International Journal of Web-Based Learning and Teaching Technologies
Volume 16 • Issue 5 • September-October 2021

Big Data and Internet of Things (IoT) Technologies' Influence on Higher Education:
Current State and Future Prospects

Vardan Mkrttchian, HHH University, Australia

Leyla Gamidullaeva, K. G. Razumovsky Moscow State University of Technologies and Management (FCU), Russia & Penza State University, Russia

https://orcid.org/0000-0003-3042-7550

Alexey Finogeev, Penza State University, Russia

https://orcid.org/0000-0002-4777-3364

Serge Chernyshenko, Moscow Pegion State University, Russia

https://orcid.org/0000-0002-2852-6878

Vsevolod Chernyshenko, Financial University Under the Government of the Russian Federation, Russia

https://orcid.org/0000-0001-6635-4168

Danis Amirov, Moscow State University of Technology and Management, Russia

Irina Potapova, Astrakhan State University of Architecture and Civil Engineering, Russia

ABSTRACT

To respond to the needs of digital transformation, universities must continue to play their role as proving ground for educating the future generation and innovation. The article is devoted to overview, discussion, and investigation of application in higher education of two modern information technologies: big data and internet of things. The article identifies the role of analytics, based on big data, in improvement of education process and outlines the challenges, related with big data mining, storage, and security. Proposed statements are based on practical experience of the authors; architecture of program and methodological solution are the focus of the article. The article contributes to theory by the new approach to combination of big data and internet of things technologies in educational resources and, at the same time, includes implications for practice, presenting examples of the approach's realization and sharing the authors' experiences of such realization.

KEYWORDS

Analytics, Big Data, Data Management, Higher Education, Internet of Things

DOI: 10.4018/IJWLTT.20210901.oa8

INTRODUCTION

Implementation of modern information technologies to practice of higher education institutions is not a fad. Traditions are important for universities, but there are at least two factors, which make reforms inevitable. Main of them is a fact that the world is very changeable nowadays; all actors of the process: students, employers, even professors themselves, are under rapid change. Second reason is the fact that new possibilities can make teaching more effective, even within the traditional paradigm.

Undoubtedly, higher education needs to upgrade its programmes to outfit students for the highly digitised and automated environment of Industry 4.0. Industry 4.0 supposes the use of network approach that is based on the ability of creating smart products and components (Vasin, et al., 2018a). “Smart” education would be a natural progression in industry 4.0., a framework for which is still emerging but would definitely require preparing education for this digital transformation. In consideration of future employment domains, students should be prepared to meet the new demands resulting from a fourth industrial revolution.

The current article is devoted to one of actual problems: how to use, in effective way, such IT technologies as Big Data and Internet of Things in higher education? Naturally, there are many ways to answer; and, probably, unlimited number of details, which can be useful for planning such activity. We shall stress on several aspects, which like for as important ones, and shall base on some practical experiences, collected by the authors, mainly at Penza State University, Russia. Main topic of the work is big data storage and processing in education process with focus on IT realization of some processes. Naturally, university can benefit from accumulation of meaningful data.

Importance of the new IT is connected with social mission of higher education. To respond to the needs of digital transformation, universities must continue to play their role as proving ground for educating the future generation and innovation. Close collaboration with social environment, with employers and other stakeholders is a core element of the strategy Education 4.0 (Chao, 2017; Hussin, 2018). According to the University 4.0 concept (Dewar, 2017), universities will be transformed to embrace know-how and ideas by adapting their administrative paradigm and the investment in human resources and giving more priority to serve the objectives of society.

The rest of the paper is organised as follows. In the first two sections, an overview of Big Bata and IoT technologies, with stress on their use in the field of higher education, is presented. The third section is about a practical experience of the authors in implementation of the modern IT in practice of the distance learning system of Penza State University. The fourth section, which consists of several subsections, is devoted to discussion of program realization of the approaches in some special cases. In conclusion section the authors presented possible applications of obtained results for the theory and practice and discussed possible future research directions.

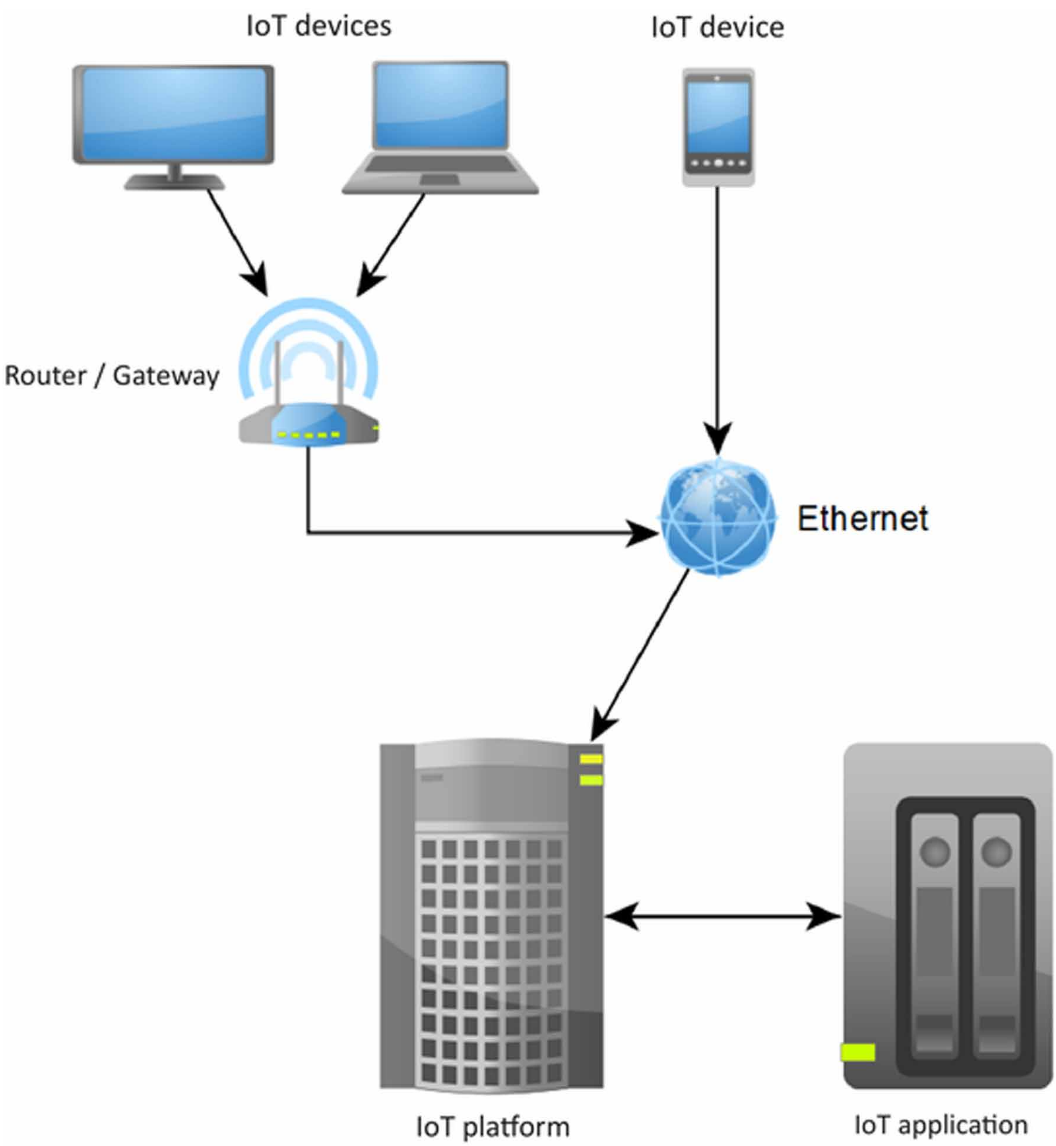
The article does not pretend on deep didactical analysis of the new methodology, although general ideas about its impact on education process have been expressed.

