Retrieved from https://library.educause.edu/~/media/files/library/2015/4/eli3035-pdf.pdf
Buerck, J. P., & Mudigonda, S. P. (2014). A resource-constrained approach to implementing analytics in an institution of higher education: An experience report. *Journal of Learning Analytics*, *1*(1), 129–139. http://dx.doi.org/10.18608/jla.2014.11.7
Campbell, J. P., DeBlois, P., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *EDUCAUSE Review*, *42*(4), 40–57.

Campbell, J. P., & Oblinger, D. G. (2007). Academic analytics. *EDUCAUSE White Paper*. Louisville, CO: EDUCAUSE.
*Cambridge, D., & Perez-Lopez, K. (2012). First steps towards a social learning analytics for online communities of practice for educators. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 69–72). New York: ACM. http://dx.doi.org10.1145/2330601.2330622
*Chang, J., Tsao, N., Kuo, C., & Hsu, H. (2016). Curriculum design: A data-driven approach. Proceedings of the 5th International Congress on Advanced Applied Informatics (AAI 2016), 10–14 July 2016, Kumamoto, Japan (pp. 492–496). Institute of Electrical and Electronics Engineers (IEEE). Retrieved from https://ieeexplore.ieee.org/document/7557660/ http://dx.doi.org/10.1109/IIAI-AAI.2016.163
Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. International Journal of Technology Enhanced Learning, 4(5), 318–331. http://dx.doi.org/10.1504/IJTEL.2012.051815
*Chen, B., & Zhang, J. (2016). Analytics for knowledge creation: Towards epistemic agency and design-mode thinking. *Journal of Learning Analytics*, *3*(2), 139–163. http://dx.doi.org/10.18608/jla.2016.32.7
Claxton, G. (2006). Expanding the capacity to learn: A new end for education? *British Educational Research Association Annual Conference* (BERA2006), 6 September 2006, Warwick University. Retrieved from https://www.education.sa.gov.au/sites/g/files/net691/f/expanding_the_capacity_to_learn_a_new_end_for_education.pdf
Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 134–137). New York: ACM. http://dx.doi.org/10.1145/2330601.2330636
Clow, D. (2013). An overview of learning analytics. *Teaching in Higher Education*, *18*(6), 683–695. http://dx.doi.org/10.1080/13562517.2013.827653
Clow, D. (2014). Data wranglers: Human interpreters to help close the feedback loop. *Proceedings of the 4th International Conference on Learning Analytics and Knowledge* (LAK '14), 24–28 March 2014, Indianapolis, IN, USA (pp. 49–53). New York: ACM. http://dx.doi.org/10.1145/2567574.2567603
Colvin, C., Rogers, T., Wade, A., Dawson, S., Gašević, D., Buckingham Shum, S., Nelson, K., Alexander, S., Lockyer, L., Kennedy, G., Corrin, L., & Fisher, J. (2016). *Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement*. Canberra, ACT: Australian Government Office for Learning and Teaching. Retrieved from http://he-analytics.com
Cooper, A. (2012a). A brief history of analytics. *JISC CETIS Analytics Series*, *1*(9). Retrieved from http://publications.cetis.org.uk/wp-content/uploads/2012/12/Analytics-Brief-History-Vol-1-No9.pdf
Cooper, A. (2012b). What is analytics? Definition and essential characteristics. *JISC CETIS Analytics Series, 1*(5). Retrieved from http://publications.cetis.org.uk/2012/521
Cooper, A. (2012c). A framework of characteristics for analytics. *JISC CETIS Analytics Series, 1*(7). Retrieved from https://pdfs.semanticscholar.org/55ef/f1f5c696a55a519dd44040bdd8111d3ce833.pdf
Cukurova, M., Luckin, R., & Baines, E. (2017). The significance of context for the emergence of implementation of research evidence: The case of collaborative problem-solving. *Oxford Review of Education, 44*(3), 322–337. http://dx.doi.org/10.1080/03054985.2017.1389713
*Dang, S., Yudelson, M., & Koedinger, K. (2017). Detecting diligence with online behaviors on intelligent tutoring systems. Proceedings of the 4th ACM Conference on Learning @ Scale (L@S 2017), 20–21 April 2017, Cambridge, MA, USA (pp. 51–59). New York: ACM. http://dx.doi.org/10.1145/3051457.3051470
Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, *84*(1), 98–107.
Davenport, T. H., Harris, J. G., & Morrison, R. (2010). *Analytics at work: Smarter decisions, better results*. Boston, MA: Harvard Business School Publishing.
Dawson, S. P., Macfadyen, L., & Lockyer, L. (2009). Learning or performance: Predicting drivers of student motivation. In R. Atkinson & C. McBeath (Eds.), *Same places, different spaces* (pp. 184–193). Auckland, NZ: ASCILITE.
Deakin Crick, R. (2007). Learning how to learn: The dynamic assessment of learning power. *The Curriculum Journal*, *18*(2), 135–153. http://dx.doi.org/10.1080/09585170701445947
Deakin Crick, R., Huang, S., Shafi, A., & Goldspink, C. (2015). Developing resilient agency in learning: The internal structure of learning power. British Journal of Educational Studies, 63(2), 121–160. http://dx.doi.org/10.1080/00071005.2015.1006574
Dede, C., Ho, A., & Mitros, P. (2016). Big data analysis in higher education: Promises and pitfalls. EDUCAUSE Review, 51(5), 22–34.
De Laat, M., & Schreurs, B. (2013). Visualizing informal professional development networks: Building a case for learning

