LEARNING ANALYTICS AS A CORE COMPONENT FOR HIGHER EDUCATION DISRUPTION: GOVERNANCE STAKEHOLDER

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ABSTRACT

Higher education institutions are at this stage, on the one hand, faced with challenges never seen before and, on the other hand, their action is moving very rapidly into digital learning spaces. These challenges are increasingly complex because of the global competition for resources, students and teachers. In addition, the amount of data produced inside and outside higher education institutions has grown exponentially, so more and more institutions are exploring the potential of Big Data to meet these challenges. In this context, higher education institutions and key stakeholders (students, teachers, and governance) can derive multiple benefits from learning analytics using different data analysis strategies to produce summative, real-time and predictive information and recommendations. However, it may be questioned whether institutions, academic administrative staff as well as including those with responsibility for governance, are prepared for learning analytics? As a response to the question raised in this paper is presented an extension of a disruptive conceptual approach to higher education, using information gathered by IoT and based on Big Data & Cloud Computing and Learning Analytics analysis tools, with the main focus on the stakeholder governance.

CCS CONCEPTS

• Social and professional topics → Computing profession • Applied computing → Education

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Keywords

Disruption, Higher Education Institutions, Learning Analytics, Governance.

1 INTRODUCTION

It is widely acknowledged that organizations have suffered a large evolution at the social, economic and technological levels where the traditional barriers of transferring information and knowledge have been progressively eliminated. This evolution allowed the elimination of silos, the breaking down of hierarchies, the connection of internal and external stakeholders and the empowering of employees [1]. Furthermore, the integration of technological innovations, such as Big Data – Analytics, Cloud Computing, Mobile Connectivity, and Social, the four pillars of digital transformation (DT), with business practice can enable significant competitive advantage [2]. From the organizations' point of view, DT can be seen as a deep and accelerating transformation with regard to processes, activities, competencies and models, in order to take advantage of the changes and opportunities offered by the inclusion of digital technologies into an organization in general, and the education in particular [3].

With the advent of the cloud, and the Big Data, the advancement of Internet technology and the popularity of various online services in all areas of society has led to the empowerment of new models of support for teaching-learning processes (TLP). These new technologies led to the traditional methods of statistical analysis are unable to effectively analyze the generated TLP data [4].

According to [5], educational systems in general, and those of higher education in particular, have not had the expected evolution in terms of the potential introduced by the adoption of technology and virtual teaching / learning approaches [6] and [7]. Although these tools are used, professors do not sufficiently exploit their great potentialities and the objectives for which they were proposed.

The actors of the higher educational ecosystem can draw important data from different sources, such as Massive Open Online Courses (MOOCs), learning management systems (LMS) [8], social platforms (LinkedIn, Facebook, Twitter) and different web tools [9], it makes the learning process of students registered and provides professors with a way to improve teaching and implement adaptive teaching. They were some of the innovations introduced in the teaching processes [10] that they intended to implement disruption, but without the expected success. However, it is clear that, within the current technologies, some are beginning to reveal significant and increasing trends in the education area, like Big Data Analytics (BDA). According to Brown [11], the process of systematically collecting and analyzing large sets of online source data for the purpose of improving learning processes is called learning analytics (LA).

The adoption of LA in higher education institutions (HEI) is not easy and Nunn et al. [12] and Arroway et al. [13] identified six challenges to consider: *"(i) There is a shortage of leadership capabilities to ensure that implementation of learning analytics is strategically planned and monitored; (ii) There are infrequent institutional examples of equal engagement with different stakeholders at various levels; (iii) There is a shortage of pedagogy-based approaches to removing learning barriers that have been identified by analytics; (iv) There are insufficient training opportunities to equip end users with the ability to employ learning analytics; (v) There are a limited number of studies empirically validating the impact of analytics-triggered interventions; and (vi) There is limited availability of policies that are tailored for learning analytics-specific practice to address issues of privacy and ethics as well as challenges identified above."*