LITERATURE REVIEW

Internet of Things: Current State and Applications in Education

The Internet of Things (IoT) is a cutting edge technology featured as a global network of machines and devices into a network that enable them to interact with each other. The idea of IoT is to integrate all devices into the network, which may be managed from net; it will offer data and knowledge in real time conjointly permitting the interaction with those who use it. The Internet-of-Things (IoT) concept traces its origins to the late 1990s when it referred to the interoperability of devices connected with RFID (radio frequency identification) technology. The Internet of Things (IoT) is a concept that describes the large and growing number of digital devices that operate between networks of potentially global scale (Chou, 2016). Therefore, we are facing a technological revolution that includes the interaction between objects and simple actions of daily life to the most complex processes of organizing entire

Figure 1. Typical organization of IoT system



industrial productions. Vermesan and Friess (2014) argue that IoT provides new and innovative ways for organizations to manage and monitor remote operations. Conceptually, it offers the possibility of connecting the physical world with the digital world through the Internet. Today, a widely accepted definition of the modern IoT is "a dynamic global network infrastructure with self-configuring capabilities based on standard and interoperable communication protocols where physical and virtual 'things' have identities, physical attributes, and virtual personalities and use intelligent interfaces, and are seamlessly integrated into the information network" (van Kranenburg, 2007)

This IoT has led to large volumes of data created by the billions of devices connected to the internet (Tannahill and Jamshidi, 2014; Zikopoulos et al., 2012).

Creating a new IoT has opened up new possibilities in using the power of information in ways never before seen. Effective use of the vast amount of data generated by industrial sensors can help improve the efficiency of industrial production processes, while data from smart devices can improve a wide range of human experiences - from monitoring the environment in the home to specialized content on social networks. The approach is closely connected with the Big Data technology, which will be considered precisely below.

The article is targeted for considering prospective of implementation of IoT technology to education sphere, mainly, to higher education. The way has different aspects. Naturally, at the moment it is in focus of attention in engineering education (Kusmin, et al., 2018). It is also very important component of different kinds of electronic and distance education, as it will be discussed below. However, step-by-step it becomes a part of usual learning. Thus, as it shown in (Sengupta, 2019), efficient restructuring of traditional education and learning methods, because of IoT, can be observed just now. Probably, the most important change is a transformation of Learning Management System, as a whole (Mershad & Wakim, 2018). Curricula becomes much more flexibly and dynamical; the system collect an ability of selforganisation. In this context an integration of IoT systems with Knowledge Base (Hedayati, et al., 2017; Sarmiento et al., 2018) can give a powerful impact for the further development of education. Although, any further progress it is not a problem of didactics only (Patarakin, et al., 2019), but depends on development of new technical abilities (Tan, et. al., 2018).

Big Data Technology in Higher Education

Bid Data tools become more and more popular in the educational sphere – the overviews can be found, for example, in (Li & Zhai, 2018; Murumba & Micheni, 2017), but their implementation meets great challenges. Data is growing every day; back in 2000, the amount of digitized information made up only 25% of the total amount of information in the world. To date, the amount of stored information in the world is of the order of zettabytes (ZB), of which non-digital information accounts for less than 2%. Internet users produce over 2.5 quintillion bytes of data on average every day (TechStartups Team, 2018). Naturally, such an explosion in generated data has mandated that Big Data storage, processing and analytics technologies go in parallel with the IoT and Big Data tools (Eynon, 2013).

Additionally, the data is presenting in various formats, making it difficult to retrieve. Big data can have as structured form (data from sensors; log files; financial data; input data; data on visits to websites, etc.), as well as unstructured one (scientific knowledge data; photo and video materials; meteorological, oceanographic, seismological observation data; satellite imagery; texts of business and official documents; survey results; e-mails and social network data (Arifin, et al., 2017), and many others).

Processing of this large amount of data in efficient way is a complex problem, solving of which can be based on using real-time and parallel methods (Estévez-Ayres, et al., 2017). Big data is data whose scale, diversity and complexity require a new architecture, methods, algorithms and analytics to manage it and extract value and hidden knowledge from it (Alamri & Qureshi, 2015).

The term Big Data unifies a set of approaches, tools and methods for processing structured and unstructured data of very large volumes and considerable diversity for obtaining human-perceptible results (Dumbill, 2015). The purpose of the technology is to increase work efficiency, create new products and increase competitiveness. Moreover, Big Data analytics can support governments and businesses make critical decisions and improve policy-making towards economic growth (Kaisler et al., 2013).

Big data can be understood also in a narrow meaning, as an object, not the technological subject. In the Oracle site one can find the state: "big data contains a great variety of information that arrives in increasing volumes and velocity" (What Is Big Data, 2019). Elementary introduction to Big Data applications in education is presented in the works (Fry, 2019; Ray, 2013). Simultaneously with positive tendencies, some negative ones is also mentioned (Jones, 2019): the main point is that the transformation should not be too fast. Both students and teachers should be ready to the reforms, and for this they need proper time frames.

Big data can be characterized by the following five properties:

1. *Volume:* typically, Big Data refers to massive volumes of data, usually in zettabytes (ZB) or more.
2. *Variety:* the data consists of a mixture of structured, unstructured and semi-structured information, drawn from such vastly heterogeneous sources as RFID, web searches, social media, mobile sensors like GPS and accelerometers, high fidelity industrial sensors, video streaming etc.
3. *Velocity:* Big Data arrives at varying speeds ranging from milliseconds to days to years, and has differing requirements on the speed with which it is to be processed.
4. *Value:* some researchers consider value as a key characteristic of Big Data, with data being considered valuable if useful information (from a business or engineering perspective) can be extracted from large data sets where individual data points may not carry any value by themselves.
5. *Veracity:* this refers to the accuracy and trustworthiness of the data. This becomes increasingly relevant when large numbers of users in the IoT may be reluctant to report truthful data due to privacy and security concerns (Saravanan, et al., 2019).

Effective use of big data requires the ability to analyze a variety of information sets regardless of where they occur, and the consolidation of data, collected during day-to-day data management and stored in repositories within institutions. The big data management should also provide reliable protection of confidential information as a key requirement for implementing this technology in the field (Daniel & Butson, 2017).

Big data in education form a new special field of activity with natural stress on analysis of educational data. As Wagner and Ice note (2012), big data technological achievements are certainly catalysts of promoting analytics in higher education. Universities can get a value from the big data analytics: mainly, it is monitoring of students' study progress and their educational needs (Maseleno et al., 2018). Furthermore, the rapid advancement of big data analytics makes it necessary for any university to coincide it with their management and measurements (Long and Siemens, 2011).

The literature review has shown that there is a gap in research of integrating mechanisms for new information technologies like Big Data and IoT aimed at its successful implementation in educational sphere. In this article, we present an overview of big data storage, processing and analytics that serve as key enablers for IoT applications on the basis of convergent educational platform. The convergent platform has now been implemented and is being used at Penza State University (Russia, Penza) to manage the educational process in accordance with the recent trends of digitalization and requirements for educational services quality.

DISTANCE EDUCATION TECHNOLOGIES: THE CASE OF PENZA STATE UNIVERSITY

As an example of practical implementation of the considering technologies in education, it is reasonable to consider the experience of the Centre of Distance Learning (CDE) of Penza State University (RF). Development of distance education courses for a number of higher education programs began in 2001. The technology included a limited number of face-to-face classroom lessons and face-to-face tests and examinations with the increased time for independent work of students. To equip students with everything necessary for independent work the learning content was initially issued on CDs / DVDs sent to them, and since 2006 it has been placed in LMS Moodle on the CDE's server. The LMS Moodle has been used to display students' results and counselling since 2006. The CDE has been granted some functions of dean's office to administer distance-learning programs of higher education.

Later the activity of CDE started to introduce some elements of online control and monitoring of online activity of students, basing on international experience (Dawson, 2010). Step by step, a special interactive learning environment has been formed, in which, last years, elements of Big Data technologies were included, similarly to (Huda et al., 2017; Huda et al., 2018).

At present PSU uses distance learning courses completely or partially for advanced studies and training of public employees and business managers, university professors and teachers, and a number of other programs. In most cases, LMS Moodle is used to conduct open and distance learning. For videoconferencing, taking into account the need to optimize the demand on the PSU's Internet channel, the university rents videoconferencing services from an external data centre.

In previous research the authors identified two important corresponding processes, organized in PSU: development of distance learning and digitalization of training that are represented now at almost every academic university (Mkrttchian, et al., 2019). The authors considered theoretical and practical aspects of the university's transition to digitalization of traditional training. In these conditions, it is important to improve the university's administration of the educational process concerning the Electronic informational educational environment (EIEE) and to comprehensively implement distance learning, as well as enhance management of external courses. Accumulation of detailed information in the Electronic informational educational environment about state with achievements of proper learning outcomes creates opportunities for emerging trends (Avetisyan, et al., 2016).

Big data analysis at Penza State University is used to classify electronic educational resources, identify patterns of students with similar psychological, behavioral and intellectual characteristics, and develop personalized learning trajectories. Notably that already during traditional training in EIEE, a rapidly increasing number of different types of data, both structured and unstructured, are stored and accumulated every year, and it is necessary to use big data technologies to process it.