analytics in the workplace. American Behavioral Scientist, 57(10), 1421–1438. http://dx.doi.org/10.1177/0002764213479364
*Dimitriadis, Y., & Goodyear, P. (2013). Forward-oriented design for learning: Illustrating the approach. Researching in Learning Technology, 21(1), 1–13. http://dx.doi.org/10.3402/rlt.v21i0.20290
*Donnelly, P. J., Blanchard, N., Samei, B., Oiney, A. M., Sun, X., Ward, B., Kelly, S., Nystrand, M., & D'Mello, S. K. (2016). Multi-sensor modelling of teacher instructional segments in live classrooms. Proceedings of the 18th ACM International Conference on Multimodal Interaction (ICMI '16), 12–16 November 2016, Tokyo, Japan (pp. 177–184). New York: ACM. http://dx.doi.org/10.1145/2993148.2993158
Dweck, C. S. (2006). Mindset: The new psychology of success. New York: Random House.
*Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. Educational Technology & Society, 15(3), 58–76.
Elias, T. (2011). Learning analytics: Definitions, processes and potential. Retrieved from http://learninganalytics.net/LearningAnalyticsDefinitionsProcessesPotential.pdf. http://dx.doi.org/10.1145/2993148.2993158
*Elson, J. S. (2016). Formative assessment in an online asynchronous learning environment (Doctoral dissertation). University of Nebraska at Omaha. ProQuest Dissertations Publishing.
Essa, A., & Ayad, H. (2012). Student success system: Risk analytics and data visualization using ensembles of predictive models. In P. Long, G. Siemens, G. Conole, & D. Gašević (Eds.), Proceedings of the 1st International Conference on Learning Analytics and Knowledge (LAK '12), 27 February–1 March 2011, Banff, AB, Canada (pp. 158–161). New York: ACM. http://dx.doi.org/10.1145/2330601.2330641
*Farrel, M. (2017). Lessons learned from a faculty-led project: Using learning analytics for course design. In S. Shehata & J.P.-L. Tan (Eds.), Practitioner Track, Proceedings of the 7th International Conference on Learning Analytics and Knowledge (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 131–139). New York: ACM.
Ferguson, R. (2012a). Learning analytics: Drivers, developments and challenges. International Journal of Technology Enhanced Learning, 4(5/6), 304–317. http://dx.doi.org/10.1504/IJTEL.2012.051816
Ferguson, R. (2012b). The state of learning analytics in 2012: A review and future challenges. Technical Report KMI-12-01, Knowledge Media Institute, The Open University, UK.
Ferguson, R. (2016). Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement (LAEP inventory). Retrieved from http://he-analytics.com/wp-content/uploads/SP13-3249_-Master17Aug2015-web.pdf
Ferguson, R., & Buckingham Shum, S. (2012). Social learning analytics: Five approaches. In S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 23–33). New York: ACM. http://dx.do.org/10.1145/2330601.2330616
Ferguson, R., Brasher, A., Clow, D., Cooper, A., Hillaire, G., Mittelmeier, J., Rienties, B., Ullmann, T., Vuokari, R., & Castaño Muñoz, J. (2016). Research evidence on the use of learning analytics: Implications for education policy. In J. Vuokari & J. Castaño Muñoz (Eds.), Joint Research Center Science for Policy Report, EUR 28294. http://dx.doi.org/10.2791/955210
Fernandez-Gallego, B., Lama, M., Vidal, J. C., & Mucientes, M. (2013). Learning analytics framework for educational virtual worlds. Procedia Computer Science, 25, 443–447. https://dx.doi.org/10.1016/j.procs.2013.11.056
Fiaidhi, J. (2014, Sept./Oct.). The next step for learning analytics. IT Pro, IEEE Computer Society, pp. 4–8. http://dx.doi.org/10.1109/MITP.2014.78
Gašević, D., Dawson, S., Pardo, A. (2016). How do we start? State and directions of learning analytics adoption. Oslo, Norway: International Council for Open and Distance Education.
Gašević, D., Dawson, S., & Rogers, T. (2014). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting learning success. Internet and Higher Education, 28, 68–84. http://dx.doi.org/10.1016/j.iheduc.2015.10.002
Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64–71. http://dx.doi.org/10.1007/s11528-014-0822-x
Gibbs, G. (2010). Dimensions of quality. York, UK: Higher Education Academy. Retrieved from http://www.heacademy.ac.uk/resources/detail/evidence_informed_practice/Dimensions_of_Quality
Goldstein, P. J., & Katz, R. N. (2005). Academic analytics: The uses of management information and technology in higher education. Boulder, CO: EDUCAUSE Center for Applied Research.
*Grann, J. (2016). Competency-based education: Capella University's excellence in assessment profile. Assessment Update, 29(19), 8–13.