The use of LA has grown because the substantial increase in the amount of data, improvement in data format, the advances in computing and the greater availability of tools for the analysis [14]. Additionally, Yang and Huang [15] proposes to collect a large amount of learning behavior data over a long period of time and analyze them through BDA to improve student learning effectiveness. In the same paper, the authors indicate that BDA can be applied to *"educational administration and teaching applications. In educational management, big data analytics can help staff recruitment, financial planning, and monitoring student behavior."* As indicated in [16] *"Learning Analytics has proven to be helpful to colleges and universities in strategic areas such as resource allocation, student success, and finance. These institutions are collecting more and more data than ever before, to maximize strategic outcomes"*. According to [17] data analysis is also beginning to have an impact on the management of HEIs. This change is due to the existence of a large variety of data on students (admissions, course enrollment, study and completion performance statistics, and alumni) and staff (teaching assessment, demographics, scholarships) and search production metrics (papers, publications and other bibliometric measures). In addition, data analysis can be used to complement existing decision-making processes in key strategic areas, including student management and institutional strategy. In this context, the higher education needs to increase financial and operational efficiency, expand local and global impact, establish new funding models during a changing economic climate and respond to the demands for greater accountability to ensure organizational success at all levels [18].

This paper aims to deepen one of the components of the disruptive conceptual approach presented in [19] for higher education, namely Learning Analytics. The interception these components with stakeholders will to be helpful in strategies area to maximize strategy outcomes.

2 BACKGROUND

In this section, the relevant concepts are presented for a better understanding and analysis of the issues under discussion.

2.1 Disruption

According to Macfadyen et al. [20] "*Educational institutions are complex adaptive systems, which tend to be stable and resistant to change due to a range of political, social, cultural and technical norms. Therefore, the challenge to bring about change in higher education institutions where complex and adaptive systems exist has been described as a 'wicked problem*'". For this reason, there is a need for a disruption in the way HEIs are managed and projected for the future and in the way the TLP is organized.

Disruption can be considered as an enabler for the transformation of any activity sector from the retail to the computers, through education, and one of its objectives is the quality and cost reduction of goods and services [21]. According to the Oxford Dictionary [21], disruption is defined as a "*Disturbance or problems which interrupt an event, activity, or process*".

In education, the problem of disruption is more complex, as indicated in [22] "*The last technological disruption in teaching happened more than 500 years ago. Until then, the role of the 'lecturer' had been clear — the word's source being the Latin 'lectura', meaning to 'read.'*". The same authors point that the role of educators has not evolved, since most use the same instruments (lessons, homework, tests, etc.) in the TLP. However, a set of paths are provided to overcome resistance to change and create a disruption in TLP, namely the possibility of having customized curricula, introducing technologies that enable LA and Adaptive Learning, the use of artificial intelligence techniques, recommendation agents, among others. Finally, there is still, according to [23] a fundamental point, the "*universities have such an investment in their existing structures that they are unwilling to change.*".

2.2 Learning analytics, educational data mining, and academic analytics

The Horizon Report 2013 identified LA as one of the most important trends in technology-enhanced learning and teaching [24].

Johnson and Cornery describes LA as [25]: *"The interpretation of a wide range of data produced by and gathered on behalf of students in order to assess academic progress, predict future performance and support potential issues"*. A reference model for LA by Chatti et al., [26] claimed that: *"Learning Analytics process is often an integrative cycle and is generally carried out in three major steps: (i) Data Collection and Pre-processing; (ii) Analytics and Action; and (iii) Post-processing"* Another definition for LA is stated by [27] *"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"*. And Siemens [28] define LA as *"the use of intelligent data, learner-produced data, and analysis models to discover information and social connection, and to predict and advise on learning"*. Different authors have complemented this definition over time: Campell [29] shown that an analysis process is composed of five steps: (i) capture, (ii) report, (iii) predict, (iv) act, and (v) refine. Later the concept of closed loop in the process was introduced to create an interactive effect [30]. In a next phase, the stakeholders are included in the previous cycle according to their visions and missions [31], complemented by anonymization in order to preserve students' privacy [32].

According to Bienkowski et al. [33] learning analytics, educational data mining, and academic analytics are closely related concepts. Educational data mining, according to [34] *"focuses on the development and implementation of methods with the goal of promoting findings from data in educational settings."* Patterns are analyzed in a large set of data related to student actions, to formulate a better understanding of educational settings and students.

