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Educational Data Analytics and Fog Computing in Education 4.0

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Abstract

Universities are generating massive amounts of educational data. Most universities are now focusing on how to harness that data to optimize and visualize it to provide better and more extended education services. Given this scenario, a literature review was used to conduct this study guided by the following objectives: (1) Assess suitable fog computing and educational data analytics architectures; (2) Examine the opportunities offered by fog computing and educational data analytics; (3) Investigate fog computing and educational data analytics challenges; and (4) Examine disruptions and future directions of these technologies in Education 4.0. The study concludes that institutions must use integrated data analytics techniques and distributed technology systems to make decisions about administration, resource allocation, student retention, performance, and improvement strategies. The study also identified the challenges of using fog computing and educational data analytics and concludes that education 4.0 is a learning style that is aligned with the fourth industrial revolution, requiring transformational learning readiness.

Keywords: education data analytics, learning analytics, fog computing, Education 4.0.

1. Introduction

Different digitally connected learning systems have achieved international recognition in the wake of educational IT-enhancing innovations. Universities are creating vast amounts of educational data and are thus trying to harness that data to visualize and optimize it to provide better and more extended education services (Amor et al., 2020). The massive volumes of data, both structured and unstructured, are generated at the universities through a variety of processes from educational and administrative systems, contributing to educational big data (Hadwer et al., 2019). Advancements in Information Technologies and the COVID-19 pandemic are disrupting the education arena. That has led several educational institutions of higher learning to turn to Virtual Learning Environments (VLEs) as part of preparing, coping, and recovery strategies. Pecori (2018) noted that conventional forms of learning are growing towards blended learning, which makes use of virtual and mobile learning frameworks. Technologies such as fog computing and big data may create an innovative teaching platform system that can minimize network

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broadband strain, reduce cloud server load, increase comprehensive computing ability, and reduce latency (Cai, Qin, Zheng, Li, Luo & Zhang, 2018). These developments, coupled with the IoT social revolution, have led to the integration of fog and cloud technologies in educational systems. Wearables and full-fledged devices (e.g., tablets and laptops) can provide valuable educational data (Pecori, 2018). It is possible to analyze and use large volumes of data generated by IoT devices to develop a variety of valuable services for end-users and customers.

Several universities are reaping the benefits of investing in information technologies that are enabling them to develop and facilitate educational strategies to attract more students. These include, but are not limited to, virtual and digitally-enabled learning systems and administrative systems. Jones (2019) observes universities' collected and analyzed students' digital behaviors using learning analytics technology. Educational data qualities, such as high velocity, volume, diversity, validity, and value, have improved learning analytics (Gupta et al., 2015; Matsebula & Mnkandla, 2017). A new computing paradigm is necessary to offer location awareness, comprehensive monitoring, and intelligent command and control because of the inherent geo-distribution of educational data. Fog computing, which extends computation to the network's edge, meets this requirement (Tang et al., 2017). The node in fog computing, as stated by Prakash et al. (2017) processes data. It must process a portion of the data before it sends it to the central server for the rest of the computations. As a result, fog is especially useful in large, scattered regions where connectivity may be uneven. As said by Raman (2019), an organization's fog computing facilities can accommodate numerous users, vehicles, wearables, sensors, and smart devices.

Many universities are facing challenges when it comes to harnessing educational big data, to optimize and visualize it to provide better and more extended education services. A new computing paradigm is necessary to offer location awareness, comprehensive monitoring, and intelligent command and control because of the inherent geo-distribution of educational data; and Fog computing, which extends computation to the network's edge, meets this requirement (Tang et al., 2017). The scenario that universities are generating massive amounts of educational data motivated the study. Because data volumes are increasing, few institutions have been able to capitalize on the benefits of information they collect daily through their core business of learning and teaching. Education 4.0 initiatives, strategic formulation, support of e-learning, and innovation are viewed as significant steps to transformation and change during a crisis, supporting the preventative measures and recovery of higher education while trying to mitigate the impact on students and learning continuity.

