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Learning analytics performance improvement design (LAPID) in higher education: Framework and concerns

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Abstract

Learning Analytics Dashboards (LAD) promise to disrupt the Higher Education (HE) teaching practice. Current LAD research portrays a near future of e-teaching, empowered with the ability to predict dropouts, to validate timely pedagogical interventions and to close the instructional design loop. These dashboards utilize machine learning, big data technologies, sophisticated artificial intelligence (AI) algorithms, and interactive visualization techniques. However, alongside with the desired impact, research is raising significant ethical concerns, context-specific limitations and difficulties to design multipurpose solutions. We revisit the practice of managing by the numbers and the theoretical origins of dashboards within management as a call to reevaluate the "datafication" of learning environments. More specifically, we highlight potential risks of using predictive dashboards as black boxes to instrumentalize and reduce learning and teaching to what we call "teaching by the numbers". Instead, we suggest guidelines for teachers' LAD design, that support the visual description of actual learning, based on teachers' prescriptive pedagogical intent. We conclude with a new user-driven framework for future LAD research that supports a Learning Analytics Performance Improvement Design (LAPID).

Keywords: Learning Analytics (LA), Learning Analytics Dashboards (LAD), Learning Analytics Performance Improvement Design (LAPID), performance measures, e-teaching effectiveness, ethics and privacy in learning analytics, pedagogical intent.

Introduction

Learning Analytics (LA), specifically the Learning Analytics Dashboards (LAD), are the newest entrants to the Higher Education (HE) industry. This study critically examines the promise of LAD to improve e-teaching. LAD is commonly described as "displays that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann et al., 2017, p. 37). LAD research evolved in recent years as a distinct, sub-topic of interest, within a broader research perspective that investigates digital traces of learners, namely 'Learning Analytics'. Learning Analytics can be defined as 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" (Siemens & Gašević, 2012, p. 1). Ferguson (2012) included learners' footprints in online learning environments and their personal data, interaction data, and academic information as the necessary sources for LA.

We begin our critical examination of LAD with a culturomics analysis (Bohannon, 2011; Rogers, 2019; Silber-Varod, Eshet-Alkalai, & Geri, 2016, 2019; Song & Xu, 2019; Soper & Turel, 2012) of the emergence of LA and LAD within HE research. Culturomics is a form of computational lexicology that studies human behavior and cultural trends through a quantitative analysis of digitized texts. We show an association between LA and Massive Open Online Courses (MOOCs) research. This association, we argue, raises concerns as to the research community bias toward MOOCs data rather than traditional HE learning environments. Moreover, we challenge instrumental uses of these new forms of data to what we phrase as the perils of "Teaching by the Numbers". Contrary to the predictive dashboards that create organizational black boxes, we suggest a more meaningful descriptive approach to LAD that reflects pedagogical intent. Furthermore, we suggest focusing performance measurement on "dynamic" rather than "static" data resources. This dichotomy reflects the two major information systems within Higher Education Institutions (HEI). Whereas static data is associated with admission data and past records, Virtual Learning Environments (VLE) or Learning Management Systems (LMS) store mainly dynamic learning traces and reflect the instructional design of e-teachers.

We conclude with a call to systematically define the evolving multidimensional space of LAD research for HEI. Within this research space, we identify five initial dimensions: Purpose, Users Identity, Data Velocity, Measurement and LA Culture. We call this new LAD research framework, Learning Analytics Performance Improvement Design under the acronym LAPID. Finally, we demonstrate how the LAPID framework can be applied to teachers' performance improvement. We claim that the visual design of LAPID for teachers should allow them to keep their eyes on the road and continuously improve the implementation of their pedagogical intent.

A Culturomics Analysis of Learning Analytics Research

The term 'culturomics' was originally coined in 2010 by the Google Books team who promoted culturomics as a research method that "extends the boundaries of rigorous quantitative inquiry to a wide array of new phenomena spanning the social sciences and the humanities" (Michel et al. 2010, p. 1). A culturomics analysis reveals that the year 2012 may be identified as the tipping point for the acceptance of learning analytics in HE research. Applying a culturomics research methodology (Rogers, 2019; Silber-Varod et al., 2019; Song & Xu, 2019), we used the Google Scholar search engine, as a reliable source for evaluating the frequency of using specific terms within the corpus of research papers and books. We conducted a year-by-year search, for the period 2000-2018, on the terms: 'learning analytics', 'dashboard', and Massive Open Online Courses – 'MOOCs', within the context of 'higher education'. These searches returned a reliable estimation of the frequency of referencing these topics.

