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Research Article

The Role of Big Data, Generative AI, and Cloud Connectors in Advancing Education IT Solutions and Sustainable Energy Technologies

Venkata Narasareddy Annapareddy*

*Enterprise Data Engineer, Email: venkata.narsreddy@gmail.com, ORCID ID:0009-0002-5385-5259

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ARTICLE INFO	ABSTRACT

This work focuses on how Big Data, Generative AI, and Cloud Connectors could advance the Education IT solutions and Sustainable Energy Technologies. Data Technology excellence is a process of value creation through information processing that increases producers' and users' welfare. Companies interested in revenue optimization from IoT-like data field data streams for big companies should resort to Big Data Dimensional Solutions for sensor network enhancement, maintenance, value extraction, and performance monitoring.

Data collection, storage, processing, and data monetization have a comprehensive technological approach and relevant business fields. Education IT solutions are concerned with applications in online learning platforms and open educational resources. Technologies currently effective in education and ICT solutions are examined. The illness stage of these technologies is proposed to be overcome. New generation technologies like Augmented Reality, Virtual Reality, and 5G are suggested to have a growing share in education. Generative AI applications are expected to gain popularity in more conservative-angle pedagogical practices and gain share as education assessment supporters.

Two-way cloud connectors extending cloud computing advantages closer to IoT edge are proposed as a means for providing administrators of multi-cloud platforms with flexible security options and vendors with interoperability indicators of their cloud services. From the functional side, the developed protocol allows metering transmissions. Public key infrastructure supports data confidentiality, authenticity, and integrity. A signature-free approach enhances security and reduces time overhead. From the performance standpoint, a dual-communication channel architecture enables quick-time transmissions with the required bandwidth and quality. Experimental validation illustrates improved privacy levels and performance gains compared to other cloud connectors. The proposed Clouds-as-a-Service provisioning framework empowers hardware-agnostic and resolvable cloud solutions' orchestration in public cloud ecosystems without vendor locking with pay-per-use costs. It extends the state-of-the-art by applying machine learning techniques to mediation service search and selection. The impact of cloud recommendations on QoS provisioning is assessed. Experimental validation highlights improved heterogeneity levels and reduced search time overhead when using the recommender system.

Keywords: Big Data, Generative AI, Cloud Connectors, Education IT Solutions, Sustainable Energy Technologies, Data Analytics, AI in Education, Smart Energy Systems, Cloud Computing, Digital Transformation, Intelligent Infrastructure, Predictive Analytics, Machine Learning in Education, Energy Optimization, Real-time Data Processing, Renewable Energy Technologies, IT Innovation, Adaptive Learning Systems, smart Grid Technology, Cloud Integration, Energy Efficiency, Personalized Education, Green Technology, Educational Technology (EdTech), Sustainable Innovation

1. Introduction

Technological advancements have brought unprecedented opportunities and challenges to the education sector. With the advent of the Internet, big data, and generative AI, there are emerging solutions in terms of learning technology infrastructures. An educational technology ecosystem combining cloud connecters allows all of the education technology vendors' tools to be used at the same time, opening endless possibilities within. Cloud connectors collect large amounts of data from diverse learning events, which can be analyzed using big data technologies for customized recommendations for learning activities. Generative AI provides tools and technologies for virtually creating and producing high-quality videos and audio contents. Although the aforementioned functions and systems do not have an impact on teaching and learning, a good design of pedagogical functions, AI, and a teaching intention for new pedagogical interactions with learners are crucial to performing a good impact on outcomes. Because of their novelty, there are few existing research studies about education IT ecosystems [1]. In this paper, 1) the emerging functions, systems, and points of view on the change they are expected to bring to teaching and learning are introduced; 2) an education IT ecosystem facilitating a movement from the wide usage of various learning tools toward integrated educational technology infrastructures and an intelligent education technology ecosystem is envisioned; and 3) the critical obstacles to practical usage in education and promising future research directions of how to overcome these challenges are discussed.

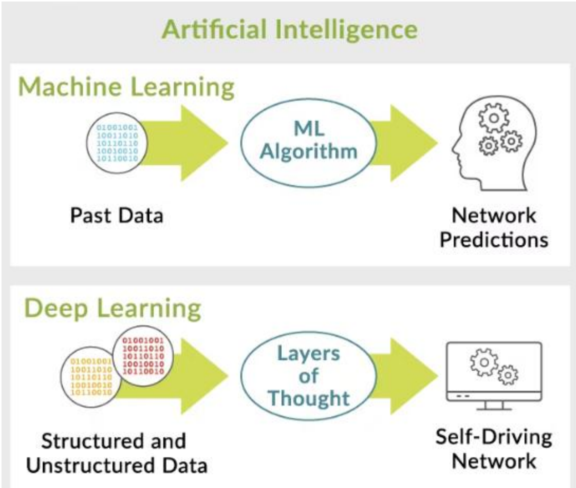

Fig 1: Technological Synergy for a Smarter Future

Emerging Educational Technology Advances. Throughout the history of educational technology, new systems, tools, processes, and interactions have regularly emerged. The classical advancements were all considered breakthroughs of some kind—printed text (books), radio, television, personal computers, relatively low-cost video cameras, and programming software. Two different types of systems were provided: content systems that served as the media of learning events and manager systems that were intended to plan or design learning events. Each of these new systems was expected to greatly facilitate teaching and learning.

2. Understanding Big Data

Big Data explains the immense volume of structured, semi-structured and unstructured data gathered from various sources and as a result of numerous activities which has the potential to be analyzed for information containing knowledge useful for producing knowledge-driven actions [2]. Big data is a term that describes a massive volume of both structured and unstructured data that is so large that it's difficult to process using traditional methods. Big Data helps with judgements and predictions that drive development and movements toward achievement of a better existence. Big data broadens big picture and ideas that can lead to actions and outcomes directly impacting education and can hugely alter the landscape of citizenship. The size and character of data have changed dramatically. It is not just about the immensity of data. With another important dimension incorporated: the data can be in diverse formats: audit trails, textual data mining, social network analysis, clickstream, sound, image, video. Other dimensions with increased attention include data veracity, i.e., biases, noise, uncertainty of data.

Big Data is involved in every possible social activity and situation revealing its potential for education. Education sector has begun investing in systems and technologies to extract valuable insights derived from the treasure of knowledge stored in data. For educators, administrators and national policy makers, these applications have value-added intelligence that can be translated into a front-end service. There are also numerous promises rooted in the big data revolution to transform education in ways never thought possible. Education within or outside school has always been the biggest producer and consumer of data. Offered services automatically record great amounts of low-level data: response time, chosen response and correctness for each item; properties of the performance carrying over time, domain of difficulty, type and so forth. Slow processing, storage, systems, reducing the chance to gather any appropriate results with impact. Adjusted to current standard storage of transaction and audit trail related to entrants, interactions and outputs.