2. Educational data analytics

Big data streams are rapidly becoming a major paradigm in data science. They appear in an ever-expanding variety of fields – novel platforms that comprise different applications, users, and devices typically generated on the web, sensing, smart systems, and so on. To deal with virtually infinite streams, non-stationary data, and constantly changing aspects of knowledge, precise methodologies and technologies are mandated (Pecori, 2018). Big data analytics refers to the process of gathering, assembling, and analyzing large amounts of data to extract useful information and patterns (Klašnja-Milićević et al., 2017). Hadwer et al. (2019), likewise big data are driving most organizations in the direction of enabling growth and sustainability. The companies like Google, IBM, Netflix, and Amazon use Big Data analytics to forecast customer behavior and usage patterns to improve products and services. Cloud services can be used to gain access to usage analytics, such as watching, purchasing patterns, and preferences, to improve target marketing. Endeavors to envision the prospect of education frequently emphasize novel technologies, such as ubiquitous computing devices, flexible classroom designs, and innovative visual displays, as well as data and analytics (Siemens, & Long, 2011). Klašnja-Milićević et al. (2017) agreed that apart from educational performances that most universities have affirmed the critical importance of analytics in resource equity distribution, administrative activities, finance, and student achievement. Alkhalil et al. (2021) ascribed that big data analytics allow universities to precisely measure and forecast key performance indicators, resulting in rational and strategic decisions. Academic achievement, educational quality, research, courses or curricula, processes accountability, growing student diversity, and student retention are the most important issues in higher education institutions around the world (Matsebula & Mnkandla, 2017). MacNeill et al. (2014) cited some of the driving forces behind educational and learning analytics applications. These encompass: (i) offering information to assist institutional administrators in making decisions about marketing and recruiting and selection, as well as effectiveness and efficiency indicators, (ii) individual students can use analytics to focus on their achievements and behavioral patterns in contrast to their colleagues, (iii) assisting teachers and support staff in developing supportive interventions for groups and individuals, (iv) identifying students who could require additional assistance and attention, and (v) providing functional groups, like as course teams, with the ability to enhance existing courses or design new curriculum offerings.

The findings of Huda et al. (2016) show that BDA is critical in improving decision-making, providing insights, discovering facts, and optimizing the education processes. Therefore, it is significant for higher education institutions to use BDA-based Education 4.0 which includes innovative teaching and learning strategies to maintain sustainability in providing students with innovative learning experiences. The primary role of learning analytics is to generate valuable information that can be used in data-driven decision-making. This information may provide insight into a student's involvement with a university (Alblawi & Alhamed, 2017). MacNeill et al. (2014) pointed out that educational data analytics and fog computing is beneficial to administrative, training, and educational materials, including how learning resources are used, by who, and under what scenario. It also provides more contextual information for strategic planning and creativity in course design and delivery. A study by Banihashem et al. (2018) indicated that educational data analytics and fog computing could provide positive effects on education, like increased student engagement, improved learning outcomes, identifying at-risk students, actually providing feedback in real-time, and customization of education for Education 4.0.

3. Fog computing

For a complicated geo-distributed network of IoT devices, Cisco has developed a new computing paradigm called fog computing. As Abdulqadir et al. (2021) pointed out, cloud computing is incapable of managing local issues involving multiple IoT parts, as well as applications requiring the swift attention of a local controller (which cloud computing lacks). Fog computing is therefore necessary. IoT components are reasonably near to cloud computing, and it keeps data in both the cloud and fog nodes. Nowadays, the Fog Computing paradigm has developed as the ideal partner for big data streams, which aim to decrease the quantity of data that has to be transferred to the cloud for processing, analysis, and storage. Goals are to increase network efficiency by moving computing resources, applications, and services to the network's edges (Pecori, 2018). Zhang et al. (2018) define fog computing as a virtualized architecture that enables services such as storage, computation, and networking across collaborating end devices and data centers. The Fog Computing paradigm, also known as Edge Computing, extends the Cloud Computing paradigm to minimize latency, increase location awareness, reinforce mobility, and drive business (Mahmood & Ramachandran, 2018). Fog Computing is capable of delivering data analytics capabilities closer to the actual equipment that generates the data, such as at the network's edge, avoiding the broader Internet (Abdulqadir et al., 2021). Prakash et al. (2017) observed that when many non - homogeneous wireless devices join and interact with each other and with the network, fog computing may perform storage and computation activities without the interference of third parties. Fog Computing distributes computing capabilities and application services in rational, efficient locations anywhere between the data source and the cloud. Fog computation is a distributed computing platform that extends the grid's typical computing cloud applications (Abdulqadir et al., 2021).