Figure 1 presents the absolute frequency of research papers or books (hereafter, publications) that include the term 'learning analytics' at least once. Over the years 2000-2018 there were about 26,000 such documents. The term 'learning analytics' started getting the attention of researchers around 2010, with 117 publications containing this term, followed by 374 mentions in 2011, and 936 publications in 2012. As Figure 1 shows, ever since, research interest in 'learning analytics' rapidly increased and reached approximately 6,000 publications containing this term in 2018. Next, we conducted a search of the two terms: 'learning analytics', 'dashboard'. The results in Figure 1, LA and LAD Culturomics, reveal that 'dashboard' was present at about 10% of the publications, which included the term 'learning analytics' during its emergence in 2010-2012, and has grown to a steady presence of approximately 15% during 2015-2018.

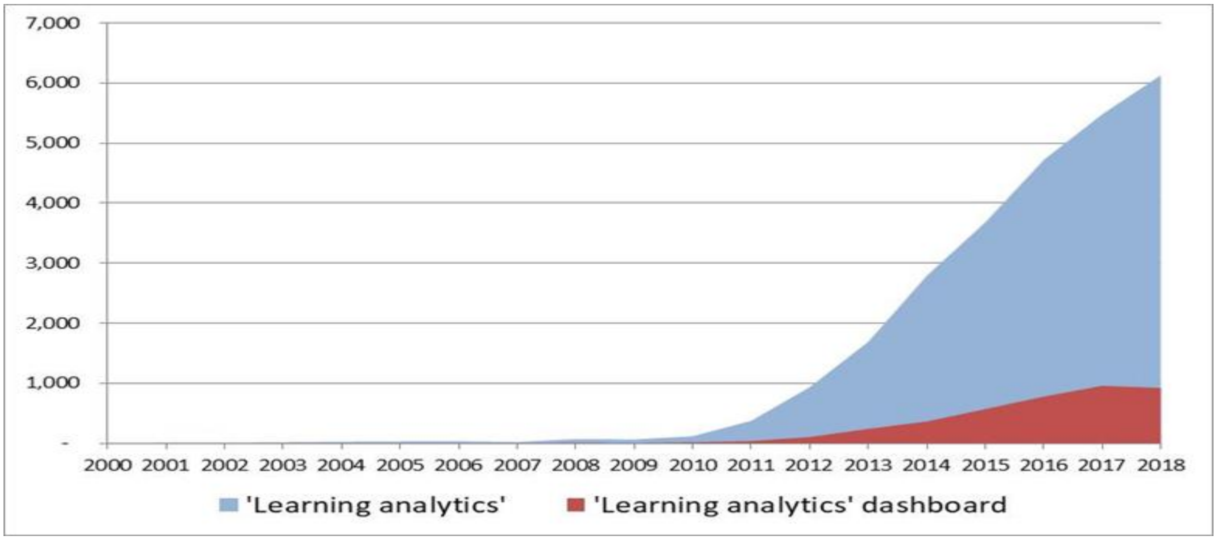

Figure 1. LA and LA Dashboards Culturomics. The emergence of LA and LAD within the context of LA research. Based on frequency of search phrases in Google Scholar publications per year (2000-2018)

Subsequently, we focused on 'higher education' and 'dashboard' within the context of 'learning analytics', which is shown in Figure 2. The highest line in Figure 2 presents the frequency of 'learning analytics' in Google Scholar publications during the years 2000-2018. The line below represents the frequency of the term 'higher education' within the context of 'learning analytics'. Ever since the inauguration of LA research, about 50% of the publications contained the term 'higher education', and the proportion is slowly rising (56% in 2018). Further below, the third line shows the frequency of dashboard within LA. Beginning in 2012, with 11% of the publications, it shows a stable proportion of about 15% during 2013-2018. This lower proportion of dashboard mentions relatively to HE mentions within the context of LA is expected, since HE represents a much broader setting. Nevertheless, the lowest line is the most interesting, since it combines both HE and dashboards within the context of LA. Since 2012, the proportion of HE within publications that contain both LA and dashboards is around 60%, and slightly rising (63% in 2018).