*Greer, J., Thompson, C., Banow, R., & Frost, S. (2017). Data-driven programmatic change at universities: What works and how. In J. Greer, M. Molinaro, X. Ochoa, & T. McKay (Eds.), Proceedings of the 1st Learning Analytics for Curriculum and Program Quality Improvement Workshop (PCLA 2016), 25 April 2016, Edinburgh, UK (pp. 30–33). Retrieved from https://www.semanticscholar.org/paper/Data-Driven-Programmatic-Change-at-Universities%3A-Greer-Thompson/c03df8c8df1aaffa4f50891816e24daf38608621

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. Educational Technology & Society, 15(3), 42–57.

Gunn, C., McDonald, J., Donald, C., Milne, J., Nichols, M., & Heinrich, E. (2015). A practitioner's guide to learning analytics. In T. Reiners, B. R. von Konsky, D. Gibson, V. Chang, L. Irving, & K. Clarke (Eds.), Globally connected, digitally enabled (pp. 672–675). Retrieved from https://www.researchgate.net/publication/309739434_A_practitioner's_guide_to_learning_analytics

Hall Jr., O. P. (2014). Teaching and using analytics in management education. In J. Wang (Ed.), Encyclopedia of business analytics and optimization (pp. 2479–2491). Hershey, PA: IGI Publishing91. http://dx.doi.org/10.4018/978-1-4666-5202-6.ch221

Haythornthwaite, C., de Laat, M., & Dawson, S. (2013). Introduction to the special issue on learning analytics. American Behavioral Scientist, 57(10), 1371–1379. http://dx.doi.org/10.1177/0002764213498850

Heilbroner, R. (1995). Putting economics in its place. Social Research, 62(4), 883–897.

*Hershkovitz, A. (2015). Towards data-driven instruction. Cognition and Learning, 10, 1–4.

Hershkovitz, A., Knight, S., Dawson, S., Jovanović, J., & Gašević, D. (2016). About "learning" and "analytics." Journal of Learning Analytics, 3(2), 1–5. http://dx.doi.org/10.18608/jla.2016.32.1

HM Government. (2013). Seizing the data opportunity. Policy Paper, UK Department for Business, Innovation & Skills. Retrieved from https://www.gov.uk/government/publications/uk-data-capability-strategy

Ice, P., Stephens-Helm, J., & Powell, K. (2011). Introduction to analytics for e-learning. In C. Ho & M. Lin (Eds.), Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (E-Learn 2011), 18–21 October 2011, Honolulu, Hawaii, USA (pp. 684–686). Chesapeake, VA: Association for the Advancement of Computing in Education (AACE).

Jacobson, M. (2016). The third wave of edtech: Bringing the future of learning to today's classes [Blog post]. Retrieved from http://staging.openforum.com.au/the-third-wave-of-edtech-bringing-the-future-of-learning-to-todays-classes/

Jayaprakash, S. M., Moody, E. W., Lauria, E., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. The Journal of Learning Analytics, 1(1), 6–47. http://dx.doi.org/10.18608/jla.2014.11.3

*Jo, Y., Tomar, G., Ferschke, O., Rosé, C., & Gašević, D. (2016). Pipeline for expediting learning analytics and student support from data in social learning. Proceedings of the 6th International Conference on Learning Analytics and Knowledge (LAK '16), 25–29 April 2016, Edinburgh, UK (pp. 542–543). New York: ACM. http://dx.doi.org/10.1145/2883851.2883912

Johnson, L., Adams Becker, S., Cummins, M., Estrada, V., Freeman, A., & Ludgate, H. (2013). NMC Horizon Report: 2013 Higher Education Edition. Austin, Texas: The New Media Consortium.

