Higher Education Disruption Through IoT and Big Data: A Conceptual Approach

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Abstract. The emergence of new technologies such as IoT and Big Data, the change in the behavior of society in general and the younger generation in particular, require higher education institutions to "look" for teaching differently. This statement is complemented by the prediction of the futurist Thomas Frey, who postulates that "*in 14 years it will be a big deal when students learn from robot teachers over the internet*". Thus, it is necessary to urgently begin a disruption of current teaching models, to be able to include in these processes the new technologies and the daily habits of the new generations. The early usage of mobile devices and the constant connection to the Internet (social networks, among others) mean that the current generation of young people, who are reaching higher education, has the most technological literacy ever. In this new context, this article presents a disruptive conceptual approach to higher education, using information gathered by IoT and based on Big Data & Cloud Computing and Learning Analytics analysis tools. This approach will, for example, allow individualized solutions taking into account the characteristics of the students, to help them customize their curriculum and overcome their limitations and difficulties, throughout the learning process .

Keywords: Education · Disruption · IoT · Big Data · Higher education institutions

1 Introduction

According to [1], 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, e-learning, m-learning [2], u-learning [3]. Although these tools are used, educators do not sufficiently exploit their great potentialities and the objectives for which they were proposed. In this context, it is possible to specify u-learning, which theoretically has great potential, since it allows the expansion of access to learning contents and collaborative learning environments, anytime and anywhere, combining physical and virtual spaces. With the stated purpose, the Massive Open Online Courses (MOOCs) and some alternative approaches (Flipped

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Classroom, Class-wide Discussion, …) were some of the innovations introduced in the training processes of students [4] 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 a significant and increasing role in the education area. For example, whenever students obtain online learning materials and need to work actively with them, it may be beneficial to observe their behavior in order to apply adjustments or corrective measures. The teacher, when asking questions such as, are students solving the tasks in the correct order? or How many times have students viewed the video or heard the podcast? Can provide the teacher with data that enable him to make a curriculum adaptation according to the students characteristics concerning the required pace of work, materials available, among others.

As previously noted, the use of observation and correction measures, Internet of Things (IoT), Big Data and Learning Analytics will play a key role in education as more and more students expect to have their "*… personalized Curriculum delivered to their desk*" [1].

Understanding both the technical support and the social impact of IoT is, and will be, crucial for the future digital professionals [5]. According to [6, 7] "*The global accessibility of education may be provided through the use of Internet of Things*". This is justified by the predictions found in the literature about the number of sensors that will be linked up to 2020. For example, Boche [8] indicates that there will be about 14 billion devices; Cisco assumes that about 50 billion will be connected and Morgan Stanley indicates that the number may currently be over 75 billion [9]. However, all the authors agree that most of these will be smart wearables, which are the latest technological trends. The increasing distribution of sensors provides a massive amount of data sources, and thus new possibilities for applications and services for higher education will emerge.

In this context, learning in the future will be determined by personalization and creativity as indicated in [10]. With the same perspective, in an interview in 1988 [11] Isaac Asimov predicted that, "*computing could allow such a personalized, one-teacher-one-student experience to be available to the masses, replacing or supplementing the one-teacher-many-students Experience of most classrooms.*"

Personalization, because smart wearables will collect enough data to "*know*" well the habits and preferences of their users and, in the case of education, to provide the means for quality training, planned and controllable, so that it is possible to perceive the advantages, conditions and limits of learning in an intelligent context. Thus, the gathering, storage and processing of data will be critical, and therefore the crucial need to use Big Data techniques.

Big Data has a comprehensive application [12], covering a wide range of areas, including science, engineering, medicine, healthcare, finance, business, education, transportation, retail and telecommunications, and organizations such as small and large companies, Government departments, human-machine interaction, etc.