Data generated from devices was already big even before the arrival of IoT. Now, this data is projected to double every two years to reach an estimated 35 ZB (zettabytes) with more than 50 billion estimated devices by the year 2020. Fig. 2 shows the exponential increase in the data generated from the IoT with the number of connected devices according.

However, the Big Data technology must surmount several key barriers including standards, security and privacy, storage, analysis and network infrastructure.

Despite significant uncertainties, the continued growth of academic analytics means (Oblinger, 2012), that we have to explore ethical issues in the institutionalization of academic analytics as a means of stimulating and student support formations (Slade & Prinsloo, 2013). The work is currently studying data management and management structures related to Big Data in higher education. This study also aims to develop the conceptual and theoretical foundations for big data analytics in higher education, as well as the development of key performance indicators, metrics and methods for collecting, processing and visualizing data.

BIG DATA ANALYTICS IN HIGHER EDUCATION

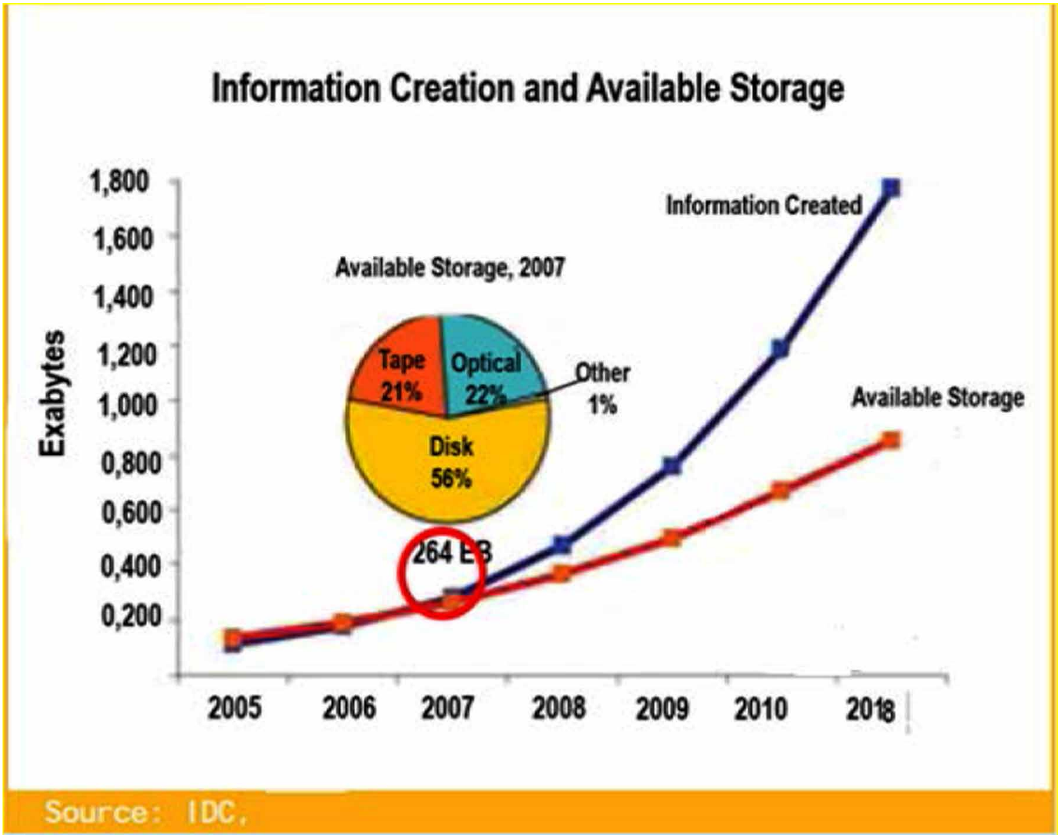
Big Data Analytics as a Part of University Quality Assurance System

As it was mentioned above, big data analytics is now becoming a big challenge in the educational sphere. Strategic aims of educational analytics includes: Helping Learners, Helping Mentors, Developing Curriculum and Learning Process and Helping Administrators (Eduventures, 2013). Institutions began to change their approach to management and began to focus on so-called "high involvement systems" (Hussein & Mohamed, 2015). The key principles for using analytics includes responsibility, transparency and consent, privacy, validity, access, minimizing adverse impacts, etc. (Martin & Thawabieh, 2017).

Success criteria of the educational process can be classified into five main areas:

- matching performance of goals and objectives (planned targets) of the educational institution, the current trend of employment and the needs of society;
- available to consumers comprehensive information about the specialties and conditions of education;

Figure 2. Exponential increase in the data generated from the IoT



- adaptation of the educational process to changes in the demands and needs of clients, innovation in the educational process;
- matching abilities of students to the level and possibilities of teachers;
- common standards for all participants in the educational process.

The monitoring of quality used aggregated and deployed (detailed) evaluation system based on «success criteria».

Performance analysis is usually done in three ways:

- in comparison with other similar units,
- in dynamics (in comparison with past states of the same unit),
- comparing the current characteristics of the unit with the target (planned) indicators.

An alternative approach to assessing the quality of education is «management approach», which proposes to use three groups of indicators:

- efficiency (cost minimization),
- effectiveness (achievement of objectives),
- efficiency (optimization in relation to the resources used performance).

The feature of «management approach» is that different branches set their own criteria for assessing the quality of education and data collection and processing procedures and decision-making using Big Data and IoT techniques.

The OECD Report-2013 of Organisation for Economic Cooperation and Development (Sellar & Lingard, 2013) suggested that it may be the foundation on which higher education can reinvent both its business model and bring together the evidence to help make decisions about educational outcomes (Fig. 3).

Figure 3. Big Data framework in higher education institution (Daniel, 2014)

Modelling Big Data Analytics in Higher Education

Learning analytics is concerned with measuring, collecting, analyzing and presenting data about learners and their contexts in order to understand and optimize learning and the external environments (Hussein, et al., 2019). For higher education, as an extremely complex, multilevel and multifactor process, an analytical monitoring (and mechanisms of its usage) is especially important.

In a broader sense, software and analytics training methods are commonly used to improve processes and workflows, measure academic and institutional data, and generally improve organizational effectiveness (Ibe-Ariwa & Ariwa, 2015). Corporate and academic partnerships are growing. However, to attract and support these partnerships, corporations demand that higher education institutions demonstrate a commitment to using and developing advanced technologies that can support applied research and the potential for knowledge transfer and commercialization (Kellen et al., 2013).

Over the last decades, a digital revolution associated with developments in new technologies is radically reshaping the mode and accessibility of learning and teaching. "The world is becoming a mobigital virtual space where people can learn and teach digitally anywhere and anytime" (Şad & Göktaş, 2013, p. 606). Searching for solutions to the problem of free and mass access to high-quality training courses, regardless of the place of residence and student status has led to MOOC (Massive Open Online Course) that are implemented in the Internet environment. The widespread recognition of MOOC in the world has shown that the method of teaching requires an examination of their methodological foundations for the introduction of elements in intramural and remote learning process in Russian universities.

MOOC is an emerging online platform for engaging the students from diversified locations in the country. MOOC based online learning platforms such as Coursera, Edx, Udacity, MiriadaX and IITBombayX are gaining the increasing number of student enrolment ratio on every year and for every course. Because of new web based technologies such as cloud computing and big data, the content creation cost of MOOC courses has been reduced, thus allows MOOCs providers to make available their content for free to the learners located anywhere with internet access (Saravanan & Srinivasan, 2018).

From an organizational learning perspective, it is well known that institutional effectiveness and adaptation to change are based on an analysis of relevant data (Rowley, 1998). Also modern technologies allow institutions to obtain information from data with previously unattainable levels of complexity, speed and accuracy. As technology continues to penetrate all aspects of higher education, students, computer applications and systems generate valuable information.