Looking at the situation that Figure 2 portrays, the immediate question is: Why? Why does the majority of LA and dashboard research is dealing with higher education? We conjecture that the reason is MOOCs, which are in the milieu of HE and lifelong learning. Therefore, we conducted an analysis that contains MOOCs, and the results are shown in Figure 3. Since 2014, more than

40% of research publications that contain the terms LA, HE, and dashboard, also contain the term MOOCs. We further conjecture that one of the main reasons for the presence of MOOCs in these publications is that the big data, which MOOCs collect as they operate online, serves for LA research, and dashboards are a main tool for analyzing these high volumes of data. Furthermore, it may be easier to get the approval of ethics boards to use MOOCs data rather than to use data of students enrolled in formal HE, or pupils who are under 18 years old.

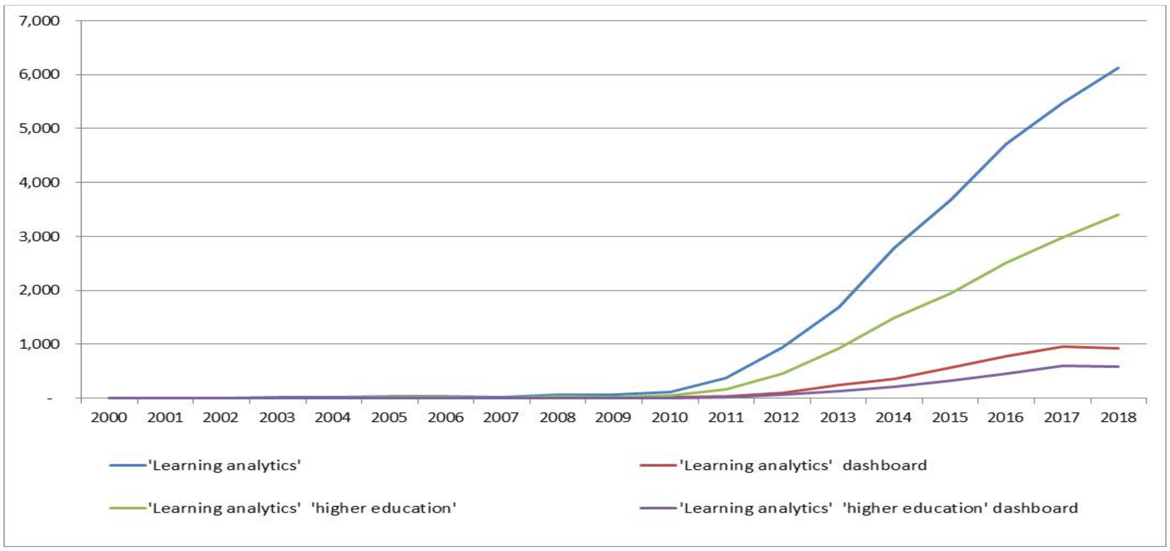

Figure 2. Frequency of Google Scholar publications per year (2000-2018) containing the terms: 'higher education' and 'dashboard' within the context of 'learning analytics'