Nowadays, the market already provides a considerable set of tools and techniques [13] for monitoring and analysis of automatically collected data on students' activities. In this way, it is possible to use these powerful features to integrate a large amount of data from multiple sources and use them to extract useful behavioral information. In addition, according to the Horizon report [14], the data gathered from the learning actions in conjunction with Learning Analytics allows to enhance the curricula adequacy with the student's profile [15]. However, behavioral analysis is a complex endeavor, given the existence of several factors that may influence students' behavior. These factors include, but are not limited to, family, friends, habits and interests, and data regarding those factors are not readily available and may raise ethical and/or legal issues in the way that they are collected and used.

Notwithstanding the above, the gather of data regarding students from higher education can be facilitated, since universities already monitor, and have available some student behavioral data. According to [16] they are: (i) Institutional databases; (ii) Personal data that may be in digital format (e-mails, digital photographs, videos, etc.), or not digital (paper documents, notes, paper photographs, etc.); (iii) Digital track on the web, if the students are connected through the university network or Wi-Fi network areas, individually or collectively. In addition, it is also possible to monitor outdoor activities, in particular the various sources of information that the university has at its disposal: (i) Data related to the entrance and exit of cars in the institution; (ii) Video surveillance data; (iii) Information on various areas of the university (canteen, bar, library, etc.) and (iv) IoT data.

With all this data, the next phase is its integration so that it is possible to extract models of behavior. In this context monitor students based on their background training, profile, performance history, demographics current interests and activities. Long and Siemens [17] show that listening to a teacher in a traditional classroom or reading a book leaves a very limited track that can be harnessed for monitoring and/or intervention. However, students produce data with "*every click, every tweet or Facebook status update, every social interaction and every page read online*," along with students' digital records, "online learning, Happening in the learning process." In this context and according to Oracle [18] through knowledge "*student's work, social, and eating habits*" it is easier to anticipate problems in the teaching-learning process (TLP) and to initiate actions to correct them.

The proper evaluation of all data, as well as the information collected from IoT objects related to a variety of physical characteristics of didactic interest, lead teachers to raise some important questions that may be decisive to choose the most appropriate curriculum, (e.g., corrective measures) to be applied to a particular student.

This article presents a disruptive conceptual approach aimed at higher using information gathered by IoT and based on Big Data & Cloud Computing analysis tools and Learning Analytics, which, for example, will allow individualized curricula solutions taking into account the students' characteristics to help them customize their curriculum and know their limitations and difficulties throughout the learning process.

2 Background

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

2.1 Main Concepts

Disruption. 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 [19].

According to the Oxford Dictionary [20], disruption is defined as a "*Disturbance or problems which interrupt an event, activity, or process*", and at [21] is "*the mechanism that ignites the true power of capitalism in two ways: And creative construction*."

Disruption can be oriented in two ways: (1) creation of a completely new market, or (2) creation of alternative, profitable business models for less demanding customers [21]. It is in the first strand where the most disruptive innovations are found, for example, the telephone, the computer, etc.

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 Learning Analytics and Adaptive Learning, the use of artificial intelligence techniques, recommendation agents, among others. Finally, there is still, according to [22] a fundamental point, the "*universities have such an investment in their existing structures that they are unwilling to change*."

IoT. Kevin Ashton in 1999 [23] introduced the term Internet of Things (IoT) in the context of supply chain management. However, its use has become more comprehensive and inclusive in relation to several areas of activity (health, transport, etc.) [24], and integrated into our daily lives by any citizen [25]. IoT [26] has gained drive due to the advancement of telecommunications, with the growth of broadband networks, integrated in a wide variety of devices (mobile devices, vehicles, etc.) that can be managed via web providing data in real-time [27]. This data can be placed in the cloud [24] for processing, with the necessary protection, since in many cases it is related to people, that is, personal data such as location, health, etc.