2.1. Definition and Characteristics

Big data analytics and its technologies are gaining momentum in various sectors including healthcare, financial, retail, smart cities, and education [1]. Big data can be referred to data with volume, velocity, variety, veracity and value. Volume refers to the size of the data generated and collected. This size is typically so large that it becomes unwieldy for traditional storage solutions. For example, a traditional, structured database with millions of drink orders would crash under the complexity of filtering, sorting, joining, and aggregating the data compared to a user-friendly, unstructured database containing millions of tweets. Velocity refers to speed of data creation. Data is continuously created in real time and those responsible for the maintenance and analysis of the database have to be able to keep up with the massive influx of data. Such a mismatch may lead to critical decisions being made using incomplete data. Variety refers to how data comes in many forms and hence has to be filtered and placed in a suitable format. Veracity refers to the trustworthiness of the data and whether users can be sure of its accuracy. Value refers to the usefulness of the data and whether it yields any desirable outcome. For a dataset to be valuable, it needs to satisfy criteria imposed on the other four properties. Generative artificial intelligence (AI) is the subset of AI wherein the machine generates media – text, audio, images and video – based on the parameters it has been trained on. ChatGPT is a key example of generative AI and as recent developments have shown, it is growing well out of hand. Generative AI has captured public attention and although it has emerging applications in a broad array of fields, it also brings books into question. Educators, researchers, authors, journalists, artists—in short, all creators of knowledge and emotion—who have so far regarded access to work as essential to their livelihoods are now forced to rethink their positions. The ready availability of AI-generated text and images, however, is only the first of several revolutions likely to upend a system built on the possible ownership of one's own skills; one's own thoughts; one's own art. As such, the implications of this AI revolution for the creation, ownership, and access to formative work may be more profound than those that have reshaped the propagation of that work. Cloud connectors are IT solutions that transport data from one geographical location to another, such as from in-house storage equipment to a cloud server, or among multiple cloud servers. In so doing, they facilitate the storage of data in a cloud and provide users with remote access to that data across various devices.

2.2. Sources of Big Data in Education and Energy

Educational data refers to the information collected in the field of education and includes participants' characteristics, environments in which the education takes place, and learners' academic achievement in order to evaluate educational policies and practices. Data collection starts with international large-scale assessments (ILSA); assessment data on learners are collected for educational evaluation across countries or districts. To transform assessment data into big data, it requires highly advanced methodologies. The analysis of participants' characteristics, educational environments, and academic achievement is possible, but the analyses need to be very extensive and hence difficult to conduct. The size of data is another important issue [1]. ILSA data do satisfy the scale but not the high volume. Well-established relationships between large-scale assessments and educational outcomes can also be used for obtaining big data.

Big data include, first and foremost, datasets that can be acquired easily and naturally via social service systems where people are recruited and participate. With the advent of the Internet of Things (IoT) or smart devices, the scale of social networks has grown enormously, yielding huge streams of big data. Data analysis methods of sophisticated technology have been applied to and resulted in the deeper understanding of typical human behavioral and psychological characteristics [3]. As a consequence, data that have once been considered rather appropriate for analyzing behavior at individual levels are now utilized in a longitudinal way to predict human anticipation on the specific contexts occurring at the group level, and even social evolution on the global scale. Among many big data, the social service systems designed for educational support are recommended to be on the big educational data map in order to gain broad insights through the extensive data analyses.

2.3. Challenges in Big Data Management

Big data management involves ensuring that data is reliable by cleaning it regularly or developing algorithms to ascertain factors such as source credibility. Once the credibility is determined, data needs to be analyzed as it may be in various formats collected from various sources. The data collected using cloud computing is mainly encrypted for security and privacy. After cleaning, credibility determination, and analysis, data management is the next challenge, ensuring that big data is adequately accessed, stored, and scalable on distributed systems. As data reaches recording levels above petabytes and forms of stings, PDF, and speech, data storage becomes one of the biggest challenges. With the complexity of big data, volume, velocity, data variety, and veracity become a great concern for organizations [2]. The goal of big data management is to certify the reliability of data such that once received, it will no longer be required to verify its credibility.

Equation 1: Data Quality Risk

$$D_q = \frac{I_d + A_d + Du_d}{T_d}$$

Where:

- D_q = Data quality risk
- I_d = Incomplete data
- A_d = Inaccurate data
- Du_d = Duplicate data
- T_d = Total data collected

This data also needs to be accessible such that the use of data entropy does not block its utilization, manageable such that tools used to manage data do not become a bottleneck, adequately stored such that the earlier stated HPC protocols can be used, and secured from growing numbers of vulnerabilities and security threats. The Higher Education Universities all over the world possess a vast amount of data resources that can improve the quality of teaching and learning for teachers and students while enhancing executive decision making. The institutions possess both massive volume of data and very diverse type of data that can be used in the above manner, and have the capability to manage it. Data have been widely agreed as the new oil in the Information Age, and who can manage Big Data is the key to Success. When compared to volume and variety, industries have access to higher velocity than HEIs. As working with Big Data with its applicability become importance, there was growing concern on whether the HEIs have the ability to manage the same. Consequently, higher education institutions were able to access vast volumes of data from numerous sources, mostly in different formats. So far, it had been a great dilemma on data collection and how to bring it all together. Ability to provide rapid response for management may be a worry for HEI executives too and became less of an issue in many streams of social networking than before. Experts in knowledge discovery through big data mining have expenses globally, but still divisions on whether enough number of such experts are available, whether access to quality data availability and availability is preventing usage. Institutions have big data to work, but there are institutional difficulties managing these Big Data. Other than the issue of collecting and integrating data from disparate sources with scalability, widely in existence are inquiries on how to mine data reliably and how much insight would be relevant and provide value add factors to strategic and tactical decision making. While skill inadequacies, lack of infrastructures and proper data treatment on undeveloped types like audio and video are primary in over 20 one hundred fifty respondents.

3. Generative AI in Education

Education represents an essential human right and social need. Its promotion and guarantee, as well as equity in access to knowledge, are included in the 2030 agenda, which lists 17 Sustainable Development Goals, with the most essential being SDG 4, which focuses on Quality Education. In this context, ensuring access to quality education opportunities involves considering different approaches that rely on pedagogical paradigms and exploring the applicability of many available or new technologies, including Artificial Intelligence (AI) and, particularly, Generative AI (GenAI). Education (or training) refers to acquiring skills and knowledge through training via various technologies and in different environments. It is also worth noting that education encompasses several dimensions that need to be observed: access, quality, equity, relevance, efficiency, and sustainability. Since AI is extensive and covers a wide range of techniques, it is essential to observe which approaches can support a particular dimension of education.

Focusing on GenAI, it is worth noting that, in the education realm, GenAI is relatively new. At first, it was viewed as a tool for an enhanced user experience that could support institutions in producing and customizing educational activities. Several AI-based solutions were made available at this point, including AI Text-to-Speech systems that would pronounce texts with different voices and emotions. Text-to-Image tools that allow generating novel images automatically; Text-to-SQL systems that could answer natural language queries about databases, including educational ones; Self-play AI systems able to simulate educational games previously fed with several sessions aiming to analyze and visualize players' behavior. However, education stakeholders also quickly raised concerns about a wide range of issues, including academic dishonesty, copyright problems, unintended bias, and a more general lack of transparency. From the perspective of AI and data sciences researchers, some optimistically anticipated that, with already available tools that focused on the admission of other technologies into the education field, the resulting disquiet would be addressed, and tools for reliably working with GenAI efficaciously would be forthcoming .

Education has benefited from numerous innovations in processes and technologies. Examples of large-scale adoption and impact of new technologies include the introduction of the printing press, radio and television, and, more recently, computers and the internet. The later advents resulted in remarkable changes in education and research forms, accelerating the generation and dissemination of knowledge across all possible means and schools, and allowing education to break barriers of time zones and locations, reaching unprecedented audiences and multiplying the possibilities of a more inclusive approach to an essential human right. At the same time, such technology tends to disrupt practices, bringing in efficiencies but also drawbacks. Since widespread adoption inhibits control, it further amplifies the need for policies and rules. AI and more specifically GenAI are in a similar situation, with the plus and minus reported in education contexts.

3.1. Applications of Generative AI in Learning Environments

Generative AI (GenAI) refers to the mechanism that generates information based on learned patterns, being able to create ubiquitous novel content. In education, GenAI can generate entire books complying with themes and styles, write musical scores and songs, and produce detailed images based on keywords. Such applications radically change the dynamics of teaching and learning pedagogical methodologies, designing evaluation scripts, and dissemination of knowledge. As a natural development of the ongoing AI revolution, GenAI impacts multiple sectors. Therefore, it sets a new path of paradigm shifts which affects education, specifically education technologies (edTechs) and learning environments [4].