Digital Educational Platform With Use of IoT and Big Data

Basic requirements for implementation of Big Data:

1. *Requirements for modern platforms for collection and processing of data:* in the IoT paradigm, data is acquired from various resources such as internet, social media, mobile sensors, RFID etc. The platform for Big Data have the technology to work with data alone (structured and unstructured), and with data in motion (powerful data streams from any type of source). Stream processing needed: overcoming the curse of dimension in data storage.
2. *Platform must be trained by real time system: t*he goal of training IT systems is undoubtedly the improvement of their characteristics on two basic factors influencing the quality of the solution: IT awareness and intelligence. Any ideas for teaching people or systems are based on applying knowledge, accumulated in the past, to make decisions in the present or predict the future. The processed data is mined using learning techniques to extract useful information, which can then be visualized and used for predictive analysis.
3. *Fata management:* several powerful Big Data technologies like MapReduce and NoSQL used to retrieve data effectively from heterogeneous sources and process it according to application needs.
4. *Free adaptive search and production of information:* the legitimate ways of extracting information are technologically implemented through the toolkit of search platforms that provide teams of analysts (IT and business) with the possibility of free creative search in all cyberspace. Modern platforms implement the concept of free search across cyberspace under the control of a creative team, with feedback on this team.

Figure 4 shows a sample Big Data architecture for IoT (Saravanan, et al., 2019).

In this typical architecture, data is collected from disparate sources that may be unstructured, sent through stream processing, where they are processed, and eventually become structured as you move through the architecture.

Any Big Data architecture for IoT applications must possess the following characteristics (Saravanan, et al., 2019).

There are different IoT platforms:

Amazon Web Services Platform IoT – provides interoperability between IoT devices by connecting to the platform.

Bosch IoT Suite – provides the basic capabilities needed to create IoT applications, such as managing IoT devices, analyzing received data and ensuring security of access to devices.

Google IoT Platform – allows you to manage IoT devices, but this platform is focused on the analytical component.

IBM Watson IoT Platform – the platform can be used to manage devices, store and access device data, and connect various devices and gateways.

Microsoft Azure Platform IoT – is a set of libraries for developing software for IoT devices.

Difficulties in the use of IoT systems:

- software dependency on platform hardware;

Figure 4. Big Data architecture for IoT

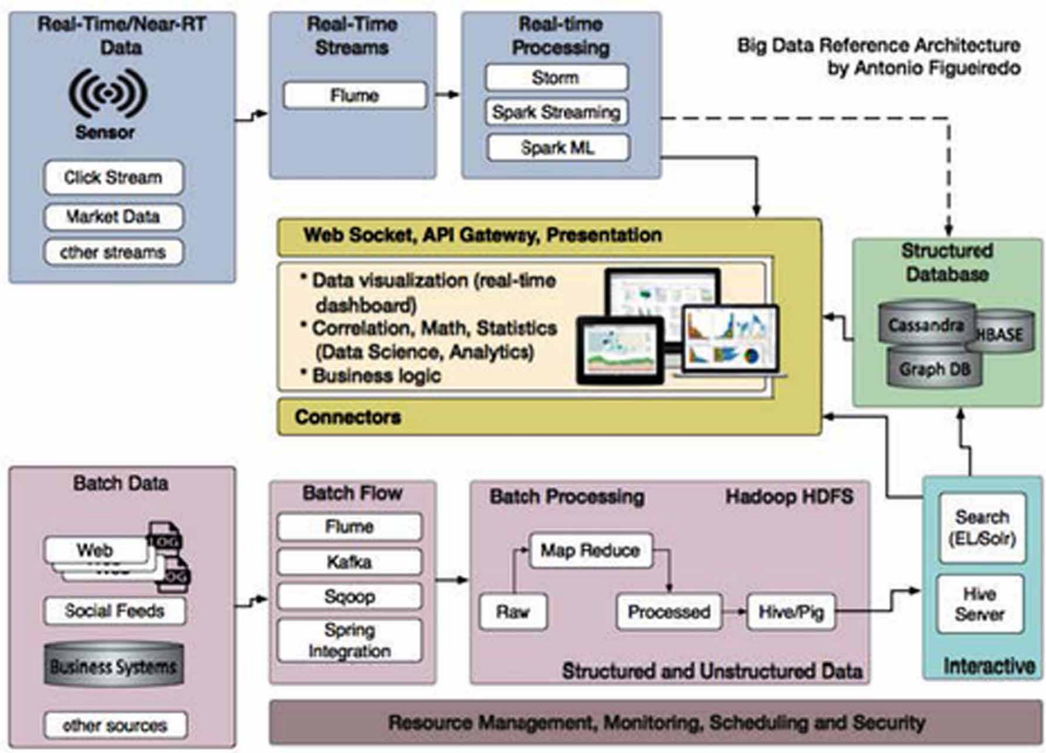


Figure 5. Big Data and IoT (Saravanan, et al., 2019)

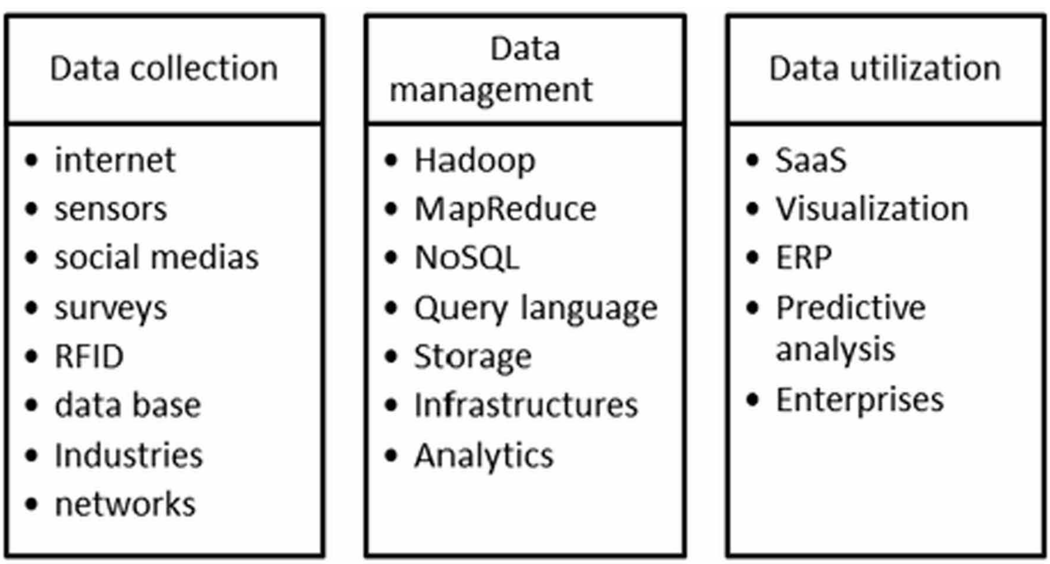
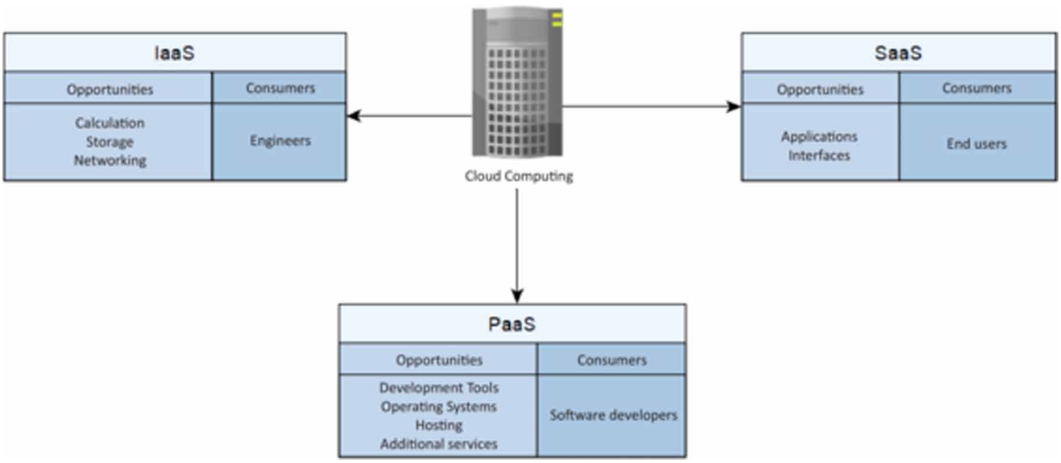


Figure 6. Types of cloud computing



- the complexity of software maintenance for IoT devices, due to the large presence of various architectures, hardware platforms and protocols;
- the complexity of developing a single software product for different devices, with different architecture.

Advantages of the use of IoT systems in higher education institutions:

- allow to make educational process more efficient and automated;
- special processing of large volumes of data;
- easy interaction with other systems through standards.

Many researchers discussed the technical and architectural problems associated with big data tools (Assuncao, et al., 2014; Hegeman, et al. 2013). In addition to the technical problems these authors state that integrating big data tools into IoT applications requires professional experience in this particular area.