Given the disruption of IoT, its definition is still not consensual, and there are several definitions in the literature. In [28] IoT is defined as "*The worldwide network of interconnected objects uniquely addressable based on standard communication protocols*." The IoT European Projects Cluster [24] defines IoT as "*'Things' are active participants in business, information and social processes where they are enabled to interact and communicate among themselves and with the environment by exchanging data and information sensed about the environment, while reacting autonomously to the real/physical world events and influencing it by running processes that trigger actions and create services with or without direct human intervention*." Moreover, Gubbi, et al. [26] defines IoT as an "*Interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with Cloud computing as the unifying framework.*"

With the emergence of these sensors, their application in TLPs is still at a very embryonic stage, due to the lack of adaptability of HEIs infrastructures, namely the investment needed and, on the other hand, the ethical and legal issues of collection, storage and treatment of personal data. In this context, the use of the definition introduced in [26] is appropriate for adaptation to the education sector.

Big Data. According to the International Data Corporation (IDC), in 2011 were created and copied 1.8 ZB, and projected that this data volume will grow about nine times in the next five years [29]. In this context, the term Big Data is used to describe large data sets, including unstructured data and their analysis in real time. To illustrate this growth it is possible to point out examples of internationally known organizations: Google processes thousands of Petabyte (PB), Facebook stores about 10 PB per month, YouTube receives from upload 72 h of videos per minute [30]. Additionally, with the growth of cloud computing and IoT, the amount of data generated will be even greater. The very strong growth in data generation, storage and analysis raises a number of issues, including how to store and manipulate heterogeneous data, the scalability of systems, complexity, and privacy that are yet to be addressed.

The definition of Big Data presents the same problem of cloud computing in its initial phase, that is, the existence of several definitions, because Big Data is an abstract concept. The definition/concept of Big Date has been a source of great discussion both in industry and academia [31, 32].

In 2010 Apache Hadoop defined Big Data as "*datasets which could not be captured, managed, and processed by general computers within an acceptable scope*." However, Big Data was already defined in 2001 by Doug Laney as the 3Vs model (Volume, Velocity, and Variety) [33]. In the "3Vs" model, Volume means, with the generation and collection of masses of data, data scale becomes increasingly big; Velocity means the timeliness of big data, specifically, data collection and analysis, etc. Must be rapidly and timely conducted, only to use the commercial value of big data; Variety indicates the various types of data, which includes semi-structured and unstructured data such as audio, video, webpage, and text, as well as traditional structured data. On the other hand, others have different opinions, including IDC, that in 2011, defined Big Data as "*big data technologies describes the new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the High-velocity capture, discovery, and/or analysis*" [29]. After this definition, a fourth V was added, with Big Data being applied as a 4Vs model, i.e. Volume (great volume), Variety (various modalities), Velocity (rapid generation), and Value (very low but very low density). Facebook's Jay Parikh says, "*You could only own a bunch of data other than big data if you do not use the collected data*" [30].

As a complement, NIST defined Big Data as "*the data of which the data volume, acquisition speed, or data representation limits the capacity of using traditional relational methods to conduct effective analysis or the data which may be effectively processed with important horizontal zoom technologies*".

In the proposed disruptive conceptual approach, the definition presented by NIST is sufficiently broad to be assumed as the most adequate.

Learning Analytics. Learning Analytics (LA) is 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*" [34].

Different authors have complemented this definition over time: Campell [35] 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 [36]. In a next phase, the stakeholders are included in the previous cycle according to their visions and missions [37], complemented by anonymization in order to preserve students' privacy [38].

In this context, and for students, all the information that is collected regarding their activity is processed in order to carry out an analysis to support the actions to be taken by both teachers and students [39]. The authors [40, 41] show that, in addition to the above analysis, it is necessary to take into account how information is presented to the stakeholders in this process information, that is, system feedback. Finally, the study of students' behavior patterns can be very useful in order to adopt strategies to improve the learning process [42, 43].

2.2 Related Technologies

Technologies presented and discussed above, as can be concluded, are directly related among each other. Cloud Computing is related to Big Data since its main purpose is to use the great capacity of computing and storage. Thus, Cloud Computing provides solutions for storing and processing Big Data. However, the two technologies have different concepts and different audiences.