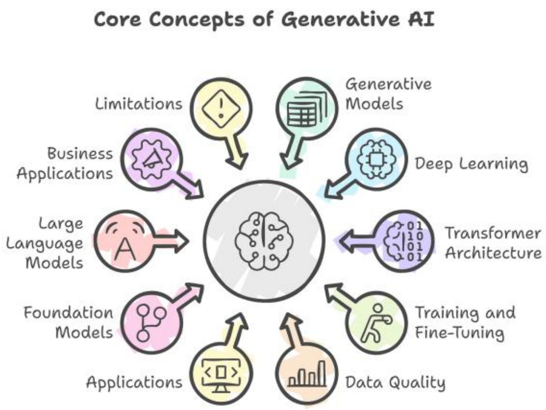

Fig 2: Core Concepts of generative AI

Among the widest applications are the generation of personalized learning contents that tailor learning materials according to students characteristics, needs, interests, and learning performances. This includes the generation of questions in different formats, extra reading texts on a given topic or difficulty level, varied summary frameworks, tailored reading companions, simulations of learning environments, among many others.

Equation 2: Learning Engagement Growth

$$E_g = (I_c + I_a + G_s) \times E_r$$

Where:

- E_g = Engagement growth due to AI tools
- I_c = Interactivity of AI content
- I_a = Interactivity of AI assessments
- G_s = Gamification score
- E_r = Engagement rate multiplier

Moreover, GenAI holds potential for more sophisticated applications, ranging from (1) semi-interactive and interactive systems able to generate automatic adaptive learning contents during student interactions, which can be personalized not only according to students characteristics but also according to students learning actions, performances, and trajectories, to respectively, learning style changes, emergent detected misunderstandings, and gaps in conceptual knowledge; to (2) advanced tutoring systems, which proactively engage students in guided teacher-like dialogue conversations about any learning topic.
Khan Academy, Coursera, and Duolingo are among the companies that recently incorporate GenAI to the most diverse aspects of their learning experiences. Such systems use GenAI to spin-off variations of existing learning contents – exercises, questions, video scripts, texts, etc. – and to generate and tailor learning contents. Such technology is spread worldwide, being adopted for both learning and teaching by most leading universities.

3.2. Impact on Student Engagement and Learning Outcomes

The development of big data business intelligence and analytics software is growing and eliminating knowledge bounds. Disruptive big data educational technologies and innovations are changing the future of education. Big data problems can be dealt with either distributed data or large data. There is a positive relationship between big data and education. Both viewing styles can enhance teaching and learning. The two educational big data types need to define phases: The 6Vs definition can distinguish old and new data; A temporal sample is defined to detect the time phases of big data. EasyAccess is an approachable and effective interface to support data interaction. Preclustering analysis using FSST can surpass the identification limit of adoptions between months [1]. Nowadays, big data overview and process tools can be used to mitigate the digital divide among teachers and students.

With a rise of education-oriented sensors and crowd-sourced data, open big data sets are booming. The quickly growing massive open online courses platforms have adopted big data repository and research. The accumulation of these education datasets has provided immense chances for new insights in teaching and learning process to foster effective learning. However, the educational data mining community has seldom studied the nature of these datasets. Novel definitions and techniques are needed to deal with unprecedented educational big data. Seven types of big data problems are introduced, together with big data viewing styles with capacity of extracting knowledge from raw data. Viewing educational data can be either by fundamental views or by big data views. The first two traditional views seem ill-suited for educational massive data, as most educational data are not analytical but raw. In comparison, the two disruptive viewing styles, distributed data and large data, have the capacity to cope with big data. With the affordance of miniaturized, almost free sensor technologies, night and day, digitally-activated technologies have generated massive amounts of human activity data whose size, velocity, and veracity outstrip previous data. There is no restriction to higher learning institutions and citizen-scientists for the submission of problem cases.

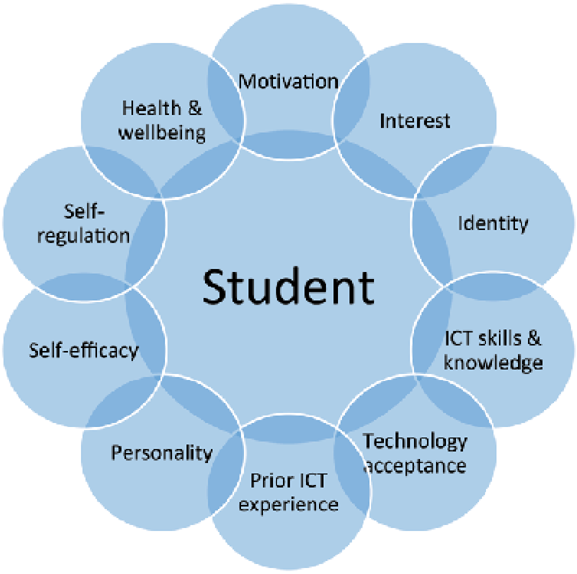

Fig 3: Facilitating Student Engagement Through Educational Technology

3.3. Ethical Considerations and Limitations

The rapid pace of technological progress, including big data analytics, artificial intelligence (AI), and cloud solutions, advanced more rapidly than educational institutions' willingness or readiness to adapt. Past implementation experiences in education technology (EdTech) have been reviewed and there are numerous possible reasons why schools enthusiastically adopt the latest technology. Consequently, expectations exceed immediate achievements, absurd criticism arises, and technological constructs are abandoned. The educational technologies available far surpassed interpretations of educational capacities. As a result, many capabilities for big data exploitation and AI generation either remained unexploited or not used in ways that are consistent with their creative affordances [1]. The same applies to cloud solutions. Well-designed but poorly adopted novel educational solutions require multidisciplinary explanations that go beyond pedagogical failures. The gulf between technology readiness and its application in education has not been narrowed in the last fifty years. A more pressing issue is now considered and human as well as system-centric factors are explicitly taken into consideration.

The scope of education is broader than that of EdTech. The latter is a collection of digital learning tools and implementations, the first a broader conception of education technology concepts—arrangements, entities, combinations, and intentions dedicated to the task of education. Compared with educational designs that do not include operations on digital data, digital education technologies often require collaboration between more operationally heterogeneous agents (significant actors) in more diverse domains. In addition to individual agents' unawareness in terms of their own here-and-now neglects, individual agents often have insurmountable operational capabilities that span future infellows, whose emergence may pose as yet unappreciated problems in project design.

4. Cloud Connectors: Bridging the Gap

Cloud architecture is defined as a platform that consists of both hardware and software that enables the provisioning, deployment, and management of cloud-based services. Cloud architecture is the basis of cloud computing and is usually composed of four basic components: front-end platform (client), back-end platform (data center), cloud-based delivery, network.