Convergent Approach, Convergent and Hyper-Convergent Systems

Big Data can also address the challenges associated with finding information at the right time when data are dispersed across several unlinked different data systems in institutions. By identifying ways of aggregating data across systems, Big Data can help improve decision-making capability (Daniel, 2014).

It is especially important for education sphere, where a lot of business processes are crossed: starting from economic and marketing aspects and finishing sophisticated topics, connected with didactics of this or that subject. We can organise, basing on Big Data approach, some “convergence” between these issues.

In the IT sphere, the convergence is associated with the development of information and telecommunication technologies. The convergence between science and technology (Lee, et al., 2018) determines the process of interpenetration of technologies and boundary-spanning between them, so that the results emerge in the interdisciplinary field of knowledge. Sometimes the convergence is regarded as a synonym to the holistic system approach based on the principle of integration and the emergent property, when new features appear in a holistic system as a result of linking of its parts.

On our mind, the convergent approach is a result of synergetic interaction and reciprocal influence of cognitive, social, informational, telecommunication technologies during the synthesis of tools intended for the obtainment of new knowledge. For example, the convergence between the technologies and systems of fixed line and mobile telephone communication has led to the situation, when subscribers have access to virtually identical services, and the systems themselves are in close interaction between each other, but it doesn't mean that they are integrating.

The convergent process leads to the development of cyber-physical and cyber-social systems and technologies as multimodal infrastructure projects. Cyber-physical systems include natural and technical objects with built-in systems of remote monitoring and control, network interface (Finogeev, et al., 2017; Finogeev, 2019; Vasin, et al., 2018b). Thus, the concept of cyber-physical world determines the system-synergetic integration of computing and physical systems and processes within the uniform internet environment of things.

Convergent systems of data processing and storage are opening a new stage of the information and telecommunication infrastructure. The convergent infrastructure often refers to network computing complexes containing everything necessary to solve university's problems. Actually, the convergent system is based on such an infrastructure that includes sensor networks and the IoT, cloud computing clusters, multiprocessor systems, and mobile computing systems.

The next stage of the evolution of convergent systems is hyper convergent infrastructures of the corporate level. The difference between convergent and hyper convergent systems lies in the fact that convergent structures include specialized interacting components (computing and data storing nodes, etc.). Hyper convergent systems represent modular solutions developed to simplify scaling by means of inclusion of new modules into the system. The capacity of convergent systems is determined by vertical scalability (scale-in), when computing hardware facilities are increased by adding of special resources. For example, in order to increase storage system capacity one may add new drives and input-output modules when the need arises. Hyper convergent systems solve the same problem by horizontal scalability (scale out), which means integration of autonomous modules so that they become a uniform complex. Besides, these modules can be geographically remote. New modules may be connected into the system virtually unlimitedly on demand. Autonomous modules merge into clusters connected via an external network. In terms of administration, a cluster is regarded as a logical unit, where information objects are represented in the global namespace or DFS.

Convergent Information-Analytical Platform

The convergent analytical platform is a set of hardware and software means interacting with each other, intended for automation of Big Data collection and processing with the help of a computing cluster, cloud technologies and mobile connection systems. The platform includes the following: a) computing means of the data processing centre, b) means of data collection, processing and downloading into a storage, cloud data storage, c) applied software packages to solve problems of the intellectual analysis and forecasting, d) an expert subsystem to adjust forecasting and analytical models, e) a remote access system, f) a system of data security administration, g) means of system functioning management and monitoring.

The information-analytical platform is a convergent system intended for decision-making support and monitoring by means of the integration of tools for searching, collection, processing and storing of information, calculation of integral indicators, intellectual analysis and forecasting the dynamics of their changes, preparation of reports and visual demonstration thereof to users, information security administration. It coordinates stages of the technological process of data processing in the system of decision-making support and monitoring, as well as executes centralized monitoring and audit of its components' functioning.

Using the developed platform, the informational and analytical support of decision-making is carried out through consolidation and multipurpose use of operative and retrospective data on the university's activity in cloud storage and through representation of the monitoring results at data marts on computers or mobile phones. The tools of the analytical platform are designed to collect and process data on educational processes from open-access Internet sources for the complex intellectual analysis.

The platform elaborates digital, graphic, text and mixed statistical and analytical reports, the access to which is granted according to group and team policies of interaction, as well as to approved security protocols. Collecting, accumulating and analyzing operative and retrospective information expand the information base of management.

Below are listed the advantages of using the informational and analytical platform:

1. Centralization of processing and storing of data on university's activities;
2. Control over integrity and invariability of data obtained from open sources;
3. Provision of consistency and completeness of data to make decisions on university's development;
4. Improvement of decision-making efficiency regarding university's strategic development by means of prompt provision of required information.

The convergent platform arranges an operating environment for applied business application intended for:

- centralized data processing;
- consolidated data storing;
- information product synthesis;
- providing data analysis results.

The environment's functions are realized by the following services: interaction with users, centralized users' access to data, generation of information products and rules of their usage, demarcation of access to reports, obtainment, accumulation, consolidated storing and integration of data, managing subsystems' functioning and interaction between them. The main requirements to the convergent platform are introduced below (Kimball, 2004).

The platform's architecture is supposed to be focused on searching and connecting new sources of data with minimum component changes, therefore, the platform components are designed on the basis of data model properties.

1. The platform must provide productivity by efficient resource distribution without software modification.
2. The platform seizes an opportunity of reusing project solutions to decrease costs by synthesizing a set of template modules that can be adjusted and modified, if expansion is required.

The informational and analytical platform has several levels of data processing:

- a data source level;
- a data integration level;
- a data storing level;
- a data analytical level;
- an access level.

The data source level is in charge of collection and primary treatment of data from various Internet sources and their representation in XML format. The data integration level determines methods of data consolidation and uploading, data control processes, technologies of unstructured and weakly structured data conversion, uploading of structured data into a cloud storage. Here Big Data undergo batch processing by ETL procedures (Extraction, Transformation, Loading). The data storing level is represented by DBMS of cloud storage. The intellectual analysis and forecasting feature are at the analytical processing level. The access level determines technologies of personal access to data and results using web services and mobile applications.

The convergent platform's architecture includes the following modular software components:

- data storing module on the basis of a cloud storage keeps retrospective data received from the system of integration, integral indicators, reports;
- data integration module consolidates and refines data, as well as converts them to be uploaded into a storage and passed into the analytical system;
- a report making module prepares reports on the basis of the information from a storage according to the regulations or on users' demand;
- a metadata keeping module synthesizes and describes metadata for primary data, cloud storage entities and data marts. As for the primary data, the module describes an infological model of data in terms of a subject area. Regarding the storage entities, the module provides description and management at 3 levels: physical, logical and infological;
- an interaction module provides users with services of controlled access to information products in accordance with rights and authorization;
- a module of personal access to data and monitoring results prepares, transforms and publishes data through a web-service or a mobile application;
- an administrating module automates the activity of system administrators regarding management of modules and platform's hardware functioning and interaction.

The convergent platform implements such models of cloud computing as Platform-as-a-Service (PaaS) and Infrastructure-as-a-Service (IaaS). The PaaS model gives consumers an opportunity to use a cloud infrastructure for locating and launching of data processing applications. The IaaS model enables to use a cloud infrastructure to manage resources of data processing and storing. A software and hardware complex of virtualization and a complex of terminal access to results are implemented to support the technology of Big Data convergence. The software and hardware complex of virtualization provides as follows:

- functioning of module servers in the virtual environment on architectural platform x86;
- putting new virtual servers into operation during scaling;
- management of computing resources for software module functioning.

The software technical complex of terminal access provides the following:

- the service of cloud access to user's virtual environment using the technology of virtual workstations;
- the service of cloud access to administrator's virtual environment using the technology of virtual workstations;
- the virtual work station interface for mobile devices.

The platform is written in Java language and designed in Java EE for operating systems z/OS, AIX, Linux and Windows. It is intended for mainframe computers (RISC, Intel x86). The platform's components are functioning on the basis of UNIX-type OS AIX (Advanced Interactive eXecutive) by IBM and IBM DB2 for AIX in the data processing center. The convergent platform utilizes the technology of parallel processing of Big Data when executing ETL procedures and analytical processing procedures. The technology is supported by a hypervisor capable of maintaining:

- up to 320 logical processes on a host server,
- up to 4 T-bytes RAM on a host server,
- up to 512 virtual machines on a host server,
- automatic distribution of virtual machines between host servers depending on the load,
- «hot» migration of virtual machines between host servers,

- hypervisor loading from an external drive via the network,
- virtual distributed network switches.