The evolution of Big Data was driven by the rapidly growing demand for Cloud Computing applications built on virtualized technologies. Consequently, Cloud Computing not only provides computation and processing for Big Data, but also itself is a mode of service; in this way, advances in Cloud Computing promote the development of Big Data, since they complement each other.

As far as IoT is concerned, there is and will be a large set of sensors embedded in networked devices around the world. According to HP, in 2030, the number of sensors will reach a trillion, and IoT data will be the "*supplier*" of Big Data's most important data, since they include heterogeneity, variety, unstructured, etc. These sensors have as main function to collect the various types of data, from environmental data to logistic data, practically passing crossing through all sectors of activity and society. According to Intel the Big Data, in IoT, has three essential characteristics: (i) many terminals generate large amounts of data; (ii) the data generated is semi-structured and unstructured, and (iii) the data is useful only when analyzed.

The data generated by IoT presents a set of characteristics that, in addition to its importance, have to be taken into account for its use: (i) large scale data (e.g. location, video surveillance); (ii) heterogeneity; (iii) strong correlation between space and time (important dimensions for statistical analysis); (iv) Effective data represents only a small part of Big Data (during traffic video surveillance, only serving frames, or rule violations or accidents).

As a conclusion, one of the biggest problems with the data generated by IoT is its heterogeneity and the complexity that has not existed until up to now [44].

3 State of the Art

The need to find solutions to the problems previously analyzed is possible, at an initial stage, by the analysis of works carried out in the area and in related areas. Almost all HEIs live today with pedagogical models of teachers and students. In the first case, teachers follow the classical model (pedagogies used from the 14th century) and mostly with face-to-face teaching. While students already follow a more "hybrid" model, since many of the materials needed for their study are already online and therefore, which fit into a b-Learning model.

One of the attempts, with greater visibility, to induce a disruption in higher education is the MOOCs in the sense of being able to challenge the education scale, but with "old" pedagogies that led to its failure [45]. However, MOOCs have left a set of clues for the future, since (i) audiences are increasingly heterogeneous, (ii) with involvement in face-to-face, virtual or mixed activities, (iii) controlled by teachers and/or by software and (iv) skills for the present century are changing [45]. With regard to the skills to be acquired by the 21st century students, according to [45], autonomy is the most critical competence, since it requires pedagogy of autonomy and initiative.

In [46] the authors propose a model to teach topics related to IoT based on a platform in the cloud web-service oriented. This model aims to provide university students with knowledge about IoT regarding concepts, possibilities and business models that allow the development of prototypes using micro devices and cloud. The model is based on traditional lessons in a Short Message Service (SMS) system. The authors suggest that educational institutions should provide students with the greatest number of didactic approaches to increase their motivation. The proposed model, given the small number of participants, did not allow significant results to be obtained on its feasibility.

The need to obtain information on how students interact with e-learning platforms is the subject of study [47]. In this article, the authors present a service-based architecture and deployed in the cloud to obtain, analyze and present information obtained from distance learning environments, for example Virtual Worlds. Teachers with the information collected regarding students' interactions with the system have extracted the necessary information to identify behaviors and/or practices that can lead to poor results and thus implement corrective procedures.

The projects used in the TLP, in several areas, using virtual worlds, such as Second Life, is a reality [48–50]. However, the important issue that raises one or more problems is how to extract data from participants' activities and how they can be used to improve TLP and students' assessment.

One of the current trends to support TLP is Learning Analytics [51–54]. This field of research is very broad and can be applied to many areas of science, according to [49] "*for example it includes issues related to software engineering architectures, data retrieval, knowledge discovery, etc.*" Beyond the coverage is an important area of research, since its integration can – on analysis of information from various sources (LMS sensors, institutional databases, etc.) – to support the definition of the custom curriculum, and student orientation and motivation during TLP. These information flows from various sources are important in decision making in learning systems that allow a disruption of current TLPs, if it is possible to have solutions that go along with all phases (data retrieval, data storage, data discovery, knowledge discovery, knowledge Representation), as indicated in [51].