4. Methodology

The study was conducted based on desktop research guided by Google Scholar using keywords such as Education Data Analytics, Learning Analytics, Fog Computing, and Education 4.0.

5. Fog computing and educational data analytics architectures

As a concept, fog computing refers to the work of a highly dispersed, virtual environment that provides processing, network, and storage services between sensors and cloud data centers. To reduce latency and network congestion, cloud-based computing has been pushed outside, resulting in "fog computing" (Adel, 2020). Further than replacing cloud computing, the goal was to grow and augment it. Cai et al. (2018) regard fog computing as an extension of cloud computing, which is the "fog server" connected to many Internet of Things (IoT) infrastructure devices. Because of highly dispersed fog nodes, fog computing is useful for Internet of Everything applications that require consistent latency in real-time (Prakash et al., 2017). Virtual computing, also known as edge computing, is a more distributed computing service model based on cloud computing that has the following characteristics: proximity to the user, low latency, high confidentiality, high reliability, a dense geographic space for the distributed network, multiple nodes, wireless access network equipment, etc. In addition to its processing efficiency, it provides network security monitoring, real-time analytics, and capabilities for close-range source management, as well as real-time interaction and cloud online analytics support (Cai, Qin, Zheng, Li, Luo & Zhang, 2018). A notable feature of fog computing is that it extends cloud services to the network's edge. It accomplishes this by collecting local resources and bringing communication, control, storage, and computing functions closer to the clients (Neware & Shrawanka, 2020).

The fog system comprises fog nodes, which are a range of devices at the edge of the network with embedded management systems. It also contains simulated data center edges. Fog computing, in relation to the study by Neware and Shrawanka (2020), acts as a connecting connection between cloud and edge users. Through the use of wireless connection platforms like Wi-Fi, Bluetooth, and 4G, fog nodes are used to link end appliances and devices with users to provide services such as data management and processing. So, the fog computing system enables the assessment of data and the decision-making process at a quick rate. Fog computing is a decentralized computer infrastructure comprising three stratified tiers which help in the computation, storage, and processing of data. It is like edge computing because it contributes to specific advantages in IT. Adel (2020) and Neware and Shrawanka (2020) describe it as a three-tiered decentralized computer architecture that aids in computation, storage, and data processing. These are:

Terminal tier: This layer is the closest to the end-user and the actual world in terms of physical closeness. Cell phones, sensors, smart cards, smart cars, etc are all included in this category. They are usually widely scattered and sense and gather information about actual events or objects, then send it to the tiers above, either for saving or processing, before returning it to the lower tiers.

Fog tier: There are many fog nodes in this layer, which are at the edge of the network. We may find nodes of fog in a variety of settings, including retail malls and bus terminals as well as parks and city streets. Because of the sensing, they can convey, quantify, and preserve data. By connecting to the cloud's data center via the IP core network, fog nodes can work collaboratively with the cloud to improve their capabilities for storing and processing data.

Cloud tier: Storage, storing, and processing capabilities are quite high on this tier, which is why it can do a broad range of computation analysis as well as store and save enormous amounts of data and information. According to IoT architecture (Adel, 2020), the cloud layer or data center layer is the uppermost layer in the system's design. This layer is responsible for enabling network access to all shared resources in the IoT network conveniently and appropriately. Figure 1 illustrates the fog architecture.