Software modules of the platform are located on dedicated resources of the software technical complex pSeries functioning on AIX OS. Databases DB2 10.1 and DB2 Spatial Extender are used to arrange cloud storing. The data integration module operates on the basis of IBM Information Server 9.1.2. Reports are compiled on Cognos BI 10.2 and IBM HTTP Server 8.0.0.0. Users and administrators of the platform communicate and interact through Websphere Application Server 8.5.5. Metadata are managed by the following tools:

1. IBM Infosphere Data Architect (data structure design, synthesis of thesaurus, data models and physical objects).
2. IBM Infosphere Information Server, including as follows:
    - IBM Infosphere Business Glossary (creation, management and viewing of a glossary);
    - IBM Infosphere Metadata Repository (metadata storage support);
    - IBM InfoSphere Metadata Workbench (metadata viewing and management);
    - IBM Infosphere Asset Manager (metadata import);
    - IBM Infosphere Datastage Designer (synthesis of ETL procedures);
    - IBM Infosphere Fasttrack (creation of data specifications).
3. Geoserver (geolocation data publishing and utilization by means of WFS-server).

The Integration System's Architecture for Data Flow Processing

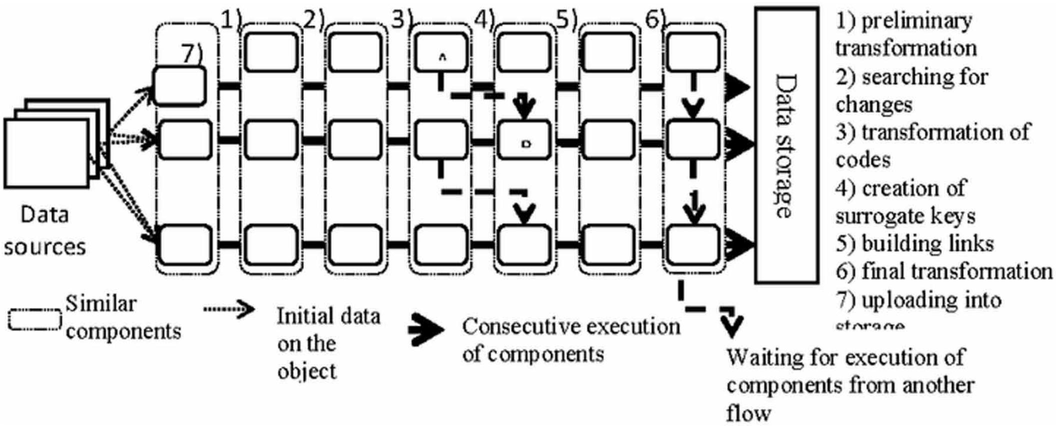
As it has been mentioned previously, the main feature of convergent and hyperconvergent systems is architectural scalability that boosts productivity and increases the amount of processed data without cardinal modernization of the whole system. This feature makes such systems irreplaceable when working with Big Data. For example, let us consider the architecture of a convergent system of data integration or an ETL system. The ETL system performs a number of processes in the field of data processing and processing progress management, including the following:

1. Extraction of data coming from sources.
2. Convergence of data from different sources into a uniform format.
3. Maintaining quality and integrity of data in a storage and their restoration in case of contingencies.
4. Data conversion (refining, standardization and consolidation) when uploaded into a storage.
5. Data uploading and updating of the data previously uploaded into a storage.
6. Monitoring, control and logging of data uploading processes.
7. Detection and handling of errors occurring in data integration processes.

Data extraction is a process, when data are grabbed and shifted into the area of data preparation. Data conversion is a process, when data coming in different formats are unified into one. At the same time, the data are transformed according to local directories, corresponding to the source of information, and the data identifiers together with the structure of the given data are standardized. Quality assurance is a process, when data in the preparation area are checked for compliance with criteria of correctness, completeness, consistency, uniformity and unification. Data transformation is a process of their refinement, supplement and modification according to the processing logic. When being uploaded the data are transferred from the conversion area into a storage.

The scalability problem is solved by means of convergent architecture synthesis. Such architecture ensures a high level of parallel processing of Big Data with possible controlling of the parallelism degree. Process paralleling enables to efficiently utilize hardware resources and to engage additional resources in case the number of data sources increases. This presupposes linking-up and application

Figure 7. The flow architecture of a convergent system of data integration



of template data processing modules (Larman, 2006). In this case, the convergent system of data integration may be represented a set of module flows interacting between each other. Each module flow performs the full process of data processing from extraction from sources to uploading into storage (Fig. 7).

Thus, the proposed convergent platform includes tools for collection, storage, processing of Big Data, managing educational context and learning trajectories in order to assess the quality of educational activities, determining effective directions for the development of higher education institution, as well as forecasting possible problems.

CONCLUSION

The analysis of possibilities, given by such new technologies, as Big Data and IoT, can essentially contribute to solving such standard problems of higher education as involving students to interactive procedures, control of learning outcomes, quality assurance, reliable support of distance education and many others. In accordance with (Daniel, 2014) approach, we can mention such outcomes as:

Performance outcomes:

- better understanding of institutional data;
- better understanding of the requirements for effective data preparation for analytics;
- solid foundation for the utilization of Big Data;
- improved standardized and streamlined data processes;
- consistent ways to effectively leverage data analytics for improved accuracy, deeper knowledge and real time decision making;
- better data-driven decision making and practice;
- foundation for hypothesis testing, web experimenting, scenario modelling, simulation, sensibility and data mining.

Process outcomes:

- better tools for collecting, processing, analysing and interpretation of data;
- better data system interoperability and system linking;
- enhanced data analytics and predictive modelling;
- better real-time rendering of analytics on students and instructors performances;
- reliable and comparable performance indicators and metrics within departments and divisions;

- better utilizations of historical institutional data to make informed decisions;
- better ability to develop and utilize "what if" scenarios for exploring data to predict possible outcomes.

Implications for theory are the following. New IT methods, like Big Data and IoT, are extremely useful for preparing new generation of educational software, especially in such fields as distance education, quality assurance and information analysis. Modern operational software is proper for development of such system. The most effective way to implement the new possibility is using the architecture of convergent and hyper-convergent system.

For further progress we need in development of methods in the both fields: education science and artificial intelligence. Education scientists have to comprehend new possibilities for study process, given by BD and IoT, and propose optimal ways of their usage, basing on pedagogical and psychological principles. IT professional should elaborate information systems, especially oriented for educational needs, as it done for some special cases in the present paper.

Implications for practice are that examples of the approach's realization have been presented. and authors' practical experience of such realization have been discussed. Practical implementation of the technologies in Penza State University has shown their efficiency. Different kind of the program platforms, to support the proposed methodological solutions, have been tested. All the main types of such platforms can be useful, but for their own special cases; selection of a platform should be based on precise analysis of objectives of the program solution's development.

The convergent platform architecture integrates several software products and allows:

1. Use tools and built-in services that enhance the capabilities of the educational management system;
2. Automate the synthesis and modernization of educational resources in accordance with the educational standards and employer's requirements;
3. Automate the synthesis of personalized learning trajectories with the educational content selection to gain demanded on the labor market competencies;
4. Synthesize and train the predictive model of training specialists in the learning trajectories;
5. Identify effective directions for the development of higher education institutions and predicting potential problems;
    5. update the educational content in accordance with the standards and employer's requirements.

The proposed convergent platform for Big Data and IoT processing can make it possible to significantly accelerate and simplify the educational content synthesis, and to realize its actualization mechanism. In the further research, new intellectual mechanisms will be developed to synchronize and interact the educational convergent platform on the basis of machine learning technologies.

ACKNOWLEDGMENT

The reported study was funded by Russian Foundation for Basic Research (RFBR) according to the project Nº 18-010-00204. The results of parts «Big Data analytics in higher education", "Convergent approach, convergent and hyper-convergent systems" and "Convergent information-analytical platform" were obtained within the RSF grant (project No. 20-71-10087).