The identification and validation of behaviors using standards allow students to perceive their usage trends in order to understand the knowledge and proficiency regarding the resources available for TLP [55–58]. This knowledge – to see whether students value and motivate themselves in TLP based on technology or content, or both – is fundamental to the introduction of new teaching models, namely when students have individualized curricula and can perform autonomously, and anywhere.

The increasing use in the development of IoT scenario's tests has been a reason for recent research. In [1] a project is presented using IoT with Arduino boards whose objective is to show that the latest technologies can be introduced successfully in TLP. This success must be guaranteed using, on the one hand, mechanisms of collection, storage, representation of knowledge, etc., in order to have as much in-depth knowledge as possible of the actions taken by the student during the learning activity and, on the other hand, these Innovations are accompanied by the evolution of teaching-learning methodologies [51]. Gomez et al. [59] present a project where the focus is the use of IoT to create more learning spaces, allowing students to interact with physical objects that surround them and that are associated with the learning activity that they are doing. The obtained results were very promising, showing that students improved their learning. However, the authors state that "*The road in front of the Internet of Objects and their applications in education is just beginning…*"

In short, no solution or project described in this section integrates all the components discussed in Sect. 2, that is, IoT, Big Data & Cloud Computing and Learning Analytics. In this context, disruption in education in higher education will only be possible if these components are used together and in an integrated manner, including the skills required for the present century as defined in [45].

4 Conceptual Approach Proposal

In this section, we present our approach to a disruptive solution using IoT, Big Data & Cloud Computing and Learning Analytics in the context of HEI.

4.1 Rational

According to Lenz et al. [60] information about people can be collected through a variety of devices, including smartphones, wearables or even other types of sensors, and therefore reflect the distinctive behavior and personality of those people. In parallel, according to [61], current HEIs receive data from various sources, namely LMS, social networks, digital libraries, student surveys and Internet logs [62]. All of these data provide a "global" digital trend in the HEIs environment. At the same time as students work in an increasingly digital environment, using their smart devices equipped with sensors, data sources are expanding on a large scale [63]. In this context, data can be related to the TLP and can be processed in order to obtain significant information and reflected in the same process. At the same time, it is also possible to use data collected from several sources other than those referred to, such as documents, audit registers, CCTV images, biometric devices, etc., [65] and in an integrated way, to obtain information to take the necessary measures in order to improve the performance of students in their academic life.

Based on all available data sources, the way traditional database systems are processed is not keeping up with the growth and complexity of current data. Thus, according to [64] the huge amount of unstructured data available does not have adequate use. This situation occurs because most HEIs do not have the appropriate mechanisms to convert this data into useful information. After due treatment of this data, its impact on management policies, and LTP may be significant, allowing the implementation of preventive actions, giving insights on the information not yet explored, which may be fundamental for institutional success. This information can be useful, through its analysis, using methods in the context of Big Data, for the personalization of curricula, for student performance, among other issues. The Big Data methods, according to [60], are determined by two basic requirements: "(i) *the ability of a multilayer information system to bring together all these different heterogeneous data and provide methods for a combined analysis of collected information*. (ii) *The ability of devices to collect user-specific data such as movements, gestures, eye movements and so on*." However, there is still very little research on the use of Big Data, IoT, and learn analytics working together within HEIs, as discussed in Sect. 3.

4.2 Conceptual Approach

As argued in the previous section, it is inevitable the junction of the various technologies. The data generated, its collection, treatment, presentation of results, and suggestions that enhance the improvement of TLP, make the combination of IoT, Big Data & Cloud and Learning Analytics inseparable from the construction of a disruptive approach to higher education. Its main objective is to allow the creation of individualized solutions taking into account the characteristics of the students to help them define their personalized curriculum and overcome their limitations and difficulties throughout the learning process.

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. In this proposal, three major groups are considered within HEIs: (i) Governance; (ii) Students; and (iii) Professors.