Hung et al. [35] defined data mining as *"data analysis techniques that, when applied, extract hidden knowledge consisting of tasks of pattern discovery and predictive modeling."* According to [35], Romero and Ventura [36] have provided a definition of educational data mining that "uses data mining algorithms to solve educational problems." Academic analysis refers to *"an application of business intelligence principles and tools to the academy with the aim of improving decision-making and performance of educational institutions"* [29].

Nunn et al. [12] make a very objective characterization of LA methods in education. In their paper they present the following methods and approaches ((i) Learning analytics process; (ii) Learning analytics analysis; and (iii) Data visualization tools and techniques), of analysis that allow to provide teachers and managers of higher education institutions with information relevant to decision making. This large amount of data analysis is only possible if used educational data mining methods (predication, clustering, data mining relationship; discovery with models; separation of data for use in the process of human judgment).

The LA has also been used to develop institutional strategic plans [37]. In this paper the authors indicate that business intelligence and visualization software are being used to make key indicators and aggregate data accessible. For example, student metrics (demographic information, enrollment, retention and graduation rates), faculty metrics (funding and scholarships, staff, demographics) and statistics on specific aspects of institutional strategy (research expenditures, faculty accomplishments, endowed assets and alumni giving rates, retention and graduation rates).

2.3 Governance

UNESCO [38] defines governance as *"Governance has been defined to refer to structures and processes that are designed to ensure accountability, transparency, responsiveness, rule of law, stability, equity and inclusiveness, empowerment, and broad-based participation. Governance also represents the norms, values and rules of the game through which public affairs are managed in a manner that is transparent, participatory, inclusive and responsive. Governance therefore can be subtle and* *may not be easily observable. In a broad sense, governance is about the culture and institutional environment in which citizens and stakeholders interact among themselves and participate in public affairs. It is more than the organs of the government."* According to UNESCO [38], this definition can be summarized in three main points: (1) Set and norms, strategic vision and direction and formulate high-level goals and policies; (2) Oversee management and organizational performance to ensure that the organization is working in the best interests of the public, and more specifically the stakeholders who are served by the organization's mission; and (3) Direct and oversee the management to ensure that the organization is achieving the desired outcomes and to ensure that the organization is acting prudently, ethically and legally.

The definition of governance provided by UNESCO is very comprehensive and applicable to any organization in any area. However, higher education system as some particular features that it is necessary to be into account. For that reason, Alfred [39] defined governance in the context of higher education as *"the process for distributing authority, power and influence for academic decisions among campus constituencies"*.

In this context, it is necessary to take into account the various governance models that exist in higher education. According to Macfadyen and Dawson [40], governance models in the context of higher education vary from one institution to another. In addition, Bichsel [41] shows that in several institutions of higher education the main incentive for the implementation of LA in governance is a cost-benefit and return-on-investment perspective, rather than a concern with management and ethics issues.

3 STATE OF THE ART

Implementing LA requires a shift to a wide range of practices across the institution. Teachers need to be involved in the design of the tools and able to evaluate any implementation of analysis tools to use them effectively. Students need to be convinced that the analyzes are reliable and will improve their learning without unduly interfering with their privacy. Support staff needs to be trained to maintain the infrastructure and to add data to the system. Library staff need to be able to use the analyzes to shape their practices and resources. University administrators need to be convinced that the analyzes implemented provide a good return on investment and demonstrably improve the quality of teaching and learning. IT staff need to put workflows together so that raw data is collated, prepared for use and made available to end users. In order to convince all stakeholders to implement the sustained effort required to make use of LA, a clear vision of the gains to be made is needed and must be maintained throughout.

As HEI data often exists in different departments and colleges, the value of the analysis will inevitably come from the interdepartmental integration of academic information (publication of results, grants) and non-academic (finance, HR). Business intelligence and data visualization data software will become increasingly important to support data-based decision making [42]. Based on demographic changes, HEIs are facing an increasingly competitive business. In this context, the use of data analysis can help HEIs to better assess and understand their strengths and weaknesses for the continuous development and monitoring of the institutional strategy.