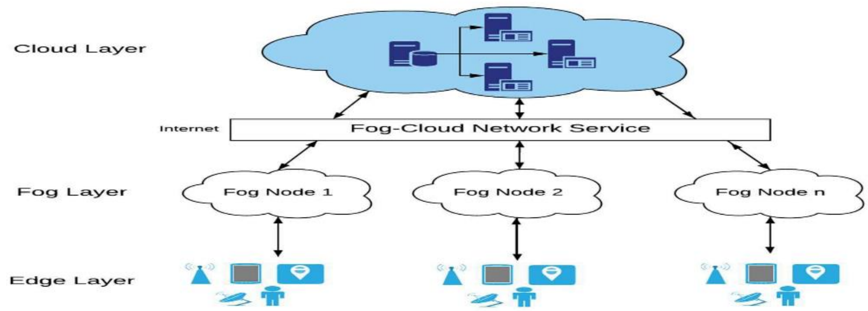

Figure 1. Fog computing architecture, adapted from Neware & Shrawanka (2020)

6. Education 4.0

Education 4.0 is the educational equivalent of Industry 4.0. It is referred to as educational reform, and it aims to satisfy the expectations of Industry 4.0, particularly the workforce requirements for it (Himmetoglu et al., 2020). Hence, Education 4.0 is a preferred learning style that aligns with the upcoming fourth industrial revolution. Higher education sectors make significant contributions to a country's overall economic and social development (Alkhalil et al., 2021). Given the fact that data volumes are increasing, few institutions have been able to capitalize on the benefits of information they collect daily through their core business of learning and teaching until recently (MacNeill et al., 2014). The advancement of novel technologies encompassing digital learner records, devices, flexible classroom plans, and Massive Open Online Courses (MOOC) is fundamentally altering the approach to learning culture and teaching(Jones, 2019). Student information systems, social networks, learning management systems, blogs, research, and so on all contribute to big data in higher education (Matsebula & Mnkandla, 2017). Higher education entailed many interconnected dimensions, such as psychological, social, scientific, cultural, human, and intellectual, all of which contributed to the achievement of its objectives and goals (Alkhalil et al., 2021). Bonfield et al. (2020) stated that currently there is no primer as to how to plan, teach, or deliver Education 4.0. Besides, it is important to note that not all institutions are the same and will therefore move at varying rates based on their economic, social, or political setting – it is indeed difficult to plan for outward disruptors like global pandemics (COVID-19), changes in regulations from the government, and technological innovations.

Tulasi (2013) postulates that the adoption of technology is greatly establishing most institutions' competencies, particularly in dealing with emerging challenges. The impact is quite motivating when appropriate technology is aligned with educational mandates such as objectives and standards. The underlying forces, both internal and external, necessitate higher education, which has no choice but to adapt quickly to the changes. By arbitrarily pushing computation nearer to where education data is created and utilizing a geographically distributed myriad of heterogeneous systems in data centers extending the wide spectrum from the Cloud to the IoT, fog computing help effectively promote time-sensitive and bandwidth IoT applications (Brogi et al., 2018). Typically, in the education field, fog computing technology enhances educational operational activities and gives an agile platform, rather than slowing or discontinuing them (Raman, 2019). The core elements defining Education 4.0, according to the findings of a study conducted by Himmetoglu et al. (2020) are free access, personalized education, mental change, digital technology integration into education, streamlined learning environments, continuous learning, explorative education, and interdisciplinary education. Their findings also revealed that the main characteristics expected of students in Education 4.0 are participation, communication skills, technical knowledge, learning skills, and personality traits. Likewise, instructors of Education 4.0 are expected to have technical knowledge, leadership abilities, intellectual growth, and personal characteristics. Finally, the key qualifications anticipated of Education 4.0 institution managers are guidance competencies, technological skills, cognitive abilities, and analytical ability.

Kruse and Pongsajapan (2012) noted that institutions are currently ecstatic about the promises and opportunities of analytics in higher education. Analytics in academic contexts aims to allow institutions to leverage the data generated through learning management systems (LMSs) and other online databases and then use it to better the lives of the university and, apparently, the learners. Decisions on the progress of academic students, future performance predictions, and the recognition of potential issues can be realized via fog analytics (Lee et al., 2020). Badidi et al. (2020) in their studies posit that educational data processing and analytics must depend solely on interoperable messaging systems, sophisticated software engines for data stream processing, and optimized data storage strategies. Fog computing plays a crucial role in this by effectively addressing big data storage issues. It facilitates fast computing and analysis of data to adapt effectively to many happenings in institutions that demand urgent decisions and actions. Learning analytics, according to Banihashem et al. (2018) provide unique insights into education; there are ethical, educational, and technical concerns with the use of learning analytics in education. Sin and Muthu (2015) claimed that researchers are interested in educational data analytics with datasets to focus on improving education, particularly via the coordination and teamwork seen between educational data mining and learning insights communities. In addition, researchers are working on developing mechanisms and dashboards for data visualization to assist students and teachers in visualizing learning trajectories.