The various possible interceptions between the technological solutions and the defined groups 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 teachers develop teaching strategies for new audiences with very different skills from the last century. The competences for the 21st century, according to [45] are: "*(i) Foundational Literacies (How students apply core skills to everyday tasks) (How students approach their changing environment).*" In this context, it can be said that these competences will play an important role in inducing disruption, which is necessary in higher education.

Figure 1 shows a conceptual approach, in its initial phase, which will serve for a disruption of education in HEIs.

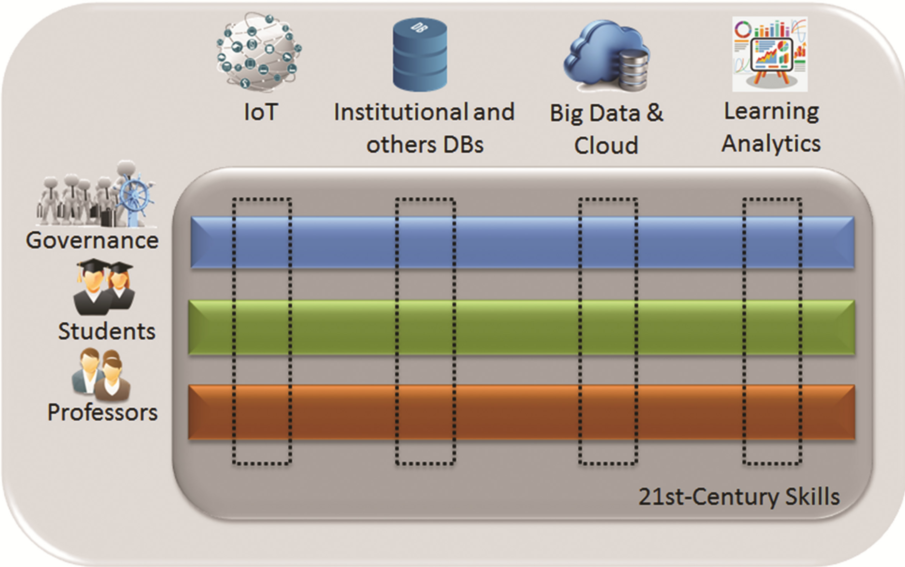

Fig. 1. Conceptual approach.

The proposed 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 subsections are presented and discussed the groups listed and how they are influenced or influence each of the other components.

Governance. 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 (IoT, Institutional and others DBs) and evaluated (Big Data & Cloud and Learning Analytics), 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 [66].

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 Big Data 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. 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 [61].

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 [67].

Students. The time of reaction to the evolution of society is taken into account in different rhythms, depending on the groups and institutions in general. Students are one of the groups that have a higher rate adaptation within the universe of HEIs, and there are factors that determine students' success or failure. Therefore, motivation, relevance of content, always in line with new skills [45], pedagogical methods and systems involving the whole TLP serve to avoid three difficult situations: absenteeism, retention, and dropout.

Student absenteeism can be measured and a knowledge base built to predict which underlying causal factors. For example, these factors may include: (i) Academic (inadequate preparation, disinterest with content, etc.); (ii) Motivational (low level of commitment to the institution, etc.); (iii) Psychosocial (social factors, emotional issues); and (iv) Financial (inability to pay school fees, etc.) [68].

With regard to retention, and dropout, it is necessary to identify student retention patterns and seek to assess the underlying reasons that lead students to leave a given particular curricular unit, or a course in general [69]. Based on the information provided, it is possible to construct and propose actions to solve these issues in a preventive manner. In both cases, according to [61], the use of Big Data, IoT and Institutional and others DBs to monitor students' learning process and performance will help to detect potential problems in advance, more efficiently and accurately than Traditional data systems. An early identification of the possibility that a student may be at risk of failing a subject or program of study should lead to corrective action by the teacher to help reduce risk. Big Data analytical tools can produce instant alerts and provide feedback to faculty and students on academic performance by analyzing complex data patterns.