Equation 3: Data Integration Success

$$S_i = \frac{C_c \times D_v}{I_c}$$

Where:

- S_i = Success rate of data integration via cloud connectors
- C_c = Cloud connector capability (API support, protocol bridging)
- D_v = Diversity of data sources integrated
- I_c = Integration complexity (number of systems × heterogeneity level)

Cloud computing is accessible from any location with an connection. Cloud architecture is a template for cloud computing services that can be public, private, or a composite of both. Cloud architecture describes the various components (hardware and software) that work cooperatively to perform cloud computing services. The importance of cloud architecture lies in its capacity to facilitate shared data and software while minimizing time, manpower, and money through resource sharing. Education cloud computing systems are being developed in multiple institutions and are constantly achieving services like cloud learning, cloud conference, cloud e-learning, cloud video courseware, and data mining. Cloud computing education, many universities nationwide have begun research into cloud computing technology and services in higher education, cloud-based services, and cloud learning networks.
A clear cloud architecture is a solution for a topic that many researchers engage in, for schools, institutions, and research laboratories that use cloud computing or are considering to use it in the future. Cloud computing now offers several services such as storing user files for access from any computer with service, cloud-based online office applications with storage available through folders in the cloud, and email and instant messaging services accessible from any computer that connects to the Internet. In addition, there are public cloud computing services providing users tools to share and communicate through file transfer, voice file sharing, photo sharing, and instant messaging. However, as cloud computing proliferates swiftly, insecurity about the privacy of files in the cloud has been raised. Some major private clouds have experienced leaks of sensitive personal information, resulting in perverse events of blackmail and identity stealing. This makes it a must for services in cloud computing to incorporate secure protections before their widespread adaption.

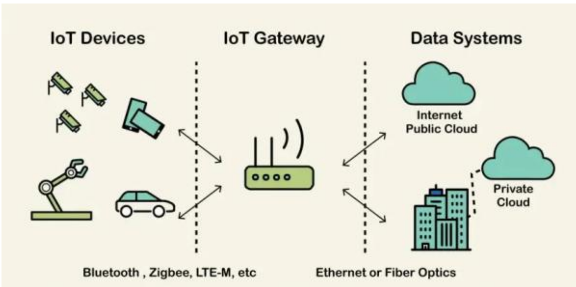

Fig 4: Role Play of IoT gateway In The Overall IoT Ecosystem

The conventional paradigm in cloud computing stores user files in the form of plain text, making them vulnerable to simple attacks. The information security of cloud computing is a critical concern now and will be more important in the future. It is inefficient for a single cloud provider to search encrypted cloud stores for the desired file. With the explosive growth of data in cloud computing, this "lazy" mode of cloud computing raises an approaching deadline. In addition, learning management system or virtual learning environment is a software application for the administration, documentation, tracking, reporting, and delivery of educational courses or training programs. As its popularity grows, the dilemma has arisen whether the context of education technology, with its heavy reliance on these central systems, lacks research focus system. Participants of significant international conferences and leading journals in the information technology in education area are viable proxies.

4.1. Overview of Cloud Connectors

Cloud computing is referred to as a dynamic global network for customers and trading partners to access a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. Cloud connectors are hardware or software that connects SaaS applications with business processes or other applications. There are many connectors that support established integration architectures utilizing different approaches but can be simplest in practice in cloud scenarios. Based on the cloud and deployment model, it classifies, views and evaluates connectors that address lesser research. It presents an approach to visualize existing cloud connectors. Cloud computing involves a group of computers and remote servers hosted on the internet to store, manage, and process data. Exposing web services and supports interfaces for two-way communication is referred to as a cloud connector. These cloud connectors expose additional functionalities and are often referred to as connectors.

There are some common approaches for cloud connectors. Firstly, enterprise back-office integrators usually require legacy system-based, customized, and ETL-focused connectors and cloud services. Secondly, cloud application connectors are built from the consumer level. After gaining popularity, rapid development of 3rd party connectors focused on easy installations of common SaaS applications were prompted. Unlike traditional connectors, integration tasks need to be constructed/created in a graphical model-driven environment. It is called for multiple enterprise-level application connectors before becoming common. There are many other software to cloud connectors and products. These established enterprise-level software provide cloud-compatible products. Migration scenarios of cloud connectors are built. Another approach for cloud to cloud connectors extends cloud platforms. There are cloud platform APIs and application stores for existing cloud application and integration/ESB platforms.
Cloud connectors passing maintained data between source and destination can persist up to three types of state representations. State Persistence Nodes allow the custom definition of a persistence strategy for the states. They persist the input and output states of a connector route execution. The execution history of connectors and error monitoring via state persistences are evaluated. Integrations can transfer data between development and production pipeline across connectors. Cloud connectors are understood as additional subsets or layers on a cloud with interfaces connecting clients and service and frameworks on the cloud to expose the web services. A cloud connector service collects data from devices, preprocesses them, and sends various refinements of information to cloud platforms. A cloud connector is implementable. This allows orchestrating the ETL runtime for the cloud connector service as SaaS application and deployable within minutes.

4.2. Integration with Existing IT Infrastructure

It is essential to address how these IT solutions integrate with existing IT infrastructure, and additionally how technical staff and the relevant education of this staff fit into the implementation and future workings of the education IT solutions. Sustainable energy technologies represent a potential approach to meeting energy demands in an environmentally sensitive manner. Growing electricity and energy needs have massive impacts on our atmosphere and environment across transportation, residential, as well as industrial consumption. Renewable energy technologies help mitigate atmospheric damage by producing clean energy in a cost-competitive manner. Hence, wind, solar, tide, wave, geothermal, and biomass energy remediation technologies are growing in scale and becoming more efficient due to rapid scientific and engineering advancements. There are two major classes of technologies for producing or harnessing energy from low-temperature resources for both the ocean and land.

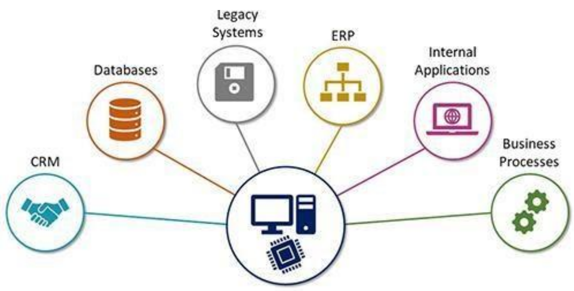

Fig 5: Benefits & Examples of Integration in IT

Efforts to generate cloud and solar thermal energy involve fluid conduction, but approaches for fluid production differ due to varying designs of the energy producers. For example, many current cloud electric energy producers proposed in patents and papers mostly harness energy from clouds using a shuttered film on the ground. Droplet condensation occurs when clouds approach and drape onto the film, forming a thin water layer. The potential energy of the collected water is transformed into electric energy by the dissipation of its gravitational energy via turbines and generators. However, with this design, the effective area of the collectors is kept small and makes the power generation efficiency low. Additionally, the water storage on the ground typically exists in bastions that are few in number. Hence, water overflows and shortens the available operation time of turbines in a short time period. Such cloud electric energy producers would face great obstacles in real applications. The cloud electric energy technologies are endeavors to generate energy from clouds and convective flows in the atmosphere in this study. These efforts promise rich energy, as almost every site with humidity and elevation change encounter clouds forming, moving, colliding, and dissipating with energy release.

4.3. Benefits for Education and Energy Sectors

In this section, we present our argumentation, analysis, and reflective views based on a range of issues that we believe are important but have received insufficient attention due to space restriction. Ultimately, our aim is to stimulate a wider and more thorough debate on the pressing need for advances in education and the ever-growing potentials of big data and AI in facilitating this progress. Such advances are urgently required to reduce the spiraling development gap in education due to the rapid progress of these technologies. More specifically, we will first focus our discussion on the education sector, which, although lagged behind, has unique needs and advantages. We will subsequently introduce several specific issues faced by the energy sector in need of attention, in the hope of facilitating educational focus in this area as well..