REFERENCES

Alamri, B. H., & Qureshi, M. R. J. (2015). Usability of cloud computing to improve higher education. *Journal of Information Technology and Computer Science*, *9*(9), 59–65. doi:10.5815/ijitcs.2015.09.09

Arifin, F., Hariadi, M., & Anshari, M. (2017). Extracting Value and Data Analytic from Social Networks: Big Data Approach. *Advanced Science Letters*, *23*(6), 5286–5288. doi:10.1166/asl.2017.7360

Assuncao, M. D., Calheiros, R. N., Bianchi, S., Netto, M. A. S., & Buyya, R. (2014). Big data computing and clouds: Trends and future directions. *Journal of Parallel and Distributed Computing*. Advance online publication. doi:10.1016/j.jpdc.2014.08.003

Avetisyan, J., Bozhday, A., Novikova, N., & Kochetkova, J. (2016). Design of the E-Systems for Training and Researching with Tools of Cloud Services-Based Stereo and 3D Content. In *Handbook of Research on Estimation and Control Techniques in E-Learning Systems* (pp. 376–388). IGI Global. doi:10.4018/978-1-4666-9489-7.ch027

Chao, R. (2017). Educating for the fourth industrial revolution. *University World News, 10*. https://www.universityworldnews.com/post.php?story=20171107123728676

Chou, S.-C. (2016). Controlling Information Flows during Software Development. *International Computer Symposium*. doi:10.1109/ICS.2016.0057

Daniel, B. (2014). Big Data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology*, *46*(5), 904–920. doi:10.1111/bjet.12230

Daniel, B. K., & Butson, R. J. (2017). The rise of big data and analytics in higher education. In *The analytics process: Strategic and tactical steps* (pp. 113–126). CRC Press. doi:10.1201/9781315161501-5

Dawson, S. (2010). Seeing the learning community: An exploration of the development of a resource for monitoring online student networking. *British Journal of Educational Technology*, *41*(5), 736–752. doi:10.1111/j.1467-8535.2009.00970.x

Dewar, J. (2017). University 4.0: Redefining the Role of Universities in the Modern Era. *Higher Education Review*, 8. https://www.thehighereducationreview.com/magazine/university-40-redefining-the-role-of-universities-in-the-modern-era-SUPG758722027.html

Dumbill, E. (2014). Defining Big Data. *Forbes*. https://www.forbes.com/sites/edddumbill/2014/05/07/definingbig-data/

Eduventures. (2013). *Predictive analytics in higher education: Data-driven decision-making for the student life cycle*. Washington, DC: Author.

Estévez-Ayres, I., Fisteus, J. F., & Delgado-Kloos, C. (2017). A distributed stream-based infrastructure for the real-time gathering and analysis of heterogeneous educational data. *Journal of Network and Computer Applications*, *100*, 56–68. doi:10.1016/j.jnca.2017.10.014

Eynon, R. (2013). The rise of Big Data: What does it mean for education, technology, and media research? *Learning, Media and Technology*, *38*(3), 237–240. doi:10.1080/17439884.2013.771783

Finogeev, A., Gamidullaeva, L., & Bershadsky, A. (2019). *Education and Information Technologies*. Advance online publication. doi:10.1007/s10639-019-09903-5

Finogeev, A. G., Parygin, D. S., & Finogeev, A. A. (2017). The convergence computing model for big sensor data mining and knowledge discovery. *Human-centric Computing and Information Sciences*, *7*(1), 11. Advance online publication. doi:10.1186/s13673-017-0092-7

Fry, S. (2019). Go Big: Data in education. *Educational Technology*.

Gamidullaeva, L. A. (2019). Towards combining the triple helix concept with competence-based approach of educational management theory. *Global Business and Economics Review*, *21*(3-4), 278–303. doi:10.1504/GBER.2019.099393

Hedayati, M. H., Laanpere, M., & Ammar, M. A. (2017). Collaborative ontology maintenance with concept maps and Semantic MediaWiki. *International Journal of Information Technology*, *9*(3), 251–259. doi:10.1007/s41870-017-0030-y

Hegeman, T., Ghit, B., Capota, M., Hidders, J., Epema, D., & Iosup, A. (2013). *The BTWorld use case for big data analytics: Description, MapReduce logical workflow, and empirical evaluation.* http://www.pds.ewi.tudelft.nl/~iosup/btworld-mapreduce-workflow13i eeebigdata.pdf

Huda, M., Haron, Z., Ripin, M. N., Hehsan, A., & Yacob, A. C. (2017). Exploring Innovative Learning Environment (ILE): Big Data Era. *International Journal of Applied Engineering Research: IJAER*, *12*(17), 6678–6685.

Huda, M., Maseleno, A., Atmotiyoso, P., Siregar, M., Ahmad, R., Jasmi, K. A., & Muhamad, N. H. N. (2018). Big Data Emerging Technology: Insights into Innovative Environment for Online Learning Resources. *International Journal of Emerging Technologies in Learning*, *13*(1), 23. doi:10.3991/ijet.v13i01.6990

Hussein, A., & Mohamed, O. (2015). Cloud computing and its effect on performance excellence at higher education institutions in Egypt (an analytical study). *European Scientific Journal*. https://eujournal.org/index.php/esj/article/view/6528/6253

Hussein, H. S., Elsayed, M., Mohamed, U. S., Esmaiel, H., & Mohamed, E. M. (2019). Spectral Efficient Spatial Modulation Techniques. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 1454–1469. doi:10.1109/ACCESS.2018.2885826

Hussin, A. (2018). Education 4.0 made simple: Ideas for teaching. *International Journal of Education and Literacy Studies*, *6*(3), 92–98. doi:10.7575/aiac.ijels.v.6n.3p.92

Ibe-Ariwa, K. C., & Ariwa, E. (2015). Green technology sustainability and deployment of cloud computing in higher education. *Social Media Studies*, *1*(2), 151–160. doi:10.15340/2147336612873

Ivashchenko N.P. (2017). Primenenie podhoda shared governance v rossijskih universitetah: postanovka problemy i napravleniya sovershenstvovaniya [The Application of the Shared Governance Approach in Russian Universities: the Formulation of the Problem and the Direction of Improvement]. *Innovations, 9*(227), 105-111.

Jones, L. (2019). Big data and education: help or harm? *Colocation America*. https://www.colocationamerica.com/blog/big-data-and-education

Kaisler, S., Aemour, F., Espinosa, J. A., & Money, W. (2013). Big Data: Issues and Challenges Moving Forward. *Proceedings of the 46th Hawaii International Conference on System Sciences*, 995-1004. doi:10.1109/HICSS.2013.645

Kellen, V., Recktenwald, A., & Burr, S. (2013). Applying big data in higher education: A case study. *Data Insight & Social BI Executive Report*, *13*(8), 3.

Kimball, R., & Caserta, J. (2004). *The Data Warehouse ETL Toolkit: Practical Techniques for Extracting, Cleaning, Conforming, and Delivering Data*. Wiley Publishing Inc.

Kusmin, M., Saar, M., & Laanpere, M. (2018). Smart schoolhouse—designing IoT study kits for project-based learning in STEM subjects. *IEEE Global Engineering Education Conference (EDUCON)*, 1514-1517. doi:10.1109/EDUCON.2018.8363412

Larman, G. (2006). *Application of UML 2.0 and design patterns*. Williams.

Lee, C., Park, G., & Kang, J. (2016). The impact of convergence between science and technology on innovation. *The Journal of Technology Transfer*, *43*(2), 522–544. doi:10.1007/s10961-016-9480-9

Li, Y., & Zhai, X. (2018). Review and Prospect of Modern Education using Big Data. *Procedia Computer Science*, *129*, 341–347. doi:10.1016/j.procs.2018.03.085

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

Martin, A., & Thawabieh, M. (2017). The Role of Big Data Management and Analytics in Higher Education, Business, Management and Economics Research. *Academic Research Publishing Group*, *3*(7), 85–91.

Maseleno, A., Sabani, N., Huda, M., Ahmad, R., Jasmi, K. A., & Basiron, B. (2018). Demystifying Learning Analytics in Personalised Learning. *IACSIT International Journal of Engineering and Technology*, *7*(3), 1124–1129. doi:10.14419/ijet.v7i3.9789

Mershad, K., & Wakim, P. (2018). A Learning Management System Enhanced with Internet of Things Applications. *Journal of Education and Learning*, *7*(3), 23–40. doi:10.5539/jel.v7n3p23

Mkrttchian, V., Krevskiy, I., Bershadsky, A., Glotova, T., Gamidullaeva, L., & Vasin, S. (2019). Web-Based Learning and Development of University's Electronic Informational Educational Environment. *International Journal of Web-Based Learning and Teaching Technologies*, *14*(1), 32–53. doi:10.4018/IJWLTT.2019010103

Murumba, J., & Micheni, E. (2017). Big Data Analytics in Higher Education: A Review. *The International Journal of Engineering and Science*, *6*(6), 14–21. doi:10.9790/1813-0606021421

Oblinger, D. G. (2012). Let's talk… analytics. *EDUCAUSE Review*, *47*(4), 10–13.