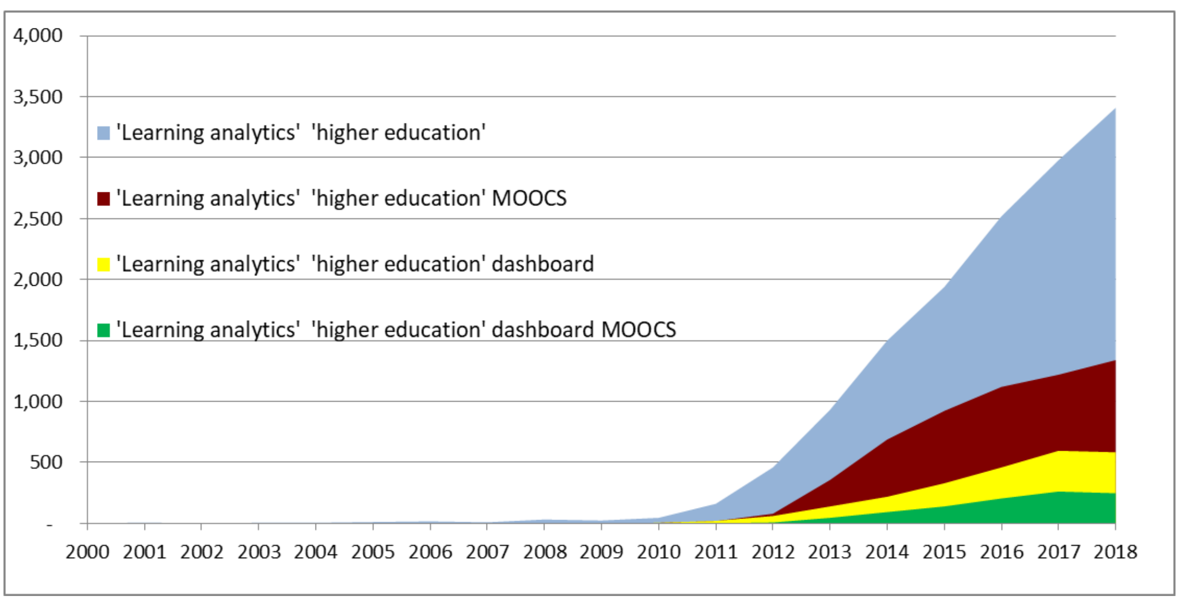

Figure 3. Visualization of MOOCs and dashboard research within the context of learning analytics and higher education, based on Google Scholar publications per year (2000-2018)

The Perils of "Teaching by the Numbers"

Having presented its rise and significant potential to improve learning, LA and LAD have also raised significant concerns. These warning signs focus mostly on the potential risks that LA and LAD can inflict on the traditional teaching practice. Gašević, Dawson, and Siemens (2015) stated that "The design of dashboards can lead to the implementation of weak and perhaps detrimental instructional practices as a result of promoting ineffective feedback types and methods" (p. 69). Moreover, West et al. (2015) claim that instead of using LAD strictly for "educational dimensions of learning environments, curriculum design, pedagogical intent, and student experience, HEI might tend to use the same data resources for supporting business dimensions of human resources, marketing, performance management, and workload" (p. 48). Therefore, we argue that this current cultural hype of HEI to adopt LA and LAD is very similar to the past experience with business analytics and dashboards. We trace the long tradition of using analytics and dashboards for business performance measurement back to the early years of the twentieth century, with managerial practices that were created for monitoring the manufacturing of Ford's model T. As early as the emergence of the first computerized information systems that were used by the biggest business organizations, in the early 1970s, the use of dashboards (not necessarily visual ones) was a common practice. Massachusetts Institute of Technology (MIT) marketing researcher John Little was one of the first to raise concerns about the prospects that analytic models and dashboards present to senior management. He argued that "Data is prolific but usually poorly digested, often irrelevant and some issues entirely lack the illumination of measurement" (Little, 1970, p. 466).

During the 1980s, Kaplan (1984) criticized the practice of running corporations by the numbers and claimed that "Yesterday's accounting undermines production" (p. 1). The proliferation of organizational information systems offered organizations ample data, which provided managers with more tools to manage by the numbers. On the one hand, some of these data were transformed into useful information, which improved performance. However, on the other hand, the availability of so much data made it harder to determine which data is relevant and should be collected, processed, stored, and presented to the users at the right time (Goldratt, 1991). The network era exacerbated the challenge (Davenport & Beck, 2001), as organizations started collecting too much data, since it was unclear which data could be turned into valuable information (Geri & Geri, 2011). Within the scope of Education, LMS may be considered as raising similar challenges. Therefore, we caution against hasty HEI adoptions of a business culture as is under the erroneous slogan of 'teaching by the numbers'.

One more concern, which might be overlooked, is cybersecurity and the need to protect such sensitive data. Business organizations are exposed to vulnerabilities and breaches that entail substantial financial and intellectual property losses, which are caused by employees due to poor cybersecurity skills (Carlton, Levy, & Ramim, 2019). Many educational institutions do not have the awareness, as well as the resources needed to effectively secure highly sensitive LA and LAD derivative outcomes such as retention figures, student's success predictions, and managerial dashboards.