Jones, D., Beer, C., & Clark, D. (2013). The IRAC framework: Locating the performance zone for learning analytics. Proceedings of the 30th Annual Conference of the Australasian Society for Computers in Learning in Tertiary Education (ASCILITE 2013) 1–4 December 2013, Sydney, Australia (pp. 446–450). Australasian Society for Computers in Learning in Tertiary Education. Retrieved from https://eprints.usq.edu.au/24352/

Khalil, M., & Ebner, M. (2015). Learning analytics: Principles and constraints. Proceedings of the World Conference on Educational Multimedia, Hypermedia & Telecommunications (EdMedia 2015), 22–25 June 2015, Montréal, QC, Canada (pp. 1326–1336). Association for the Advancement of Computing in Education (AACE)

*Kim, D., Park, Y., Yoon, M., & Yo, I. H. (2016). Toward evidence-based learning analytics: Using proxy variables to improve asynchronous online discussion environments. The Internet and Higher Education, 30, 30–43. http://dx.doi.org/10.1016/j.iheduc.2016.03.002

Kitchenham, B., & Charters, S. (2007). Guidelines for performing systematic literature reviews in software engineering. Keele University and Durham University Joint Report.

Klug, J., Ogrin, S., & Keller, S. (2011). A plea for self-regulated learning as a process: Modelling, measuring and intervening. Psychological Test and Assessment Modeling, 53(1), 51–72.

*Knight, D. B., Brozina, C., & Novoselich, B. (2016). An investigation of first-year engineering student and instructor perspectives of learning analytics approaches. Journal of Learning Analytics, 3(3), 215–238. http://dx.doi.org/10.18608/jla.2016.33.11

*Krumm, A. E., Waddington, R. J., Lonn, S., & Teasley, S. D. (2012). Increasing academic success in undergraduate engineering education using learning analytics: A design-based research project. Paper presented at the Annual Meeting of the American Educational Research Association (AERA). Vancouver, BC, Canada. Retrieved from https://ctools.umich.edu/access/content/group/research/papers/aera2012_krumm_learning_analytics.pdf

*Kuh, G. D., Ikenberry, S. O., Jankowski, N. A., Cain, T. R., Ewell, P. T., Hutchings, P., & Kinzie, J. (2015). Beyond compliance: Making assessment matter. Change: The Magazine of Higher Learning, 47(5), 8–17. http://dx.doi.org/10.1080/00091383.2015.1077661

Kumar, V. S., Kinshuk, M., Clemens, C., & Harris, S. (2015). Causal models and big data learning analytics. In M. Kinshuk & R. Huang (Eds.), Ubiquitous learning environments and technologies (pp. 31–54). New York: Springer. http://dx.doi.org/10.1007/978-3-662-44659-1_3

LAK (2011). Definition of learning analytics from the 1st International Conference on Learning Analytics and Knowledge (LAK '11), 27 February–1 March 2011, Banff, AB, Canada. Available at https://tekri.athabascau.ca/analytics/call-papers

*Liu, D. Y. T., Bartimote-Aufflick, K., Pardo, A., & Bridgeman, A. J. (2017). Data-driven personalization of student learning support in higher education. In A. Peña-Ayala (Ed.), Learning analytics: Fundaments, applications, and trends: A view of the current state of the art to enhance e-learning (pp. 143–170). Cham, Switzerland: Springer. http://dx.doi.org/10.1007/978-3-319-52977-6_5

*Liu, D. Y. T., Taylor, C. E., Bridgman, A. J., Bartimote-Aufflick, K., & Pardo, A. (2016). Empowering instructors through customizable collection and analyses of actionable information. In J. Greer, M. Molinaro, X. Ochoa, & T. McKay (Eds.), Proceedings of the 1st Learning Analytics for Curriculum and Program Quality Improvement Workshop (PCLA 2016), 25 April 2016, Edinburgh, UK (pp. 3–9). Retrieved from http://www.academia.edu/24453494/Empowering_instructors_through_customizable_collection_and_analyses_of_actionable_information

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. American Behavioral Scientist, 57(19), 1439–1459. http://dx.doi.org/10.1177/0002764213479367

Long, P. D., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 31–40.