7. Leveraging opportunities and applications in education

Ciolacu et al., (2017) showed that many tasks and activities that humans have traditionally performed will be displaced because of the impact of digital transformation on industries. The great potential of Industry 4.0 is found in data and the effective use of newly acquired opportunities and challenges. Students' active and interactive presence contributes to higher learning quality in the fourth revolution in Education. It is crucial to acknowledge that simply having data access will not have a major effect on higher education institutions; people must contextualize, respond to, as well as understand the data (MacNeill et al., 2014). Viberg and Grönlund (2021) indicated that gathering, evaluating, and presentation of data about learners and their contextual factors for the aim of comprehending and improving learning and surroundings is referred to as educational data analytics. Educational fog data analytics can have a large-scale influence on student learning by providing important insights into the mechanisms of online and face-to-face learning, along with promoting active learning through data analytics. The overall aim of intelligent education under intelligent architecture is to deliver customized services and a seamless learning experience for every individual (Zhu et al., 2016).

One of the major benefits of using fog computing in the system is the time that it takes for fetching and processing information from educational databases. Recent studies are looking at how to utilize capabilities across the Internet's edge to cloud data centers to support the latest fog computing and their requirements. Computational nodes near the edge could well act as filters, limiting the amount of educational data sent out to the Cloud, as well as computing power, generating educational analytics nearer to where data is used (Brogi et al., 2018). The competitive pressures force firms to adopt innovative strategies that leverage existing IT artifacts such as BDA, which enable novel business processes and productivity through data-driven decision-making (Müller et al., 2018). Alkhalil et al. (2021) agreed that because of competition and economic pressures, higher education systems have become gradually more absorbed in the application of big data analytics. Fog and Big data is a game-changer capable of changing the way businesses are run in various organizations for long-term competitive advantage (Muhammad et al., 2020). To foster high-quality higher education, processes must be goal-oriented, and the curriculum is relevant to discipline-specific subjects that comply with the needs of business and industry, and effective teaching, and learning norms (Alkhalil et al., 2021). Tulasi (2013) pointed out that higher education must employ novel methods of monitoring and improving institutional policies and student success. In regard to adoption of education analytics would require institutions to be more purposeful and intelligent in their use of data and evidence for administration, resource allocation, and decision-making.

Siemens and Long (2011) denounce that the value of education analytics encompasses its role in supporting technological advancements in higher education as well as supporting educators to improve learning and teaching. Learning analytics is critical for breaking through the fog that has engulfed more of higher education. Instructors, students, and administrative staff require a solid foundation to implement change. For instructors, having real-time information about performing students, including at-risk students, can also be a tremendous help in planning instructional methods. Analytics about one's performance compared to their colleagues or progress toward one's personal goals can inspire students. Eventually, administrative staff and decision-makers in education are experiencing challenges with tremendous unpredictability because of budget cuts and competitive pressures. Amor et al. (2020) recommended a fog-based secure e-learning scheme that realizes the confidentiality of data, well data control, and well no tampering. Data analytics improve student placement processes, accurate enrollment forecasting, and early warning systems by predicting and detecting students who are at risk of failing or dropping out, as well as increasing competitive advantages in higher education (Matsebula & Mnkandla, 2017). Fog computing is a cutting-edge technology that has the potential to improve daily operations in a variety of industries, such as education (Raman, 2019). Fog computing features that facilitate effective education analytics involve: (1) mobility reinforcement, including both IoT devices and affiliated fog nodes; (2) context-specific location awareness and low latency, allowing processing to occur near the source of data; (3) the heterogeneity and interoperability of various IoT, fog, and cloud nodes and telecommunications systems; (4) bandwidth savings by evading time-consuming data transfers to the Cloud when they are not required; and (5) spatial distribution, to perform decentralized decision-making using highly scattered nodes (Brogi et al., 2018).