Another risk of managing by the numbers is using the available easy to measure data, which is not necessarily the appropriate performance measure for evaluating progress towards achieving the goal. We are already seeing this common phenomenon in the context of MOOCs evaluation. The generally used measure for evaluating the performance of a specific MOOC is the rate of registrants who completed the MOOC. There are major concerns regarding the typical 5% completion rate of MOOCs. However, as Kalz, Kreijns, Walhout, Castaño-Munoz, Espasa, and Tovar (2015) argued, MOOCs registrants have diverse goals; therefore, measuring MOOCs' success by the general completion rate is wrong, as well as misleading. Henderikx, Kreijns, and Kalz (2017) suggested measuring the success of lifelong learning via MOOCs by learner-centered measures, such as satisfaction and fulfillment of learner intentions. Cognitive measurements such as the impact of video length on the attention span of learners (Geri & Winer, 2017), can further indicate how learning contexts affect learning patterns.

One of the major risks of using the wrong performance measures is that it encourages people to erroneously act in ways that impede reaching the goal (Goldratt & Cox, 1986). People adjust their behavior to the manner in which their performance is measured. Performance measures, which sometimes are visualized by dashboards, are supposed to encourage people to behave in a way that promotes the organization's goal (Geri & Ronen, 2005). However, although the goal of business organizations is supposedly well defined, i.e., maximize shareholder value (Copeland, Koller, & Murrin, 2000; Ronen, Lieber, & Geri, 2007), the goal of HEI is more ambiguous. Furthermore, people may perceive conflicting goals of the same organization, or may narrowly focus on achieving the purpose of a sub-unit within the organization, while decreasing the performance of the organization as a whole.

For example, consider the controversial case of the target set in 2000 by the National Health Service (NHS) in England, which instituted a maximum length of Emergency Department (ED) stay of four hours, known as the 4-hour rule. The intentions of the NHS were good. However, since it did not matter whether a patient stayed two hours or almost four hours, it led to higher proportion of patients leaving the ED within the last 20 minutes before the 4-hour cutoff, particularly, the elderly (Mason, Weber, Coster, Freeman, & Locker, 2012).

Keeping these words of caution in mind, we focus the discussion on the specific visual aspects of representing data, namely dashboards. Within the scope of higher education, these tools provide even more opportunities to collect students' log data through the LMS or VLE and other external repositories and may therefore further encourage the tendency and current call to "teach by the numbers". Finally, to counter the bias towards MOOC research contexts, we wish to limit our discussion to the design of LAD for teachers within traditional HEI.

Dashboards for Teachers

Dashboards can support the continuous program improvement for marketing purposes by presenting the measurement of engagement across the customer lifecycle (Earley, 2016). However, can HEI mimic marketers' requirements? What should be the goal of HE faculty members? What measures should be presented to teachers? To answer these questions, we suggest re-visiting the origins of the dashboard metaphor and seek performance-driven metrics that can improve the e-teaching practice.

Originally, the term ‘dashboard’ was used to define “a barrier of wood or leather fixed at the front of a horse-drawn carriage or sleigh to protect the driver from mud or other debris "dashed up" (thrown up) by the horses’ hooves” (Dashboard, 2007, para 1). The term dashboard can later be referenced to the automobile industry. The car’s display dashboards included an array of simple controls instrumentation to show speed, fuel level and oil pressure, climate control and entertainment systems. These dashboards provide drivers with the ultimate driving experience of keeping the eyes on the road while occasionally making a brief glimpse at relevant information. Additional alerts mechanisms trigger sounds and lights in the occurrence of an event that requires the immediate attention of the driver.

It is obvious that dashboards allow drivers to improve their performance. However, drivers are not the only ones to look at these dashboards; consider passengers, car technicians and maybe future control centers that get dashboard data from autonomous cars. Can these secondary users make sense of driver-dashboards? Going back to the HE context of using dashboards, we argue that teachers need a very fine tailored design to make use of dashboards while keeping an eye on their students throughout the semester. What about additional HEI stakeholders? We wish to elaborate the discussion on this question.