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 S. Buckingham Shum, D. Gašević, & R. Ferguson (Eds.), Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (LAK '12), 29 April–2 May 2012, Vancouver, BC, Canada (pp. 184–187). New York: ACM. http://dx.doi.org/10.1145/2330601.2330647

Macfadyen, L. P., & Dawson, S. (2012). Numbers are not enough: Why e-learning analytics failed to inform an institutional strategic plan. Educational Technology & Society, 15(3), 149–163.

Macfadyen, L. P., Dawson, S., Pardo, A., & Gašević, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge. Research & Practice in Assessment, 9, 17–28.

Marzouk, Z., Rakovic, M., Liaqat, A., Vytasek, J., Samadi, D., Stewart-Alonso, J., Ram, I., Woloshen, S., Winne, P., & Nesbit, J. (2016). What if learning analytics were based on learning science? Australasian Journal of Educational Technology, 32(6), 1–18.

*McDonald, J., Bird, R. J., Zouaq, A., & Moskal, A. C. M. (2017). Short answers to deep questions: Supporting teachers in large-class settings. Journal of Computer Assisted Learning, 33(4), 306–319. https://dx.doi.org/10.1111/jcal.12178

*Means, B., & Anderson, K. (2013). Expanding evidence approaches for learning in a digital world. Washington, DC: U.S. Department of Education, Office of Educational Technology.

Miliron, M. D., Malcom, L., & Kil, D. (2014). Insight and action analytics: Three case studies to consider. Research and Practice in Assessment, 9, 70–89.

Moissa, B., Gasparini, I., & Kemczinski, A. (2015). A systematic mapping on the learning analytics field and its analysis in the massive open online courses context. International Journal of Distance Education Technologies, 13(3), 1–24. http://dx.doi.org/10.4018/IJDET.2015070101

*Mojarad, S., Lewkow, N., Essa, A., Zhang, J., & Feild, J. (2017). Quasi-experimental design for causal inference using Python and Apache Spark: A hands-on tutorial. Proceedings of the 7th International Conference on Learning Analytics and Knowledge (LAK '17), 13–17 March 2017, Vancouver, BC, Canada (pp. 502–503). New York: ACM. http://dx.doi.org/10.1145/3027385.3029428

*Molinaro, M., Steinwachs, M., Li, Q., & Guzman-Alvarez, A. (2017). Promoting instructor and department action via simple, actionable tools and analyses. In J. Greer, M. Molinaro, X. Ochoa & T. McKay (Eds.), Proceedings of the 1st Learning Analytics for Curriculum and Program Quality Improvement Workshop (PCLA 2016), 25 April 2016, Edinburgh, UK (pp. 34–38). Retrieved from http://ceur-ws.org/Vol-1590/paper-07.pdf

*Morse, R. K. (2014). Towards requirements for supporting course redesign with learning analytics. Proceedings of the 42nd