Conventional information models currently used in the HEIs do not take into account the feelings and skills related to behavior. According to [70, 71] the analysis of feelings and behavior data (social networks, notes of student-teacher meetings, and so on) of students in online courses showed the differences between successful and unsuccessful students. In this context, the tools of Big Data analysis and Learning Analytics, according to [72] can reveal the true behavior of the students in a more precise way.

Finally, in addition to concerns about absenteeism and retention and drop-out, it is necessary to motivate students, who are on the right track and have a profile of researchers, to be integrated as early as possible into research projects.

Professors. Teachers will be able, according to [60] to observe the behavior of the students during the classes, as well as throughout the training time, with the help of IoT. For example, authors highlight the use of speech recording devices, reading progress recording tablets or wearables to record heart rate, student eye movement, among others, which will enable the teacher to obtain a more complete view of the students' behavior.

In addition, it is still possible to use the data collected by IoT to be used in combination with other data collected context-oriented data to improve TLP [72].

One aspect not to be overlooked by teachers is the mistaken assumption that all students begin at the same time, and follow practically the same course, and at the same rate [61]. This behavior can be overcome as presented in Sect. 3. These examples show that data collection from various sources of information (from institutional databases and unstructured data collected from sensors), and with the help of Big Data and Learning Analytics, gives these differences, often significant. These differences lead to the need, for a disruption of the current models, of learning to be increasingly personalized. With this type of learning the teacher can observe the students in order to realize which area within a program of study is that they find it difficult and spend most of the time, the sections they recommend to their peers, learning styles Which they prefer, and the time of day that they learn best [69].

Learning can be increasingly personalized and the teacher should be able to observe his/her students in order to perceive which area, within a curriculum is considered more difficult and concentrate most of the time to overcome these difficulties, or which curriculum sections need adjustments, what learning styles they prefer, as well as the time of day that they learn best [72].

Another very relevant aspect is the form of evaluation of the contents taught, i.e. whether the evaluation should be at the end of the lecture of all the contents, or if a formative and phased assessment should be carried out. In [61] it is suggested that with the help of Big Data and Learning Analytics, it is possible for the teacher to formulate appropriately challenging or demanding formative assessments according to each student's talent and learning ability. The same authors suggest the creation of groups based on the capacity within the system and/or the assignment of a student to an appropriate group, as well as, according to [64] teachers can calculate student attention levels and prepare more interesting sessions, to increase levels of attention. In this context, the results obtained will be indicators of the next steps (more advanced learning, or different or more practical content on the same topic), allowing the implementation of a continuous improvement of individual TLP.

5 Conclusions

With the advent of IoT, Big Date, Learning Analytics, among other technologies, changing the behavior of society in general and the younger generation in particular, how to "look" for higher education, has to adapt urgently. This 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 IoT devices, almost all data and services are now in the cloud. The data that used to be considered "waste" is now having more value to decision-making in different areas of activity and in particular in education through Big Data Analytics and Learning Analytics, allowing a more effective analysis of student learning. With these analyses and their results, investment issues in the education sector require effective use of "new" resources.

These technologies will allow the development of new decision support systems that will be based on evidence of analysis of the behavior and feelings of students and teachers, by analyzing their behavior and activity patterns and adapting them to students, avoiding absenteeism, retention, and dropouts.

In order to respond to the issues discussed above, a disruptive conceptual approach directed to higher education TLPs is proposed, using information gathered by IoT and based on Big Data & Cloud Computing, Institutional and others DBs and Learning Analytics. The result is the definition of individualized solutions taking into account the characteristics of the students, including a personalized curriculum in order to meet their limitations and difficulties throughout the TLP.

The proposed approach, still in its embryonic phase, assumes that we are not all equal and, as a result, there will be different variables for different people that can be analyzed, in order to construct meaningful behavioral patterns that can be used. For a personalized system, behavior has to be analyzed and training must be provided to all, that is, to meet the needs and desires of society. In this context, it is possible to defend the idea that the education system could benefit from IoT data collection, based on Big Data & Cloud Computing analysis tools, Institutional and others DBs and Learning Analytics, so that HEIs can conduct their activities to train better professionals and citizens.

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