In the education sector, the gap between technology readiness and its demand for application has rapidly widened. Various technologies in general and big data and AI in particular have been rapidly advancing, while educational sectors have been the slowest in adopting these technologies among various different industries. In fact, most are still at a very primitive level. There is an explicit need to bridge this gap as this may lead to an ever-expanding divide in human development and welfare. Education is a key. It is expected to afford all citizens with the knowledge and skills become competent participants in a flourishing economy and society. However, reliance on mass education with the same resources for all subjects in a centralized manner cannot hold in a knowledge economy and society to be able to learn on demand is required. With the rising complexity of knowledge generation, requirement, and transfer, concurrent applications of all areas of expertise would become increasingly unlikely. In addition, with rising and diversifying knowledge, controls of contents in the knowledge economy and society may explode beyond government manageability.

5. Advancements in Education IT Solutions

The educational sector has witnessed a substantial transformation brought about by the rapid advancement of technology in recent years. Within education, educational technology has made significant strides in reforms in education and assessment. Teachers and professors are now more interested in computer-based systems in assessments, such as computer-based testing and examination proctoring systems. With the increasing trend of smart learning environments, smart classrooms, online lecture capture, active learning spaces, and so forth have been integrated into education. Consequently, a massive amount of information is generated, including various types of interaction behaviors, performance-related data, resources for learning, social role preferences, and behavioral, affective, and cognitive engagements. The information comprises both external and internal data points, such as observable behaviors and physical states, respectively. Educational big data refers to the vast information collected from technology-enhanced learning environments encompassing structured, semi-structured, and unstructured formats. Educational big data denotes different but related concepts according to different contexts. Regarding data usage, educational big data comprises either the data itself or the data-generated posterior, encompassing knowledge, patterns, metrics, profiling, and attributes [1].

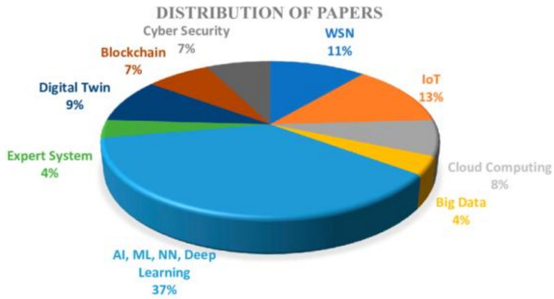

Fig: Bar Chart to show the percentage of technologies in the literature

In contrast, AI as educational technologies can deliver automated algorithms that generate data and posterior from educational big data. AI-encompassing software or systems refers to both the data product and the data-generated posterior. Educational big data and AI are being widely adopted across various sectors and domains, including education. However, rapid technological breakthroughs have far outpaced educational utilization. Thus, governments are increasingly determined to stimulate the adoption of big data and AI in education, and businesses are rising to tackle the immense market, with an impressive lineup of educational technologies across the sectors of P-12 and higher education. This is evidenced by the continuous rise in funding for the development of educational big data and AI technologies and companies during the last decade. Nonetheless, most current educational technologies are mostly exploratory, as subsequent applications in educational systems experience challenges. In particular, many attempts have failed due to unsuccessful data collection; software and hardware incompatibility; the rise in privacy concerns; assessment inappropriate to the individual levels; and perceived high alternatives switching costs. Even more pressing, while great efforts are spent extensively on educational product development, fewer parallel resources are allocated to comprehend and implement these new products in educational systems.

5.1. Personalized Learning Experiences

Personalized learning is a learning approach tailored and customized to each student's needs, abilities, interests, and learning patterns. Personalization could partly happen at the level of engagement, content, and process. In the past decade, there has been a rising interest in personalized learning in education. New data sources, computing technologies, and online platforms available in classrooms today provide opportunities to advance this intention. The use of big data and computing technology advanced the reform effort to help students learn better and more effectively in ways previously inconceivable [1]. To better practice personalized learning, there is a growing demand for developing automated tools and techniques to utilize information produced in digital learning environments.

Crowdsourced data, clickstream data, sensor data, text, image and video content, and knowledge structure data provide new opportunities to build next-gen educational data mining methods. The automation of personalization in making adaptive recommendations and suggestions needs advanced natural language processing, vision, and deep learning methods. Using advanced AI techniques produces complementary and improved performance to traditional data-driven methods. To take advantage of these advantages, it is necessary to tackle new challenges on the education side. How to chunk knowledge into diversified curriculums, and adjust difficulty levels depend on factors containing in data representations. Moreover, how to measure and improve learning experience is also open yet under-explored. For scaling up, translating developed algorithms and solutions to large online platforms and widespread user base also raises usability and maintainability issues. These challenges call for collaborative research efforts of multidisciplinary experts and developing integrated education data mining and AI platforms.

5.2. Data-Driven Decision Making

Education increasingly emphasizes the significance of learning analytics and data-driven decision-making. Amidst the escalation of big data, educators are being challenged to effectively highlight the importance of data analytics and how to analyze rich data sources stemming from different learning platforms to grab meaningful insights to enhance the learning experience. Research that truly helps educators to be aware of the importance of data-driven decision-making, a kind of knowledge digest that summarizes previous research outputs addressing this challenge, is greatly anticipated. This research puts forward nine questions regarding data-driven decision-making and delivers a comprehensive literature analysis targeting such questions. Fifty-six articles from the last two decades were reviewed based on this research agenda.

The results were summarized regarding the research focus, methods, and theories of reviewed articles, shedding some lights on framing future research directions. Numerous scientific documents address the conception of data-driven decision-making artifacts in educational contexts. At the landscape level, two contrasting schools focus on goal chain establishment and disagreement resolution mechanism building. At the topic level, three clusters point to quantifying focus dynamics, understanding the sense-making of data-driven decision-making practices, and investigating social influence and construction of learning 'trace points'. Yet, research investigating big data or generative AI with a data-driven decision-making perspective remains very limited. There is a pressing need to conduct distinctive research and motivate educational practitioners to utilize big data technologies and generative AI tools [1].

Generative AI tools have significantly impacted state-of-the-art models in many disciplines. Amidst rapid development, attention from society was recently drawn to a class of generative transformer-designed models that have shown great capabilities in generating human-like text responses, resulting in the all-around flourish of generative AI tools. Such large-scale generative AI tools are of paramount importance to aid STEM educators and researchers to create excellent free pedagogy resources rapidly. However, their burgeoning popularity and ever-increasing use worldwide also pose many challenges. There is an urgent need to review the current state and envision the future of generative AI in the education and training field.

5.3. Collaborative Learning Platforms

Collaborative Learning Platforms (CLPs) represent a promising solution for fostering students' interactions and engagement through the use of Web technologies. They allow students to form groups of varying sizes on the basis of shared interests or learning goals and support task-oriented interactions while fostering turn-taking among the group members. Unlike traditional Learning Management Systems, which are mainly instructor-centred, new CLPs promote social interaction, group work, and peer-to-peer dialogue among students, thereby providing a platform to study the dynamics of social interaction at a rich and fine-grained level. With this aim, it is important to study the usage patterns and interactive paths of CLPs and correlate them with students' engagement dynamics and learning achievements. To this end, continuous and automatic data collection methods are required to extract usage data and compute centrality measures.

Understanding the social interaction dynamics of collaborative learning systems is crucial for devising techniques to promote the rise of discussion and learning-oriented dialogues. However, most of the current research on the dynamics of social interaction has focused on synchronous discussion platforms such as chat systems or forums. On the other hand, CLPs are mainly designed for running discussions in a rather controlled environment, where student interactions are kept on task all the time. This makes the study of interaction dynamics much more challenging. In addition to the well-known need to study the usage patterns and behavioural roles from a graph-theoretical perspective, it is also important to examine more granular usage and performance patterns on students' interactive paths. Beyond focusing on a single event level (such as post creation), it is also crucial to explore small sequences of student interactions (two consecutive events) and examine their relationships with deeper interaction levels.