Jørnø and Gynther (2018) suggested that “actionable insights” promise to “marry the practitioner’s need for a concrete focus on how to utilize LA with the researcher’s ambition to operationalize theory” (p. 198). However, they showed that current research uses concepts such as “risk calculations” “dispositional indicators”, and “performance indicators” without specifying to which end they are applied. This, they claimed, creates an institutional reality in HE where data collection is tacitly tied to a plethora of institutional goals. Jørnø and Gynther (2018) specifically splited students log data between student behavior that leads to a degree and student behavior that leads to learning. However, they did not preach for a simple dichotomy between teachers and administrators but rather show the need to explicitly define the “multiple audiences for whom the data collected has to serve many competing goals” (Jørnø & Gynther, 2018, p. 202). Therefore, we argue that the design of every dashboard within the HE context should explicitly define its lead ‘driver’.

Bichsel (2012) claimed that the complex landscape of HEI creates barriers that prevent data from being used systematically and effectively despite increasing interest in employing learning analytics to increase the quality of teaching and learning. This, Bichsel (2012) argued, raises the need to further investigate “data quality, data ownership, data access, and data standardization” along with organizational culture, and expertise available to implement learning analytics” (p. 15). Bichsel showed that within current HEI, teachers need to “compete” with other stakeholders on the primacy of dashboard design.

After exploring the multi-purpose potential of dashboards to various HEI stakeholders, we wish to raise the challenge of interpretation among teachers faced with LAD. Jørnø and Gynther (2018) argued that without an appropriate statistical background, teachers find it almost impossible to connect data with their teaching. The challenge of interpreting data is also common within the business sector. A recent survey of 2,719 managers in organizations from around the world, finds that the foremost barriers to creating business value from analytics are the difficulties to translate analytics back into business actions (Ransbotham, Kiron, & Prentice, 2015).

We follow Lockyer, Heathcote, and Dawson (2013) who called to consider learning design as a "form of documentation of pedagogical intent that can provide the context for making sense of diverse sets of analytic data" (p. 1,439). They further claimed that all learning designs include: a set of resources, tasks and support mechanisms to assist in the provision of resources and the completion of the tasks. Finally, they suggested to distinguish between two types of analytics: 'Checkpoint Analytics' and 'Process Analytics'. Checkpoint analytics refers to student login behaviors and provide teachers with indicators about students' commencing of a given learning sequence. We prefer to name the Checkpoint Analytics as 'Visits' to reflect students' initial acquaintance with actual learning materials and assessment tasks. Process analytics provide "direct insight into learner information processing and knowledge application" (Lockyer et al., 2013, p. 1,448). Again, we suggest amending this definition to assessment of task 'Completion'. With a clear distinction between 'Visits' and 'Completions', a strong link is set between LA and the instructional design of courses. Having presented the multi-purpose of dashboards to various organizational stakeholders and the integral difficulty to make sense of data, we wish to add a third layer of concern, namely the black box nature of predictive dashboards.

Predictive Dashboards as Black Boxes

Pasquale (2015) argued that the last decade has witnessed the rise of a black-box society. He showed that algorithms, based on sophisticated machine learning models trained on big data, are able to predict individuals' behavioral patterns. However, these algorithms remain unintelligible to most teachers, and appear as back boxes. HEI have only recently joined this trend, following the footprints of business applications such as credit risk, health status, digital marketing, and online trading. We argue that predictive dashboards (PD) within HEI teaching environments reflect a problematic black box approach for various pedagogical intervention initiatives.

Previously, PD relied mostly on static risk factors (Scholes, 2016) that are largely historical and not expected to significantly change over time. Institutions can relatively easily extract this information from the student admissions office and aggregate it within common business intelligence infrastructure. Static data includes student records such as students' grades, course evaluations, and basic demographic data such as age, gender, religion, address, prior degrees, high school records and sometimes family financial records (when financial aid is offered).

Recent studies raise ethical concerns as to the relevance of static risk factors. Scholes (2016) claimed that "static risk factors are not usually easily amenable to change" (p. 951). Students that were flagged as "high risk" may keep this status regardless of any risk-reducing efforts they have made over this time. A more fundamental concern is raised by Heath (2014) claiming that students' consent to provide their personal demographic data in the student application, admission, and administration context do not necessarily apply in any other context. Specifically, they do not necessarily agree to the flow of their private information to secondary uses of data for learning analytics activities. This claim is also consistent with recent European Union (EU) General Data Protection Regulations (GDPR) (European Commission, 2019).