Patarakin, E., Burov, V., & Yarmakhov, B. (2019). Computational Pedagogy: Thinking, Participation, Reflection. In *Digital Turn in Schools—Research, Policy, Practice* (pp. 123–137). Springer. doi:10.1007/978-981-13-7361-9_9

Ray, S. (2013). Big data in education. *Gravity*, 20.

Rowley, S. (1998). Tetraplegia and Paraplegia. *Physiotherapy*, *84*(12), 623. doi:10.1016/S0031-9406(05)66165-2

Şad, S. N., & Göktaş, Ö. (2013). Preservice teachers' perceptions about using mobile phones and laptops in education as mobile learning tools. *British Journal of Educational Technology*. Advance online publication. doi:10.1111/bjet.12064

Saravanan, K., & Srinivasan, P. (2018). Examining IoT's Applications Using Cloud Services. In *Examining Cloud Computing Technologies Through the Internet of Things* (pp. 147–163). IGI Global. doi:10.4018/978-1-5225-3445-7.ch008

Saravanan, V., Hussain, F., & Kshirasagar, N. (2019). *Role of Big Data in Internet of Things Networks. In Handbook of Research on Big Data and the IoT*. IGI Global. doi:10.4018/978-1-5225-7432-3.ch016

Sarmiento, Q., Alejandro, P., & Quispe, E. (2018). Body of Knowledge on IoT Education. *14th International Conference on Web Information Systems and Technologies*, 449-453. doi:10.5220/0007232904490453

Schuster, K., Groß, K., Vossen, R., Richert, A., & Jeschke, S. (2016). Preparing for industry 4.0–collaborative virtual learning environments in engineering education. In *Engineering Education 4.0* (pp. 477–487). Springer. doi:10.1007/978-3-319-46916-4_36

Sellar, S., & Lingard, B. (2013). The OECD and global governance in education. *Journal of Education Policy*, *28*(5), 710–725. doi:10.1080/02680939.2013.779791

Sengupta, S. (2019). Internet of things: Applications in education sector. *Teaching Learning with ICT: An Innovative Approach, International Conference*.

Slade, S., & Prinsloo, P. (2013). Learning Analytics. *The American Behavioral Scientist*, *57*(10), 1510–1529. doi:10.1177/0002764213479366

Tan, P., Wu, H., Li, P., & Xu, H. (2018). Teaching Management System with Applications of RFID and IoT Technology. *Education Sciences*, *8*(1), 26. doi:10.3390/educsci8010026

Tannahill, B. K., & Jamshidi, M. (2014). System of Systems and Big Data analytics – Bridging the gap. *Computers & Electrical Engineering*, *40*(1), 2–15. doi:10.1016/j.compeleceng.2013.11.016

TechStartups Team. (2018). How much data do we create every day? *Tech Startups Site*. https://techstartups.com/2018/05/21/how-much-data-do-we-create-every-day-infographic/

van Kranenburg, R. (2007). *The Internet of Things. A critique of ambient technology and the all-seeing network of RFID*. http://networkcultures.org/blog/publication/no-02-the internet-of-things-rob-van-kranenburg/

Vasin, , Gamidullaeva, Finogeev, & Parygin. (2018). Exploring regional innovation systems through a convergent platform for Big Data. *SMART-2018: Proceedings of the 7th International Conference on System Modeling & Advancement in Research Trends*, 292–296.

Vasin, S., Gamidullaeva, L., Shkarupeta, E., Palatkin, I., & Vasina, T. (2018). Emerging trends and opportunities for industry 4.0 development in Russia. *European Research Studies Journal, 21*(3), 63-76.

Vermesan, O., & Friess, P. (2015). *Building the Hyperconnected Society*. Building the Hyperconnected Society. doi:10.13052/rp-9788793237988

Wagner, I., & Ice, P. (2012). Data changes everything: Delivering on the promise of learning analytics in higher education. *EDUCAUSE Review*, *47*(4), 33–42.

What Is Big Data? (2019). *Oracle Website*. https://www.oracle.com/big-data/guide/what-is-big-data.html

Zikopoulos, P.C.; Eaton, Ch.; Deroos, D.; Deutsch, T., & Lapis, G. (2012). *Understanding Big Data, Analytics for Enterprise Class Hadoop and Streaming Data*. The McGraw-Hill.

Vardan Mkrttchian graduated from State Engineering University of Armenia, the Faculty of Cybernetics as an Electronics Engineer & received his Doctorate of Sciences (Engineering) in Control Systems from Lomonosov Moscow State University (former USSR). Dr. Vardan Mkrttchian taught for undergraduate and graduate student's courses of control system, information sciences and technology, at the Astrakhan State University (Russian Federation), where he was is the Professor of the Information Systems (www.aspu.ru) six years. Now he is full professor CAD & Economy departments of Penza State University (www.pnzgu.ru) . He is currently chief executive of HHH University, Australia and team leader of the international academics (www.hhhuniversity.com). He also serves as executive director of the HHH Technology Incorporation. Professor Vardan Mkrttchian has authored over 400 refereed publications. He is the author of over twenty books published of IGI Global, included ten books indexed of SCOPUS in IT, Control System, Digital Economy, and Education Technology, and 41 works in SCOPUS and 15 in WoS. He also is Editor-in-Chief of International Journal of Applied Research in Bioinformatics (IJARB).

Leyla Gamidullaeva graduated from Penza State University, the Faculty of Economics and Management, getting qualifications of an economist. L. Gamidullaeva got her PhD in Economics from Penza State University of Architecture and Construction in 2010 followed by the title of associate professor in 2018. Now she is associate professor at the department of management and economic security of Penza State University, K.G. Razumovsky Moscow State University of Technologies and Management (FCU). Currently, L. Gamidullaeva is doing her doctoral research in the regional innovation system management at St Petersburg State University. She has authored more than 200 refereed publications and over ten books in innovation management, regional economic growth, networking and collaboration.

Alexey Finogeev, Doctor of Science (Engineering), Professor, Honored Worker of Higher Professional Education of the Russian Federation received his Doctorate of Sciences from Penza State University (Penza, Russia). During his research career worked as an engineer (Penza Politechnical Institute), researcher (Ottawa University), assistant professor, associate professor, professor (Penza State University). Since 2004, he is the fulltime professor at the Department of Computer Aided Design of Penza State University. The area of the scientific research is connected with information technologies, network technologies, wireless technologies, technologies for digital economy, Big Data, sensor networks, SCADA system, 3D modeling and virtual reality, computer aided design. Main science activities are related with design of intellectual and analytical systems, wireless sensor networks, fog and grid computing, SCADA systems, adaptive decision-making systems, geoinformation systems. Member of The Russian Academy of Natural History.

Serge V. Chernyshenko is involved in ecological researches since 1982, when he graduated from Dnepropetrovsk State University (former USSR) by the major of "Applied Mathematics". In 1986 he received his Doctorate of Sciences (Physics and Mathematics) in Mathematical Modeling from Shevchenko Kiev State University (former USSR) and the degree of Doctorate of Sciences (Biology) in Ecology from Dnepropetrovsk National University (Ukraine) in 2006. In his research, he is focused on mathematical modeling of forest ecosystems and has more than 100 publications in the field. During his scientific career he has the position of professor in several universities: Regional Moscow University, Sholokhov State University for the Humanities (Russia); Dnipropetrovsk National University, Khmelnitsky National University (Ukraine); Marie Curie-Sklodowska University (Poland), Koblenz-Landau University (Germany). Also he delivered lectures, as an invited professor, in universities of Italy, UK, Spain and Portugal. The main topics of his lectures are the following: Mathematical Modelling; Systems Analysis; General Systems Theory; Ecological Modelling; Data Mining; Mathematical Statistics and so on. He was a supervisor of about 20 international and national research and educational projects. He is the author of two monographs on mathematical ecology, over thirty books, more than 150 articles, published in various conference proceedings, books and journals in Mathematical Modelling, Ecology, IT, Control Theory, Education Technology. Dr. Vsevolod Chernyshenko is work in Financial University under the Government of the Russian Federation Dr. Amirov is work at department of Information systems and technologies in Moscow State University of Technology and Management Dr. Irina Pinotapova is Dean of department of Economy Astrakhan State University of Architecture and Civil Engineering.