To address these issues, a framework for modelling the usage patterns of CLPs is needed to capture, store, and analyse rich information about how students interact in these environments. To this end, a methodological framework is proposed for the continuous and automatic extraction of usage and performance data from CLPs. Building on the LogParser software, which automatically captures and stores detailed data about students' interactions with the CLPs, this framework computes three usage measures of students' actions in the CLPs, namely the number of CLP tasks performed, the number of complex events performed on tasks, and the utilitarian centrality. These measures are then related to the cognitive and affective engagement and learning achievement constructs, thereby paves the way for understanding how students' usage of CLPs relates to their corresponding engagement dynamics [6].

6. Sustainable Energy Technologies

Tackling climate change should begin with energy efficiency, but most if not all data center operators are currently over-provisioned for peak energy usage, which has a cost to customers, scrambles their long-term forecasts of climate impact, and undermines claims of corporate responsibility. Many cloud providers have already teamed with renewable energy producers for long-term renewable energy procurement contracts, but this is valuable only if a big cloud customer can keep enough workloads on that cloud for the duration of the contract. It seems clear that in order for corporations to effectively tackle scope 2 emissions, new regulations need to direct the carbon emissions attributable to their cloud workloads to the cloud provider [7]. Overlaying infrastructure visualization with rainfall predictions could also allocate workloads to less-parched data centers; if they all switched to using water-less cooling, how much energy would that save? Similar ideas could take advantage of weather forecasts, solar satellite images, and 7-day power production predictions. There's much play here on how real-time pricing works together with this kind of discussion, such as forecasting power prices or using dispatchable assets or batteries [8]. This is most important because this is the only way data-driven firms can expect to make meaningful progress on sustainability. Understanding how workload travels through the global infrastructure will necessarily unlock on-the-ground knowledge to inform design decisions to affect big-picture changes. Designing genuinely flexible workloads that can be moved with consideration beyond merely latency would prevent most of their carbon footprint despite cloud providers' choice of infrastructure, which is currently almost entirely fixed in place. Even without this, data-driven companies could take a key role in an ongoing conversation about using their visibility into the energy mixes of the grids upon which they run and their customer utilities, and how it financially benefits providers to flatten peaks. Unsurprisingly, taking action here requires a firm understanding of the financial levers cloud providers have over their cells.

6.1. Role of Big Data in Energy Management

Data is becoming one of the most precious resources in the current world. Data knowledge is summarized into information, and, therefore, both concepts are important [8]. As a consequence of the "Internet of Things" (IoT) development, there is a big amount of data that must be analysed to offer valuable information. In a university, all campus departments are generating useful information for the administrative area. Business Intelligence platforms have been used for this purpose, but this technology handles a limited amount of information contained in defined variables. These variables generally behave dynamically, including in many cases a growing amount of data. In this way the analysis of variables is needed to offer value or knowledge from the gathered data. This process is complicated by the need to create a friendly interface for system users who do not master programming language. With regards to energy management, it becomes a manifest necessity because it is common to notice the misuse of energy resources on university campuses.

An Administrative point of view needs to be developed, since energy management acquires greater value because of the importance of its good use. Daily, climatic and event changes can modify previous behaviour; by having a diversity of systems that are monitoring each area of the campus on a continuous basis, the detection of any anomaly is feasible [3]. The issue is that, technically, this process is complicated. Another point to bear in mind is the amount of variables that can change dynamically. It is necessary to be aware of this fact because of the extensiveness of this research. Therefore, not only the past performance should be monitored, but also the analysis of the current behaviour of these variables is needed with the consequent increase in the amount of data that no Business Intelligence platforms could handle. Big data is a technology made from existing technologies that addresses needs that were not met. When talking about big data in educational environments, it is the focus of academic management. It acts in the use and management of resources and provides knowledge of the raw information stored in these environments, which has an impact on real-time decisions and contributes to the successful management of such environments.

6.2. Generative AI for Energy Efficiency

Artificial Intelligence (AI) has transitioned into a new era. Large Language Models (LLMs), the latest generation of AI-designed models, have quickly grown to be several times larger than their predecessors, requiring increased computational resources to train and run. These models present new capabilities and prospects, but they also present new issues that must be resolved as they gain acceptance in numerous industries, such as education, policy, industry, investment, etc. Whether one believes that these models embody a significant advancement in intelligence, there is no doubt that more sophisticated models are teaching us more and more about all topics, including their strengths, capabilities, and serious limitations [7]. As these models spread into new markets, their user base and query volume are anticipated to explode exponentially, reaching a dimension similar to contemporary search engines. Additionally, it is compulsory that routine inquiries informing political decisions or controlling industrial operations, for example, should not overload underlying processes, leading them to fail and possibly fail catastrophically. To offset the unforeseen and selfish energy footprint of these robust new AI models, answers must be proactively uncovered and developed; new training and multitasking techniques must be invented; novel hardware focused on the robust neural structure should be created. Every byte saved would aid in reaching broader goals of fairness and accessibility, notably for developing markets. Education is today being revolutionized by generative AI at all levels, including kindergarten, university, and lifelong learning. Teslas, Google maps, and colorized timelines are just a few examples of unanticipated, groundbreaking, and adorable use cases that make education more affordable and accessible. On the other hand, misuse and malpractice issues arise inexorably. Few debated technologies in the history of mankind have triggered so immediate and heated arguments about their relevance for education as AI chatbots.

6.3. Cloud Solutions for Renewable Energy Systems

The importance of standards, trusted organizations, partnership, and collaboration in evaluating the feasibility of specific solutions is addressed with regards to the application of cloud solutions for energy technology and energy system modeling software. Open standards for clouds to ensure compatibility and interoperability for services using the infrastructure, data, and business models for clouds. The expected importance of trusted organizations to ensure cloud service security and reliability is indicated [8]. As a key characteristic of cloud-generated economies of scale, local clouds are needed with regard to national security and data protection problems. Beyond national borders, specific clouds for specific tasks are needed. However, it is important to ensure that local provision of cloud solutions arises and that techno-economic issues are resolved. The conditions for public-private partnerships to cover long-term contracts are defined. To promote a more sustainable energy system, the creation of coherent and extensive modeling systems and cloud-based solutions for energy systems is described. This includes development and maintenance costs, the increase of modeling fostering local consultancy companies, and the qualification of university experts. Learning initiatives for user groups from commerce, industry, and academia provide an excellent chance for competence building. The importance of cooperation with additional educational institutions and business development initiatives is emphasized.

The status and perspectives of cloud solutions for renewable energy technologies and systems are reviewed. Possible visions for the deployment of cloud technology for renewables are discussed and the necessity for active monitoring of growing interest and market impact of cloud solutions for energy technologies and systems is suggested. However, with respect to the present capabilities of cloud computing, the a priori feasibility of specific application areas is expected to be tightly controlled by technical performance issues, and existing applications do not automatically make further ones feasible. The capability of cloud computing appears dependent on a combination of the availability and cost of computer power, the size and need of withers for optimization, scalability of software and number of tasks to be performed. It is thus expected that concerns over security, ownership of data, interoperability issues, and risk of lock-in will to address. Furthermore, making cloud solutions commercially available will require market-ready providers. Instead of testing risks, broadening the application range of cloud computation is expected to be challenging.

7. Case Studies

7010 System The Big Data and AI framework for Data Monitoring on a Smart Campus is based on cloud computing and microservices. The applied framework guarantees high availability and scalability. These factors allow the framework to adjust to the needs of any environment. The integration of AI with technologies is imminent. AI allows us to take the results of the data analysis and learn from them to personalize the learning. In addition, it will allow for the execution of autonomous processes, combining production and efficiency.