Vialardi, Bravo, Shafti, and Ortigosa (2009) cautioned that predictive models that derive data stored within institutional information systems can be directly associated with an individual student identity. This, they claimed, may be in conflict with government and institutional policies that may impose strict regulations to ensure privacy and anonymity of this data, mainly to teachers that need to solely focus on course-specific achievements.

From a statistical perspective, a recent cross-institutional study shows that learning design activities strongly influence academic retention (Rienties & Toetenel, 2016). Moreover, this study shows that the primary predictor of academic retention is the relative amount of communication activities throughout the learning module. Furthermore, using predictive technologies may raise the potential risk of biases in machine learning algorithms. These risks have already been presented in medical contexts where machine learning–based clinical decision support tools, were found to be over relaying on algorithms based on biased data that do not provide information that is clinically meaningful (Gianfrancesco, Tamang, Yazdany, & Schmajuk, 2018).

We suggest that these ethical concerns and statistical findings should eventually lead HEI towards a self-limiting LA culture that minimizes the use of static data resources for teaching purposes. A good alternative might be the use of more dynamic data resources that can be retrieved from VLE or LMS. Research focusing on dynamic data stresses the importance of aligning LA with the instructional design of courses. Lockyer et al. (2013) argued that learning design reflects the pedagogical intent of teachers and can, therefore, provide the required context for making sense of diverse sets of analytic data. Corrin et al. (2015) claimed that learning analytics delivers data to teachers in ways that can inform the design and facilitation of learning activities. Choosing dynamic rather than static information resources can therefore, mitigate the ethical and statistical findings, while supporting the justification to collect, and analyze student logs.

We further claim that teachers' focus on minimizing dropouts does not necessarily align with the pedagogical goals of continuously improving the instructional design of their courses and teaching practices. Moreover, we propose that presenting teachers with retention PD might lead them to adjust their teaching practice to the manner in which their performance is measured. Consequently, this might lead to a conflict with their mission to provide the appropriate scope, quality, and difficulty levels of scholarly education. Therefore, we suggest adopting a descriptive rather than a predictive approach for continuously improving the teaching practice. Such an approach may replace the black box culture with understandable descriptive, rather than predictive, dashboards. These descriptive dashboards should visually reflect the pedagogical intent of teachers and their learning design. We suggest that HEI can cautiously adopt PD as part of their student support teams (SST). PD can trigger academic counseling, administrative and career advice and orientation initiatives for new students who can benefit from sharpening their learning skills. SST have the broadest organizational perspective on all prior communications with each student and can therefore, provide a single point of contact to all the HEI services. Only in specific cases where content-related difficulties occur, can students be referred by SST specialists to their teachers for content-specific assistance. PD can also support managerial decisions for various administrative departments such as estimating future registrations and the effectiveness of marketing campaigns. This culture of defining useful black box applications of LA and minding their harmful risks is the third layer of concern.

Discussion: A Blueprint for a LAPID Model

Having presented the three layers of concern and several suggestions to mitigate their potential harmful effects, we conclude with a call to systematically map the evolving multidimensional space of LAD research for HEI. We call this new LAD research framework, Learning Analytics Performance Improvement Design, under the acronym LAPID. Whereas the LAPID framework can be applied to various HEI stakeholders, we demonstrate its application to improving teachers' performance. However, in order to generalize the LAPID framework to additional HEI stakeholders, we wish to present five initial dimensions: Purpose, Users Identity, Data Velocity, Measurement and LA culture.

The intent of dashboards varies according to the various stakeholders of HEI. Ransbotham et al. (2015) defined three types of analytics: descriptive, predictive, and prescriptive. Each type of research intent leads to a different dashboard approach. We showed that regardless of their type dashboards by nature, provide guidance and direct the performance of their users, and hence direct the improvement of the measurements. The 'Purpose Dimension' will, therefore, deal with the users' intent and business goals. Only after these have been clearly defined, can further design considerations take place with a choice of the appropriate type of analytics to drive the performance improvement: descriptive, predictive, and prescriptive. A descriptive LAD design focuses on the visual manifestation of the business or pedagogical model or structure. The predictive perspective of LAD design provides future estimation of quantifiable goals based on current measurements. Finally, the prescriptive LAD supports a clear call to action and decision making as a desired practical result driven outcome.