Niet et al. [43] present a decision-making model that supports managers of HEIs when making academic decisions. This project was carried out at a university in Latin America, but is still in a pilot phase. The results presented are limited to only the educational area, namely undergraduate project management and academic performance management.

Leitner et al. [44] presented a literature review in LA in higher education, analyzing 101 relevant publications and lists the used LA methods, limitations and stakeholders, mas only in educational perspective (students and professors).

The study presented in [45] investigates the current capabilities of LA in HEIs to explore the importance of data sources to validate the LA framework. However, it does not present in an integrated way all the possible sources of information that exist today, and will be present every time, in the HEIs, nor for all the groups involved. In the course of the investigation Ifenthaler [45] presents a matrix of benefits for LA. In this matrix three analytical perspectives are established (Summative; Real-time; Predictive) for the various stakeholders. For the present study, the nuclear stakeholder is Governance. In the perspective Summative the author identified "Apply cross-institutional comparisons", "Develop benchmarks", "Inform policy making", "Inform quality assurance processes", while for Real-time perspective identified "Increase productivity", "Apply rapid response to critical Incidents", "Analyze performance" and finally, to the Predict perspective identified "Model impact of organizational decision-making" and "Plan for change management".

Tsai and Gasevic [46] present the results of a review of eight policies presented by several institutions, organized into two groups: (i) support organizations and research consortia and (ii) higher education institutions. In this analysis the authors show the importance of these policies to face the challenges in adopting LA. These results reveal that there is still a lack of guidance in how end-user data are used to assess progress and impact on learning.

Prinsloo and Slade [47] explore issues related to the use of data from a moral and legal point of view in the allocation of resources to increase the performance of the TLP of students. In this work, no emphasis is given to the global vision for the disruption of the TLP in HEIs.

The Sydney case study shows how LA can be aligned with the university's strategic objectives and strategic priorities. The European SHEILA [48] offers a seven-step approach to LA's institutional implementation: (i) defines a clear set of overarching policy objectives; (ii) map the context; (iii) identify the key stakeholders; (iv) identify learning analytics purposes; (v) develop a strategy; (vi) analyze capacity and develop human resources; And (vii) develop a monitoring and learning system (evaluation). This is an iterative process, and these steps can be repeated many times. In order to effectively implement analytics, leaders are likely to require skills in change management. The European SHEILA project is currently identifying the different elements that need to be taken into account in the LA deployment in order to help higher education to carry out this process.

The application of LA is not only useful for detecting the problematic students paths in a timely manner, but in agreement with [49] it allows all actors (rectors, administrators, professors and course developers) in the higher education ecosystem, it can obtain information that allows a more adequate and more sustainable decision-making.

In summary, all papers presented and analyzed previously, none presents an integrated view of a disruptive model for higher education, as will be presented in the next section.

4 CONCEPTUAL APPROACH: GOVERNANCE

As argued in the previous section, all data generated, stored, analyzed and presented will have different meanings whenever the angle of observation is changed, that is, they depend on the observer group or stakeholder. In the proposal presented in [19] is discussed a new approach to the disruption of HEIs, where three major groups/stakeholders are considered: (i) Governance; (ii) Students; and (iii) Professors.

The various possible interceptions between the technological solutions and the defined stakeholders will allow, on the one hand, the necessary knowledge for the elaboration of policies of institutional and scientific-pedagogical management of HEIs. On the other hand, allow the students to be monitored appropriately to their profile and professors develop teaching strategies for new audiences with very different skills from the last century. The skills for the 21st century [50] will be the ideal basis for the induction of disruption that is necessary to perform in HEIs.