Annual ACM SIGUCCS Conference on User Services (SIGUCCS ’14), 2–7 November 2014, Salt Lake City, UT, USA (pp. 89–92). New York: ACM. http://dx.doi.org/10.1145/2661172.2661199
*Nguyen, Q., Rienties, B., & Toetenel, L. (2017). Unravelling the dynamics of instructional practice: A longitudinal study on learning design and VLE activities. Proceedings of the 7th International Conference on Learning Analytics and Knowledge (LAK ’17), 13–17 March 2017, Vancouver, BC, Canada (pp. 168–177). New York: ACM. http://dx.doi.org/10.1145/3027385.3027409
Nguyen, Q., Tempelaar, D., Rienties, B., & Giesbers, B. (2016). What learning analytics based prediction models tell us about feedback preferences of students. The Quarterly Review of Distance Education, 17(3) 13–33.
Norris, D. M., & Baer, L. L. (2013). Building organizational capacity for analytics. Louisville, CO: EDUCAUSE. Retrieved from https://library.educause.edu/resources/2013/2/building-organizational-capacity-for-analytics
Ocumpaugh, J., Baker, R., San Pedro, M., Hawn, M., Heffernan, C., Heffernan, N., & Slater, S. (2017). Guidance counselor reports of the ASSISTments college prediction model (ACPM). Proceedings of the 7th International Conference on Learning Analytics and Knowledge (LAK ’17), 13–17 March 2017, Vancouver, BC, Canada (pp. 479–488). New York: ACM. http://dx.doi.org/10.1145/3027385.3027435
Pardo, A., Dawson, S., Gašević, D., & Steigler-Peters, S. (2016). The role of learning analytics in future education models. Technical report. Telstra. Retrieved from https://www.telstra.com.au/content/dam/tcom/business-enterprise/industries/pdf/tele0126_whitepaper_5_spreads_lr_notrims.pdf
*Pardo, A., Ellis, R. A., & Calvo, R. A. (2015). Combining observational and experiential data to inform the redesign of learning activities. Proceedings of the 5th International Conference on Learning Analytics and Knowledge (LAK ’15), 16–20 March 2015, Poughkeepsie, NY, USA (pp. 305–309). New York: ACM. http://dx.doi.org/10.1145/2723576.2723625
Pardo, P., Mirriahi, N., Martinez-Maldonado, R., Jovanović, J., Dawson, S., & Gašević, D. (2016). Generating actionable predictive models of academic performance. Proceedings of the 6th International Conference on Learning Analytics & Knowledge (LAK ’16), 25–29 April 2016, Edinburgh, UK (pp. 474–478). New York: ACM. http://dx.doi.org/10.1145/2883851.2883870
Picciano, A. G. (2012). The evolution of big data and learning analytics in American higher education. Journal of Asynchronous Learning Networks, 16(3), 9–20.
Piety, P. J., Hickey, D. T., & Bishop, M. J. (2014). Educational data sciences: Framing emergent practices for analytics of learning, organizations, and systems. Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK ’14), 24–28 March 2014, Indianapolis, IN, USA (pp. 193–202). New York: ACM. http://dx.doi.org/10.1145/2567574.2567582
Polikoff, M. S. (2010). Instructional sensitivity as a psychometric property of assessments. Educational Measurement: Issues and Practice, 29, 3–14. http://dx.doi.org/10.1111/j.1745-3992.2010.00189.x
Prieto, L. P., Sharma, K., Dillenbourg, P., & Jesús, M. (2016). Teaching analytics: Towards automatic extraction of orchestration graphs using wearable sensors. Proceedings of the 6th International Conference on Learning Analytics and Knowledge (LAK ’16), 25–29 April 2016, Edinburgh, UK (pp. 148–157). New York: ACM. http://dx.doi.org/10.1145/2883851.2883927
Prinsloo, P., & Slade, S. (2014). Educational triage in open distance learning: Walking a moral tightrope. International Review of Research in Open and Distance Learning, 15(4), 306–331. 10.19173/irrodl.v15i4.1881
*Rangel, V. S., Bell, E. R., Monroy, C., & Reid Whitaker, J. (2015). Toward a new approach to the evaluation of a digital curriculum using learning analytics. Journal of Research on Technology in Education, 47(2), 89–104. http://dx.doi.org/10.1080/15391523.2015.999639
*Rienties, B., Boroowa, A., Cross, S., Kubiak, C., Mayles, K., & Murphy, S. (2016). Analytics4Action evaluation framework: A review of evidence-based learning analytics interventions at the Open University UK. Journal of Interactive Media in Education, 1, 2. http://dx.doi.org/10.5334/jime.394/
Sabourin, J., Rowe, J., Mott, B., & Lester, J. (2011). When off-task is on-task: The affective role of off-task behavior in narrative-centered learning environments. Proceedings of the 15th International Conference on Artificial Intelligence in Education (AIED ’11), 28 June–2 July 2011, Auckland, New Zealand (pp. 534–536). Springer. Retrieved from https://www.intellimedia.ncsu.edu/wp-content/uploads/sabourin-aied-2011.pdf http://dx.doi.org/10.1007/978-3-642-21869-9_93
Saqr, M., Fors, U., & Tedre, M. (2017). How learning analytics can early predict under-achieving students in a blended medical education course. Medical Teacher, 18, 1–11. http://dx.doi.org/10.1080/0142159X.2017.1309376
Schneider, D., Class, B., Benetos, K., & Lange, M. (2012). Requirements for learning scenario and learning process analytics. In T. Amiel & B. Wilson (Eds.), Proceedings of the World Conference on Educational Multimedia, Hypermedia & Telecommunications (EdMedia 2012), 26–29 June 2012, Denver, Co, USA (pp. 1632–1641).