7020 Important challenges Some of the most important challenges the implementation of big data and AI in a smart campus will have to face include energy efficiency, climate alerts, internal mobilization or waste management. The areas concerning green energy sources could have a great development in smart campuses. In the next few years, the smart campus will be able to take advantage of the new discoveries affecting green energy. Researchers exploring the new membrane technology will most likely offer an excellent opportunity to develop new green energy.

7031 Overview of the challenges and issues confronting researchers and practitioners Integrating Big Data and AI into smart campuses, including architecture, technologies, applications, advantages, challenges, etc. Critical research issues and directions for future research hope to present a timely review for providing useful insights into researchers and practitioners. Smart campus, big data, AI, Internet of Things, cloud computing, and service-oriented architecture.7040 Cloud computing Cloud computing is an emerging architecture for providing scalable services and has three essential characteristics: (1) on-demand self-service, (2) broad network access, and (3) resource pooling. It has become a revolutionary computing paradigm benefiting higher education institutions. In addition, the services provided in the cloud can be delivered through Software as a Service on the pay-per-use model. Users only need to pay for the services they need. Multitenant architecture and virtualization ensure the privacy and security of users.7049 Internet of Things Wireless sensor networks allow for lower-cost communication, lower-cost hardware design, and low-power design. Different sensors can communicate and collaborate while ensuring efficient data processing and storage. With the connection of the physical world, WSNs become the Internet of Things through standards such as IPv6. The communication of a variety of sensors can be managed and controlled through the Internet.

7.1. Successful Implementations in Education

Education plays an important role in sustainable development, and technologies can serve as advantageous tools to elevate the quality of education. In recent years, big data and AI technology have been widely adopted in such fields as the Internet of Things (IoT), connected vehicles, online healthcare, security and surveillance, and forecasting. Meanwhile, the educational domains have also entered the social big data and AI era. The tremendous and increasingly scalable data in the educational domain can be thought of as "educational big data," which represents the evolution from traditional data sources to modern interconnected and diversified sensors and traces.

Fig 6: Effective course delivery

Innovative algorithms, largely powered by AI simulations such as natural language processing or generative AI, have been transitioning from defining/explaining phenomena to addressing problems and making choices in real-world systems. With the ubiquity of computer-based education, the educational domain has mushroomed with rich data available for detection, analysis, and action, and secondary educational systems have been well-represented in the research domains of education and technology. Meanwhile, the rapid growth of the Internet has facilitated the accessibility to educational data collected worldwide and strengthened the need for generalized educational knowledge representation and reasoning to leverage the educational big data in real-world applications [5].

7.2. Innovative Energy Solutions Using AI and Big Data

The rising tidal wave of data generation and energy consumption from various sectors is pervading the education ecosystem like never before. Hence, historic energy consumption data and its patterns need to be mined, analyzed, and extracted for bringing forth relevant generative AI solutions that can improve energy efficiency. As a starting point for efficient energy solutions using AI in the education domain, the data can be converted into knowledge-for-action and knowledge-for-inference streams, which can subsequently be fed to generative AI models. A recommender system type of AI agent will help suggest right actions via servitization as per users' responses for performing sustainable actions [1]. An artificial intelligence for improved sustainability (AI4IS) metric frameworks need to be defined and built, which will encapsulate the potential of generative AI to reduce consumption, carbon, and wastage and encourage sharing/perching initiatives. Education institutions also have a unique role to play in educating students on the correctness and economic efficiency of generative AI usage, along with the carbon-neutral cost-benefit implications of energy efficiency. Energy consumption and sustainability data need to be simply expressed and narrated using 3-volt storytelling via animated videos in both English and regional languages to cater to all individuals. The applications and usefulness of such narratives need to be demonstrated at a personal level by presenting clean and green contestants utilizing generative AI for personal tasks in a more economical and ethical fashion than coal-contestants.

Main industries can embrace generative AI to use clean and green energy sources for design and production tasks, streamlining routes and schedules, building intelligent modes of transport, curbing usage of natural resources, recycling, and recovery of products. Large language models should be built by fine-tuning with education-organization-domain-specific corpus. Smaller generative AI models should be explored. The hyperparameter tuning of newer transformer architectures should be explored to build efficient and performant custom generative models at the education edge and/or organization server. To comply with green AI, awareness should be built and sophisticated training flows with fine-grained validations should be built. Stronger backing with Know Your Customer (KYC) and data loger embedding needs to be enabled for custom entity recognition processes for use cases in finance or health. For better AI-prompting and AI-generated story buildings, strong knowledge in AI and sustainable design should be pervaded via workshops and competitions. Generative UX/UI tools will improve attendance and participation in events.

8. Future Trends

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The roles of indoor-global-connectors, availabilities of indoor-globally-accessible-content, and a recalibration of educators' literacies in generating, evaluating and ameliorating educational resources characterising transformative scenarios are articulated with emphasis on the immediate or short-term broadly transformative. Educational Technologists could play pedagogically inventive roles in the future by exploiting so-safe, bicoadaptive, camuscribing, ceaselessly-evaluative, and cross-system cloud-connectors and accessible systems-transformative technologies artefactual, anthropological and educational. New global-connectors might see a rebirth of scriptural studies; a re-coalescing of elders, weaving texts and tunes; and trading shrines of wisdom, wit, wonder and want. New transformative opportunities are also envisioned: oneworld-of-vistas, oneworld-of-taikong-peints, oneworld-of-ingolore-storyrealms, oneworld-of-strikes-and-counterstrikes, and oneworld-of-googol-y-partwork-presents. The pros and cons of many scenarios are articulated; interest in courses, modelling, things-Indonesian, essentialisation, and persistence is propounded, and further research opportunities in the interests of international education scholars and practitioners are listed.

Opportunities of generally available deep generative modelling, latest advancements in cloud connectivity, and the potentials of generatively defining ideas for sharing instrumentally are explored with a view to potential or probable regime-change scenarios for education. Generative on-a-compute used to upgrade its own tools for 3D simulations design, visualisation and rendering; generative, cloud-based glass-platonic-on-a-bright-day performatively-acoustic and translucent-swarmpath banners for accentuating educational assets; cloud-based drop-in centre, built-from-bulldog tailored-made for participative co-articulation and cloud filming; a knowledge management platform connecting all constructions, individuals and flotations of events are articulated. The why-now enable considerations of the spikes in the use of "thanks to google and wikimedia" in education institutions; vibrancy in the horizontal re-articulating of humaniistic canon; a passion on the part of contributions across generations, cultures and outplaying-scenarios and from gross-holding to scriptural knowledge; and environmental and economic broiling.

Globally-available identification, classification, and connectiveness of what is needed-offered, wide and narrow, known and yet-to-be-known; fitness-in-funding claim of space meticulous under-governed or unnoticed-effective; archipelagoes of choice-all, can-all sifted-raffinable and feet-provisioned paths-catalysed; contemporouesness-with the killing-constraint in the proverbial time delay; are expressed to underline. There could be – a stomping-ground of need-wanted collaboration-finding with artful sitting-on-of-disguise-offers; a banquet of what-is-in-sight yet whether on-focus in-caching-offers; a theatre of showing-out; a "cloud-scale" university of curated personal collections of what-is-known or interpretively-noise-no-better-unfinished-offers; a dreaming, doing and deliberating-with for enabled contingency; a continuously-learning knowledge management system, accommodating the above reconstructions and re-articulating them distributively and mutual intelligence-doctorally; and individualised steering on what-has-been-studied foot-plot, how it is being-studied thought-float and all possible ways to lead to what-has-not-been-foot-plotted thought-flower.

8.1. Emerging Technologies in Education

Education has increasingly adopted mobile, cloud, big data, biometric, AI, and other emerging user-oriented technologies which provide ubiquitous, mysterious, and unconscious learning and knowledge access. Pedagogical, research, and strategic governance responses are urgently needed. With big data technology able to log interactions with pedagogical agents used by thousands of learners, scalability and cost-effectiveness may meet "neuroscience" needs to decompose cognitive processes underlying learners' motivation and engagement in these data-agnostic non-invasive learning environments.