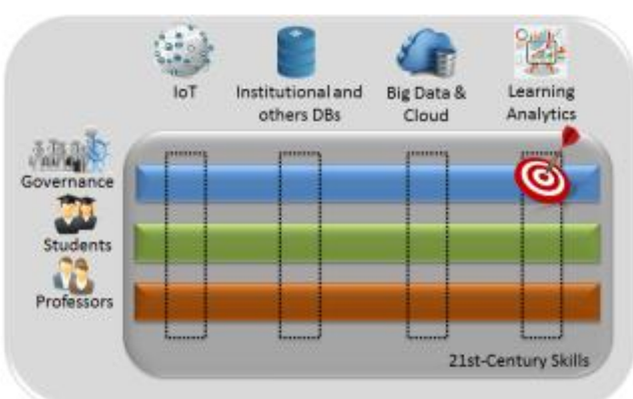

Figure 1: Conceptual approach: Governance stakeholder.

Fig. 1 show a conceptual approach, in its initial phase, which will serve for a disruption of education in HEIs, and described in [19]. In this context, the approach is composed of four components and three groups of interlocutors, the components are: IoT, Institutional and others DBs, Big Data & Cloud, and Learning Analytics; and, the groups: Governance, Students, and Professors, with all interceptions based on 21st-century skills. In the following subsection is presented and discussed the Governance group listed and how it is influenced or influence the LA component.

4.1 Governance

According to a survey presented in [51] it was perceived that HEIs were focused on exploring, planning and using different tools, and applications aimed at improving their analytical capacity. Although the analysis has been the subject of much attention in institutions, for example, what was less clear was the extent to which the focus of the analysis would be on the strategic and business dimension of human resources, marketing, performance management, and workload allocation. These dimensions must be integrated so that the Governance group can make the most appropriate decisions. Thus, Elouazizi [52] presented an interesting study where identified for Governance stakeholder the areas for using LA, sources & data types, and most important the critical challenges. He identified three main areas: (i) Improving accountability; (ii) Creating transparency; and (iii) Assess impact of policy changes. While for sources and data type: (i) ERP systems: enrollment, retention historical data, etc.; (ii) Additional analytics and visualization tools generated data; (iii) Student Information System (SIS) generated data; (iv) CRM: customer relationship management systems. The main critical challenges are: (1) the ownership of the data, which is inherently a distributed ownership; (2) the interpretation of the learning analytics data; and (3) the “evidence”-based decision making grounded in learning analytics data.

Due to the multiplicity of sources of information, as discussed previously, and illustrated in Figure 1, it is necessary to use a framework that can interconnect the data of all groups and all sources of information and special the interpretation of the learning analytics data (involve both information technology (IT) and institutional research (IR) data) to better the decision-making process and answer the new challenges. In this context, the framework presented by Daniel and Butson [53], and illustrated in Figure 2, meets our objectives, enhancing integration for decision making and responding to the challenges listed in [54]. As can be observed the LA is the component that has direct influence in the institutional analyses.

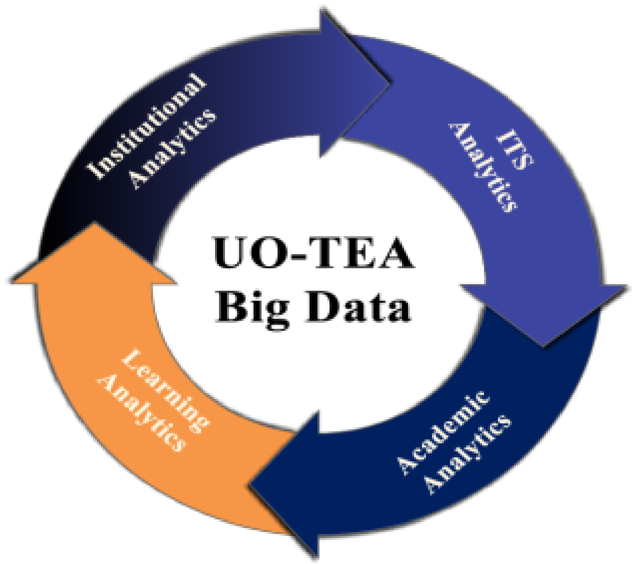

Figure 2: Conceptual framework [53].