Association for the Advancement of Computing in Education (AACE). Retrieved from https://archive-ouverte.unige.ch/unige:37258
Schön, D. (1983). The reflective practitioner: How professionals think in action. New York: Basic Books.
Sclater, N. (2014). Code of practice for learning analytics: A literature review of the ethical and legal issues. JISC, Bristol. Retrieved from http://repository.jisc.ac.uk/5661/1/Learning_Analytics_A-_Literature_Review.pdf
Sclater, N., Peasgood, A., & Mullan, J. (2016). Learning analytics in higher education: A review of UK and international practice. JISC, Bristol. Retrieved from https://www.jisc.ac.uk/sites/default/files/learning-analytics-in-he-v2_0.pdf
Sclater, N., Webb, M., & Danson, M. (2016). The future of data-driven decision-making. JISC, Bristol. Retrieved from https://www.jisc.ac.uk/reports/the-future-of-data-driven-decision-making
Sergis, S., & Sampson, D. G. (2017). Teaching and learning analytics to support teacher inquiry: A systematic literature review. In A. Peña-Ayala (Ed.), Learning analytics: Fundaments, applications, and trends — A view of the current state of the art to enhance e-learning (pp. 25–63). Cham, Switzerland: Springer. 10.1007/978-3-319-52977-6_2
Shacklock, X. (2016). From bricks to clicks: The potential of data and analytics in higher education. Higher Education Commission. Retrieved from http://www.policyconnect.org.uk/hec/sites/site_hec/files/he_commission_press_release_-_from_bricks_to_clicks.pdf
Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 46(5), 30–40.
Simon, H. (1957). A behavioral model of rational choice. In Models of man, social and rational: Mathematical essays on rational human behavior in a social setting. New York: Wiley.
Simon, H. A. (1967). Motivational and emotional controls of cognition. Psychological Review, 74(1), 29–39. http://dx.doi.org/10.1037/h0024127
Simon, H. A. (1996). The sciences of the artificial, 3rd ed. Cambridge, MA: MIT Press.
Simon, H. A. (1993, May). Altruism and economics. The American Economic Review, 83(2), 156–161.
*Souza, J. M. (2013, March 14). Embedded assessment and evidence-based curriculum mapping: The promise of learning analytics. NILOA Newsletter. Retrieved from http://fisherpub.sjfc.edu/pharmacy_facpub/23/
Strader, R., & Thille, C. (2012). The open learning initiative: Enacting instruction online. In D. G. Oblinger (Ed.), Game changers: Education and information technologies (pp. 201–213). Louisville, CO: EDUCAUSE.
*Strunk, V., & Willis, J. (2017, February 13). Digital badges and learning analytics provide differentiated assessment opportunities. EDUCAUSE Review. Retrieved from https://er.educause.edu/articles/2017/2/digital-badges-and-learning-analytics-provide-differentiated-assessment-opportunities
Sundorph, E., & Mosseri-Marlio, W. (2016). Smart campuses: How big data will transform higher education. Reform report. London, UK. Retrieved from http://www.reform.uk/publication/smart-campuses/
Swan, K. (2012). A special issue on learning analytics. Journal of Asynchronous Learning Networks, 16(3), 322–323.
Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2017). Towards actionable learning analytics using dispositions. IEEE Transactions on Learning Technologies, 10, 6–16. http://dx.doi.org/10.1109/TLT.2017.2662679
Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. New Haven: Yale University Press.
Toffler, A. (1980). The third wave. New York: Bantam Books.
*Valkanova, N., Cukurova, M., Berner, A., Avramides, K., & Mavrikis, M. (2016). Opening the black box of practice-based learning: Human-centred design of learning analytics. CEUR Workshop Proceedings, 1601, 40–46.
van Barneveld, A., Arnold, K. E., & Campbell, J. P. (2012). Analytics in higher education: Establishing a common language. EDUCAUSE Learning Initiative. Louisville, CO: EDUCAUSE. Retrieved from http://net.educause.edu/ir/library/pdf/ELI3026.pdf
van Harmelen, M., & Workman, D. (2012). Analytics for learning and teaching. JISC Cetis Analytics Series, 1(3). Retrieved from http://publications.cetis.org.uk/wp-content/uploads/2012/11/Analytics-for-Learning-and-Teaching-Vol1-No3.docx
van Leeuwen, A. (2015). Learning analytics to support teachers during synchronous CSCL: Balancing between overview and overload. Journal of Learning Analytics, 2(2), 138–162. http://dx.doi.org/10.18608/jla.2015.22.11
*van Leeuwen, A., van Wermeskerken, M., Erkens, G., & Rummel, N. (2017). Measuring teacher sense making strategies of learning analytics: A case study. Learning: Research and Practice, 3(1), 42–58. http://dx.doi.org/10.1080/23735082.2017.1284252
Waddington, R., & Nam, S. (2014). Practice exams make perfect: Incorporating course resource use into an early warning system. Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK ’14), 24–28 March 2014, Indianapolis, IN, USA (pp. 188–192). New York: ACM. http://dx.doi.org/10.1145/2567574.2567623
Wagner, E., & Ice, P. (2012). Data changes everything: Delivering on the promise of learning analytics in higher education.