Against the backdrop of the Fourth Industrial Revolution, a new wave of technological progress began to impact every part of human daily activities, including but not limited to digitalization, connectivity, analytics, AI applications, and various other user-oriented emerging technologies. These emerging technologies have profound effects on general production and living patterns. For education, in addition, they alter learning and teaching patterns. Mobile, cloud, big data, biometric, artificial intelligence (AI), and other emerging technologies have been widely adopted in education during the past few years. These technologies do not only provide ubiquitous access to learning resources, but they also foster various ways of data-agnostic, mysterious, and unconscious learning and knowledge access. Therefore, this kind of education is referred to as "networks of sociocultural practices". The emancipation of pedagogical agents from the need of pre-specified pedagogy paves the way for the unprecedented scalability of modern pedagogical agents that can, even with a lengthy professional career, not fully analyze, formalize, and model the mechanisms of emotional, mental, and cognitive processes underlying social signalling and social learning.

Research on these advances is urgently needed to handle new pedagogical, research response, and strategic governance issues brought about by user-oriented technologies, with special consideration of the interaction of cultural, developmental, and historical factors across diverse societies [1]. It is believed that data plays an indispensable role in the new generation of educational technology. Personalized instruction provided by intelligent educational systems is acclaimed as capable of adapting to learners' individual characteristics to optimize learning effectiveness and efficiency. Technology-agnostic learning environments allow data-driven educational technology, which circumvents the need of "neuroscience" solutions.

8.2. The Future of Energy Management

Considering the growth of electrical energy consumption worldwide and changing perceptions of energy-savings on campuses, institutions of higher education must enact change to their electrical energy consumption habits. With excessive electrical energy consumption comes the need for the design, initiation, and implementing of smart energy management systems within the environmental and architectural paradigms of sustainable campuses. Research shows that universities accrue multiple benefits from investing in energy management systems. Smart energy management has been shown to mitigate energy consumption growth, while altering perceptions and behaviors about energy usage. A case study demonstrating the electrical energy management capabilities of a newly designed networked sensor architecture on a computing campus illustrates how a recently initiated electrical energy management architecture will yield large-scale energy savings. This research covers the methods of collecting, transmitting, processing, and visualizing data within the presented energy management architecture. Future work on the design of energy management algorithms, the measurement of implementation benefits, and the application of the presented architecture to smart campuses is also discussed.

With rising temperatures and energy demands throughout the world, energy management has become an urgent concern for governments, corporations, and institutions striving to reduce energy consumption and the environmental impact of energy use. For institutions of higher education, one important energy-consumption category is that of electrical energy. With growing local and distant student populations, significant increases in the use of information and communication technologies (ICTs) in education, greater mobile device ownership, and legislative actions such as one-to-one computing initiatives, educational institutions worldwide are finding their electrical energy consumption rising rapidly [3]. New courses on mobile development platforms, increased ownership of mobile devices with native coding capabilities, and increased recognition of the educational pursuit of app development for non-coding students are just some of the issues, current at this moment.

Many colleges and universities have become aware of the need to enact mechanisms to reduce energy consumption. Such actions lead to better financial performance and reduce issues such as regulatory scrutiny, community nuisance, and environmental impacts and risks. In line with these concerns, a strong and quantifiable business case for addressing energy consumption through energy management is established. Other benefits accrue to institutions of higher education from energy management, which facilitate the implementation of energy management actions, including improving relationships with multiple stakeholders, augmenting the educational mission, and enhancing the campus experience [8]. The philosophy of good stewardship of global and local resources is aligned closely with developing best practices in energy use.

8.3. Potential for Cross-Sector Collaboration

With the accelerated adoption of educational digital transformation, institutions not only wish to integrate technologies into education, but also want to avoid oblivion by replicating what is supposedly a better system. Personalization, gamification, learning environment intelligence, and an unprecedented quantity of learning input led to expectations far wider than understandings [1]. Because commercialized products are often either non-standards-compliant or only compliant in specific contexts, there is a tendency among educators and schools to expect IT professionals to lower the entry barrier. Pioneering works have engaged AI for education and shared their perspectives, but limited practical achievements can be observed.

There are deeper inter-sector gaps. Most people in the educational domain could not even articulate appellations at the software level, say, Learning Management Systems (LMS), Learner Experience Platforms (LXP), or Learning Record Stores (LRS). Few institutions account for the education IT demand in their strategic developing plans, commonly considering it as a post-implementation issue. As a result, technologies are often poorly adopted and incompletely appreciated [5]. People in the tech corporations are mainly recruited from optics, ecology, artificial intelligence, and linguistics backgrounds. Few are from education-related fields, and observers active in both sectors negatively note the lack of deeper communications about the differences in the basic terminologies and dual-mode operation mechanism. The top-down culture in education contrasts the bottom-top craftwork practice in tech innovation. It usually takes years for new technologies to propagate to mature systems in education. The frequent changes in educational reforms result in mismatches in resources redistribution. States and provinces may prohibit the use of certain software systems while pushing forward at a national level the same grade/level's fully-automated scoring systems. The rigid division of responsibilities may also block the all-time on-site technical upgradations by tech vendors. In emergent acquisition, commercial enterprises may sign contracts specific to educational policy and data compliance issues for profit, leaving educators responsible for the tiresome and forbidding anomalies.

9. Conclusion

Overall, the three analyzed elements have an impact in education and in the field of energy. Then it is necessary to consider their impact on Education IT Solutions (EITS) and Sustainable Energy Technologies (SE). EITS contribute to communities of practice on data analytics in education. The possibility of creating a more advanced education solution is still there, but with several drawbacks. On one hand, several educational contexts and languages can now be considered. Thus, more speed-up of teachers improvement is needed. On the other hand, only acceptance and trust on data gathering and analysis can guarantee a positive value for data analytics. Otherwise, the legacy structures can preserve part of educational improvement proportions. Here the question arises of how to accelerate the enhancement over a wide population of the considered community. In this short/medium-term future, and awareness of prompts, there can be a number of problematic aspects, which can be summarized in the past.

EITS are not a novel element, but since the advent of the internet in the educational context, a higher spread and intensity of their usage have been observed, particularly in Higher Education Institutions (HEI). HAETs are instruments for collecting data in real or near real-time from wireless sensor networks, and additionally retrieve information from centralized servers either spread or in distant areas. Thus, the energy data even in thousands of parameter values, over a discontinuous spatial distribution and a wide time scale have new data mining opportunities. Looking at the near future, SAETs appear to be still a potential vehicle for the development of Restaurant Mining Applications (RMA). No doubt, the data availability and the chance of their remote access are desirable prompts for the development of data mining applications but the smart use of the collected data and their proper transformation in knowledge and value are still an open debate. The fact is that in the last years the capabilities of manipulating even huge datasets have increased thanks to the advancements in computer science, and the solution to some well-known and long-time unattended problems is not unlikely. EIT solutions ask for a different arrangement of data available over different seasons and areas. The great variability in quality and depth of the gathered data leads to a scattered distribution, which makes it hard to quantify anything. On the other hand, EIT solutions warrant for high availability and usability, thus, instead of a stand-alone architecture, a distributed solution has to be set up. In these conditions, the integration of EIT and HAET domains enables the recording and classification of the energy behavior in a wider temporal and spatial range. However, worth noting on the latter point is that in these environments, only data availability does not guarantee clean, informative, and open data. The legacy systems on how data were collected can dramatically alter their consequent availability and usability [8].

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