8. Implementation challenges

Between IoT sensors or devices in the educational environment and the cloud's data centers, fog computing functions as a sort of middle layer, and is therefore fraught with difficulties (Wani, Batth & Rashid, 2019). Gedeon, Heuschkel, Wang and Mühlhäuser (2018) argue that the Fog System Service Level Agreement is one of them. A service level agreement (SLA) for fog systems does not exist. As a fog computing system spans several domains, a new and prospective service level agreement (SLA) will be necessary for the future. Most fog computing scenarios include highly mobile individuals and devices, making data and application migration an enormous task. They move reactively fog instances, rather than proactively. Fog systems reduce capacity in the major network. The bandwidth limitation must be kept to a minimum with the addition of more devices. To handle IoT networks, current fog computing techniques are not scalable enough. Algorithms should be designed with scalability in mind so that they may smoothly integrate fog systems with IoT networks in the future.

The challenges of using fog computing and educational data analytics in higher education are broad and include both technical and organizational aspects (Hadwer et al., 2019). They relate the technical challenge to limited infrastructure and a lack of a comprehensive BDA framework in universities to manage and control processes, as well as data management and visualization. The organization's challenges include a lack of reputable institutional data governance processes and a driven strategy for successful BDA implementation. In the word of Jones (2019), the increased collection and use of personal and confidential student data raises additional privacy concerns. The major challenges in implementing fog computing and data analytics in education are data profiling, confidentiality, and learner entitlements in terms of individual behavior capturing (Klašnja-Milićević et al., 2017). Higher education faces challenges such as how to collect, analyze, store, manage, and present data to be used for determining various outcomes. Also, the increasing number of a student dropping outs and transferring from one institution to another. Alblawi and Alhamed (2017) describe some factors that determine student retention which include: (i) Out-of-institution factors such as health, finance, and social lifestyle; (ii) Academic Integration – for instance, student performance, satisfaction, academic experience, and classes or programs interest; (iii) Institutional Commitment encompassing finance, technological, academic assistant, proactive learning skills, and academic counseling; and (iv) Social Integration includes peer relationships, social support; and co-curricular activities.

9. Future direction for Education 4.0

We live in a world that is marked by volatility, unpredictability, complexity, and incoherence. The widespread use of IT artifacts and the COVID-19 pandemic denote disruptive changes (Wallner & Wagner, 2016). Today, organizations value data as a novel digital innovation. It is a requirement because of the rapid growth and evolution of long-term competitive advantage in the higher education system (Muhammad et al., 2020). Higher education is increasingly competing with practices to achieve the success of the institution, through the addressing of issues concerning education and retention, admissions, raising funds, and operating excellence (Lee et al., 2020). Therefore, education 4.0 is improving student performance and retention by progressively using academic and learning analytics. Alblawi and Alhamed (2017) exclaim the need to improve decision support systems used by education in the administration and management of learning processes and stakeholders for practical applicability and performance. A strong integrated learning analytics framework and distributed technology system are essential for academic authorities and advisors at educational institutions to make effective decisions about student retention rates and performance improvement strategies. Learning analytics can cut through the fog of uncertainty surrounding resource allocation, create competitive advantages, and enhance the quality and value of the educational experience (Siemens & Long, 2011).