EDUCAUSE Review, 47(4), 32–42.
Wiener, N. (1951). Cybernetics and society. New York: Executive Techniques.
*Wilson, M., & Scalise, K. (2016). Learning analytics: Negotiating the intersection of measurement technology and information technology. In M. J. Spector, B. B. Lockee, & M. D. Childress (Eds.), Learning, design, and technology (pp. 1–23). Springer, Cham. http://dx.doi.org10.1007/978-3-319-17727-4_44-1
*Wise, A. (2014). Designing pedagogical interventions to support student use of learning analytics. Proceedings of the 4th International Conference on Learning Analytics and Knowledge (LAK '14), 24–28 March 2014, Indianapolis, IN, USA (pp. 203–211). New York: ACM. http://dx.doi.org/10.1145/2567574.2567588
*Wise, A., Vytasek, J., Hausknecht, S., & Zhao, Y. (2016). Developing learning analytics design knowledge in the "middle space": The student tuning model and align design framework for learning analytics use. Online Learning Consortium, 20(2), 155–182.
Wong, W. Y., & Lavrencic, M. (2016). Using a risk management approach in analytics for curriculum and program quality improvement. In J. Greer, M. Molinaro, X. Ochoa, & T. McKay (Eds.), Proceedings of the 1st Learning Analytics for Curriculum and Program Quality Improvement Workshop (PCLA 2016), 25 April 2016, Edinburgh, UK (pp. 10–14).
*Xie, C., Zhang, Z., Nourian, S., Pallant, A., & Bailey, S. (2014). On the instructional sensitivity of CAD logs. International Journal of Engineering Education, 30(4), 760–778.
*Xing, W., & Goggins, S. P. (2015). Student assessment in small groups: A spectral clustering model. Proceedings of iConference 2015: Create, Collaborate, Celebrate, 24–27 March 2015, Newport Beach, CA, USA. Illinois Digital Environment for Access to Learning and Scholarship (IDEALS). Retrieved from https://www.ideals.illinois.edu/bitstream/handle/2142/73711/36_ready.pdf?sequence=2

APPENDICES

Appendix I

Databases used: Google Scholar, Academic Search Premier, Education Resource Information Center (ERIC), Teacher Reference Center, and Scopus.
Search phrases:

"Learning analytics" AND	**Google Scholar** (AND "Intervention") Since 2007 —Games —MOOC	**Academic Search Premier Education Resource Information Center (ERIC) Teacher Reference Center**	**Scopus**
actionable insights	30	1 (1)	6 (11)
actionable data	68	0	0 (1)
actionable intelligence	110	1 (1)	3 (5)
actionable knowledge	50	0	0
actionable information	146	0	6 (6)
actionable steps	5	0	0
actionable value	1	0	0
actionable measures	1	0	0
actionable strategies	7	0	0
actionable feedback	32	0	1 (1)
actionable interventions	6	0	0
Intervention	–	32 (42)	100 (146)
	300	34	116
		130 (150)*	
	353 (300+130=430)		

Note: The number in parenthesis refers to the actual number of results before the application of exclusion criteria. Duplicates were removed automatically first and manually second.

Appendix II

	Total:		353
A	Academic & Institutional	20	67 Data mining Prediction
	Business Intelligence, Big Data, Data-driven Decision-making, Data Mining	47	
B	Teacher, instructor	9	39 Learning Design & Support structure
	Curriculum, Assessment,	14	
	Design	12	
	Tutoring, Student support	4	
C	Student behaviour, dispositions	9	115 Prediction Social analysis
	Engagement	11	
	Performance	7	
	Collaboration	12	
	Prediction, Early-Warning	64	
	Self-regulated Learning	12	
D	Specific formats	15	
	LMS	10	
	Social media	5	Social Network Analysis
	Specific Technology	12	
	Semantic	8	Semantic analysis
	Writing	13	Semantic analysis
	Visualization	18	Visual data
	Ethics	14	