The Institutional Analytics, according [53] *"refers to a variety of operational data that can be analyzed to help with effective decisions about making improvements at the institutional level."* With this assumption, the information collected from the first three components shown in Figure 1 (IoT devices, Institutional and others DBs, Big Data & Cloud), are essential for decision-making in all areas of intervention in the HEI. However, according to the same authors *"Institutional analytics include assessment policy analytics, instructional analytics, and structural analytics"*, which will allow to have a broad view of HEI to provide *"an institution with the capability to make timely data driven decisions across all departments and divisions."*

When students arrive at HEIs, they generally do not have a clear view of what they want and what they can find. Therefore, at an early stage, the use of LA can play an important role in the analysis of previous trends provided by the students (profile study, previous knowledge about the area, activity in social networks, etc.), designing predictive models and performing analysis of feelings and behavior (Academic Analytics stage from conceptual framework [53]). The intelligent combination of this data with the Institutional and others DBs can be used to make forecasts, projections or to trigger actions in different areas.

These Institutional Analytics [53] will be the responsibility of Governance stakeholder and will direct influence in a set of dimensions proposed by [54]: (i) Decision-making culture, including senior leadership commitment and the use and cultural acceptance of analytics; (ii) Policies, including data collection, access, and use policies; (iii) Data efficacy, relating to quality, standardization, "rightness" of data and reports, and the availability of tools and software for analytics; (iv) Investment and resources, consisting of funding, an investment versus an expense mentality, and the appropriateness of analytics staffing; (v) Technical infrastructure, consisting of analytics tools and the capacity to store, manage, and analyze data; and (vi) IR involvement, capturing interaction between IT and IR.

To answer the previous concerns the constitution of the governance board is always the most critical step for the success of a change like this. This entity will set objectives, goals, develop exchange programs, among others, based on data collected from various information sources and evaluated (Learning Analytics), and related to students. This governance board will also be responsible for selecting the type of infrastructure and software needed among other important technical issues to enhance change. For example, governance will have to decide whether the infrastructure will be supported by a private cloud, or a public provider, by analyzing the advantages and disadvantages of each option. In a pragmatic view, starting a project of this size, non-investment in private infrastructure may be a good option not to consume monetary resources related to its maintenance, thus releasing those same resources to other areas of intervention. From this perspective, the team can focus on the appropriate strategy to achieve the stated objectives, using existing services.

However, it is necessary to have a strategy that allow understand the major academic or business challenges facing HEI that need to be or potentially could be addressed using learning analytics. For this the governance group should develop a high-level analytics strategic plan and guide action. This should include making the business case for why the HEI should be pursuing LA, as this will be crucial to securing executive buy-in and funding. This strategic plan should take into account the data to be collected (IT and IR), so that it is possible to proactively establish LA processes, policies and documentation. The importance of data quality will increase confidence in the implementation of changes required for disruption. Additionally, it is necessary to define a set of metrics to regularly evaluate the implementation of the measures of the strategic plan, in order to perceive the success of the same. This process can be supported by the framework presented in [53].

Finally, this body will be responsible for the introduction of policies to be followed within the HEIs facilities. These policies serve to maintain control of the premises so that they are protected and safe, avoiding any kind of threats.

5 CONCLUSIONS

With the advent of new technologies the behavior of society in general and the younger generation in particular is changing. This behavior changing will have a great influence in the way the young people "look" for higher education. This new and fast change requires a disruption of current TLP models in order to be able to include in this process the technology and habits of the daily lives of the generations that are coming year after year to higher education.

With all this technologies almost all data and services are now in the cloud. These data are of great value to the education sector if appropriate Learning Analytics methods are used. However, the question of storage and use of computing resources to obtain results in real time requires the achievement of considerable investments in HEIs.

In order to respond to the issues discussed above, a disruptive conceptual approach directed to higher education TLPs is proposed [19], and extended in this paper the Learning Analytics component and its influence in the three groups (Governance, Students, and Professors), with special emphases in Governance group.

The proposed approach is still in its embryonic stage, so there is still a lot of work to do. As future research we will be carried out a survey of those responsible for Governance of higher education institutions, using quantitative and qualitative items. In addition, several focus groups will be composed of leaders and professionals from IT, IR, industry experts and researchers dedicated to analytics. During these meetings it was intended to discuss and evaluate the improvement made to address the current situation found. Throughout these meetings were collected, mostly qualitative data, which will be complemented by the bibliography research performed.

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