Defining the primary users of every LAD is paramount. Under a user-driven-design, every type of user is provided with a tailored dashboard that supports its unique organizational perspective. Moreover, 'Users Dimension' addresses for each LAD its accessibility rights, privacy of its users' data, and accuracy. We stress the concern of adding conflicting measures of stakeholders from different sub-unit within the organization. Therefore, LAD design should initiate with a clear understanding of how the various user-driven LAD design can add up to improve the performance of the organization as a whole.

Having presented the limitation of black box predictive analytics against the advantages of descriptive LAD for teachers, we suggested adopting a self-limiting policy for the use of static data and favoring the use of dynamic data that is gathered throughout student's engagements with the VLE. However, for marketing, financial purposes, and student support initiatives, these parameters might provide valuable insights. The 'Data Velocity Dimension' calls to evaluate the nature of the data to be used for analysis. This call is also backed by the abovementioned ethical regulations, organizational policies and statistical considerations that distinguish between the two types of students' data velocity dynamic and static.

The 'Measurement Dimension' presents the challenge of selecting and defining the appropriate criteria for collecting and aligning, and finally measuring relevant data. With the current abundance of data sources and endless opportunities to collect students' digital footprints, we conceptualized the LAPID guidelines for selecting the relevant data measurements for teachers. Finally we presented the historic risk of managing by the numbers and suggested to clearly state the justification or purpose of measurement for every parameter.

The fifth dimension focuses on the LA culture as a prerequisite to the organizational adoption of LAD within HEI. The SHEILLA (Supporting Higher Education to Integrate Learning Analytics) framework was developed to assist HEIs to develop institutional policies for LA. This organizational-wide perspective is aimed at meeting "individual institutions' unique contexts and ensures a responsible and effective use of student data for LA" (Tsai Moreno-Marcos, Tammets, Kollom, & Gašević, 2018 p. 321). Within the specific context of LAD, we indicated that failing to formulate an organizational LA culture, might lead to conflicting LAD adoption among sub-units while decreasing the performance of the organization as a whole. A LA cultural change might derive from HEI core values, the strategic potential of integrating relevant and meaningful LA measurements and LAD into current practices.

Whereas current cultural research on LA adoption focuses on the organizational level, we agree with Russ (2016) that there is an urgent need to evaluate the capital gained by the entropy of information, or what he calls the 'new gold'. Within the widest cultural context of HEI, the entropy of student data, requires a broad multidisciplinary and transdisciplinary discussion and synthesis towards what might be seen as a new form of intellectual capital.

Having presented the initial dimensions of the LAPID framework and demonstrated its application to teachers, we conclude with some future research opportunities.

Conclusion

Guri-Rosenblit (2018) argued that in most HE institutions, new technologies are used mainly for add-on functions and not for substituting face-to-face encounters or for an intensive web-enhanced teaching. She suggests that the discourse and research on e-learning should be complemented by an "e-teaching co-equal", focusing on the new roles that teachers should acquire in order to effectively manage e-learning practices of their students. Following this call, we focused this paper on developing guidelines for better use of LAD within HE settings.

We used the acronym LAPID to make sense of the ever growing body of LAD theory, evidence based research and practices. The LAPID model provides guidelines for HE institutions, as they set out to the long maturity process of internally adopting LAD and tailoring their dashboard design to their online offerings and organizational LA stakeholders. We suggest to clearly distinguish between prescriptive and predictive dashboards and to avoid a black-box perception of the e-teaching practice. Moreover, we propose that dashboards for teachers should reflect the tight links between instructional design and actual learning. These guidelines may lead to effective measurement of performance that supports the continuous improvement of teaching and learning practices.

Future work will further develop the LAPID framework for additional audiences within HEI. Additionally, there is a growing need to better understand the user experience and user interface design considerations of LAPID implementations. We also wish to deepen the philosophical foundations of LAPID as a safeguard against the tendency to instrumentalize teaching into a "teaching by the numbers" practice. Finally, we wish to show evidence support for the actual effectiveness of the LAPID framework and its ability to sustain the performance improvement of twenty-first century higher education institutes.

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