Following the human-centered learning analytics method, based on a user-focused approach that spans over years in the realm of interaction between humans and computers, learning analytics should emphasize more on usage context and learner experience (Viberg & Grönlund, 2021). They itemize the following factors critical in the institution's alignment with educational data analytics, and technologies for insightful decisions: (i) Include students and examine their part in data usage; (ii) It is critical to involve both data analysts and teaching professionals to make sense of data and improve teaching and learning processes; (iii) The development of educational data analytics is a necessity, to begin with, for the teaching and learning of problems and goals. Do not begin with data; (iv) Engaging in multiple data sources and types of data may be essential to seizure performance, students, learning perspectives, and procedures; and (v) Determining data requirements based on objectives and practice. Do not be satisfied with what is readily obtainable. West et al. (2016) articulated that to address a wide range of educational issues in the future, it is essential to connect academic staff to learning analytics as well as engagement in the spheres of: (1) Teaching and curriculum quality; (2) Student achievement; (3) The educational experience; (4) Duties and responsibilities related to teaching; and (5) Participation of students. Establishing data literacy in students and staff will be necessary to stimulate the culture change needed to move to data-driven planning and decision-making strategies in Education 4.0 (MacNeill et al., 2014). Research by Wallner and Wagner (2016) pointed out that to prepare our students for the future Education 4.0, we should consider: (i) For provision of a necessary range of educational processes in our universities, we can rely on self-organization at both the individual and collective levels; (ii) The complexities we encounter in the "external" world are mirrored in every part of our academic work; (iii) In order for self-organization to flourish, students must specify their own study objectives. We must also assist and guide the aforementioned process; (iv) Finally we can hardly contribute meaningfully to complexity with complexity.

Based on a study by Zhu et al. (2016), in the future, their expectations for smart education, with smart learning environments brought forward by educational data analytics and fog computing will reduce learners' cognitive load, allowing them to focus on context making and ontology development. Students learning experiences must be strengthened for students' growth. Learners can understand more adaptively and cohesively in smart learning environments, which may promote the improvement of students' learning individually and collectively intelligence. Besides that, better-customized learning support for learners raises their expectations. Education 4.0 need to be adopted, as well as learning interaction with various learning technologies, like the management of learning systems or courses with new tools, including intelligent early warning systems, that can monitor and predict many elements of learner's performance and behavior (Lee et al., 2020).

10. Summary, conclusion, and recommendation

The scenario that universities are generating massive amounts of educational data motivated the study. Because data volumes are increasing, few institutions have been able to capitalize on the benefits of information they collect daily through their core business of learning and teaching. With the fact that this institution is increasingly competing with practices to achieve the success of the institution, through addressing issues concerning education and retention, admissions, raising funds, operating excellence, and resilience over the pandemic. The biggest lesson for everyone else may be to adopt e-learning technology before a major disaster. Presently, we are compelled to engage in online virtual learning; things might be different if we had already perfected it. We evaluated appropriate fog computing and educational data analytics architectures; then investigated the opportunities provided by fog computing and educational data analytics; and summarizes the fog computing and educational data analytics implementation challenges, as well as emerging disruptions and future directions of these technologies in the education sector. The paper's findings showed the need for establishing data literacy in students and staff to stimulate the culture change needed to move to data-driven planning and decision-making strategies in Education 4.0. Similarly, the great potential of Industry 4.0 is originating in data and the effective use of newly gained opportunities and challenges. Besides, the architecture of fog computing has a lot of potential as a future education 4.0 strategy. Education 4.0 initiatives, strategic formulation, support of e-learning, and innovation are viewed as significant steps to transformation and change during a crisis, supporting the preventative measures and recovery of higher education while trying to mitigate the impact on students and learning continuity. Pandemics have shown us that preparation is essential. Improving preparedness by utilizing the infrastructure of higher education (such as virtual learning and education resources) and human resources to solve the challenge of minimizing learning lost opportunity. Most institutions were prepared for and adapted to the crisis's effect by providing online classes. Already, the government and institution administrators are trying to implement measures and strategies to reclaim lost period through strategies of preparation, having to cope, and recovery, such as adjusting the academic calendar, implementing new learning styles, and continuing with virtual learning concurrently to physical learning to prepare for cases of emergency and to strengthen the system. The study identifies the need for preparedness amongst institutions to quickly adapt to changes in the environment and respond to new modes of delivery, such as virtual learning in pandemic circumstances – for example, COVID-19. Institutions must develop contingency plans (such as preparing, coping, and recovering strategies) in the event of a global epidemic or disaster. Higher education institutions should ensure resilience in their learning frameworks. Education 4.0 is a preferred learning style that aligns with the upcoming fourth industrial revolution; however, more research is required to determine educators' readiness for this transformational learning.

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