A survey of federated learning approach for the Sustainable Development aspect: eLearning

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Abstract. Throughout the years, sustainable development has been the concern of many governments. The United Nations have launched the agenda for sustainable development, containing 17 goals. Achieving it, is considered to be a challenging task as it requires balancing different aspects, the economic, social and ecological ones. One of the most important aspects of sustainable development is eLearning. It is green and does not require students to move to classes or waste energy. It has been widespread globally, especially after the pandemic. Artificial intelligence solutions have been used to implement eLearning; however, they still have some shortcoming, that were handled by newer technologies. Federated learning is among them. It came with more robust, and intelligent solutions to effectively implement the eLearning concept. Hence, in this work we will explain how eLearning helps in achieving sustainability, and then how technology can serve this virtual concept. We will focus on one of the latest technologies of AI that helps in implementing eLearning, which is Federated Learning. Therefore, we will try to filter the most interesting works in eLearning, especially the ones using Federated learning.

Keywords. Sustainability; SDGs; artificial intelligence; federated learning; sustainable development; eLearning; online learning

1 Introduction

In recent years, several countries and governments have been working continuously to integrate the concept of sustainability in their plans and agendas. Sustainable development is defined as ensuring the basic needs for present generations and future ones while keeping the ecological systems' ability to be regenerated [1]. It includes three basic dimensions: economic, social and ecological. [2]

In September 2015, the UN general assembly released the agenda of 2030. It contained 17 Sustainable Development Goals that identified the challenges faced currently. This includes five main areas: people, planet, prosperity, partnership and peace. This has brought a newer way of perceiving sustainability. It showed that it is not the government's responsibility only; it requires the involvement of all social actors. Hence, our future can be sustainable if the

entire society is involved in building the economic, social and environmental pillars of any nation, without forgetting about the development of humans. [3]
In several countries, within the process of having a more sustainable world, some institutions have embraced the concept of eLearning. This refers to adopting technology allowing the access to educational materials, not by being present in a physical classroom, but through connecting to online platforms using any connected device. This can be done from anywhere, as long as the trainer is connected to the internet [4]. In recent years, especially after the pandemic, eLearning has been widespread globally. Most educational institutions use this approach [5]. This is because online education presents new methods and approaches to students, with interesting course materials. It allows students to challenge themselves and work at their proper rhythm [6]. The course materials can be updated anytime, and from anywhere using the internet. Furthermore, teachers would have the opportunity to discover and work with different tools and technologies to prepare the online courses' materials. This will improve their digital skills and help them stay aligned with students' needs [7].
Lately, artificial intelligence techniques have been employed in this domain to offer more intelligent and robust eLearning systems. Machine learning and deep learning approaches have been used in that sense. For example, MOOCs, and IBM's Watson Classroom were among these systems that were used widely. However, they have some shortcomings like the inability to assess how far the learners have understood the materials, and what they did actually learn [8]. As to overcome the shortcomings of these models, newer techniques have been introduced, such as federated learning. It is a method that allows building interesting models in terms of performance and prediction while keeping the privacy of users' data [9].
In the literature, we did not find a review of how federated learning implemented the concept of eLearning illustrating sustainable development. Motivated by this lack, we have decided to perform a concise survey that synthesises the works done previously in this topic. Such review will be useful for researchers who are interested in this domain of sustainable development and technology, as they do not have to start the process from scratch. Therefore, in this paper, we will explain how eLearning contributes in achieving sustainable development, along with its aspects and illustrations. We will move to presenting how technology helps in the enhancement and implementation of this sustainable way of learning, then we will dig into one of the latest concepts of AI which is Federated Learning which has been used in many eLearning related works.

2 Methodology of research

2.1 Research Protocol

In our research journey, and according to the literature, we have followed five steps. First, we started by the specification of the scope of our research work, and the keywords we will be using. Then, we moved to the identification of the search engines we will be searching in. Later, we moved to the identification of the journals and conferences. Then, we set the inclusion and exclusion criteria we will be using in the selection and filtering process. Finally, we ended by the extraction of convenient articles based on the examination of titles and abstracts.
Our research questions are:
How does eLearning promote the sustainable development of nations?
How does technology serve eLearning?
What are the latest advances of Federated learning technology applied to implement eLearning?

2.2 Results of applying the methodology

In this section, we will describe how we applied the chosen methodology to conduct our research. First, we identified the scope of our research, which focused on the role of eLearning in the promotion of sustainable development, and how federated learning implements this concept. For the selection criteria, we selected papers that were published starting 2017, and were written in English. Also, we filtered articles based on their convenience in titles and abstracts. For the key words, we used eLearning, sustainable development, federated learning, energy saving and artificial intelligence. Then we combined federated learning with eLearning, and online learning. As far as the search engines are concerned, we have worked with Scopus, IEEE, Springer and web of science. This is due to their credibility and good reputation in the research community.

After going through these steps, we have identified around 80 articles, and filtered them to keep 28. In the following sections, we will be presenting the results of our findings.

3 How can eLearning shape a more sustainable world?

eLearning refers to using computer technology in a learning experience that has led to many changes in the traditional learning, without having to be physically present in a classroom or educational institution. In fact, eLearning is considered as a green option to learn. It is more sustainable compared to the classical way of learning. This is due to many factors. According to several studies, embracing eLearning helps in saving energy, limiting paper usage, reducing pollution and emissions and other positive consequences.

Concerning the reduction of energy consumption, since learners do not have to be present in a physical classroom, and they can connect from anywhere, schools consume less energy for heating, and cooling, so less electricity is consumed. A recent study by the Open University Design Innovation Group (DIG) showed that overall, eLearning allows saving almost 90% of energy compared to the classical method. This is because it allows saving lighting and important energy uses, since no classrooms are used. In addition, this method allows reducing the CO2 emissions [10].

As far as the paper usage is concerned, eLearning helps in reducing its usage and protecting the environment from its waste. In fact, in the traditional learning way of physical attendance in classes, many resources are consumed including class handouts, tests and textbooks. According to the National Wildlife Foundation, around 60% of wastes at schools are generated from paper usage. Also, according to studies, between 55 to 100 million trees are needed to respond to papers' needs. However, only 53% of papers are recycled. Fortunately, eLearning helps in reducing deforestation by decreasing the paper's usage. This is fulfilled thanks to online materials, e-books and tests, that are accessible through any connected device [10].

Another important aspect of the contribution of eLearning to the process of developing a more sustainable world, is reducing the emissions of transportation. This is given that, the means of transport are considered to be one of the main contributors to the climate change and degradation of the environment. Within the context of eLearning, learners can get their training from home. They do not need to be physically present in the classroom. Hence, this approach helps in reducing the emissions generated by transportation. According to a study performed by the University of West Georgia, eLearning allowed reducing CO2 emissions by 5 to 10 tons per semester.

eLearning allows saving another natural resource that is vital to our environment and humans survival, which is water. This is due to the fact that schools and campuses consume water in heating, cooling, restrooms, and kitchens. Whereas, at home, people who adopt online learning tend to consume less quantities of water. Besides water, other natural resources are saved like food, raw materials including plastics, metal and woods [11].

All these aspects have a positive impact on the environment. This makes eLearning more sustainable compared to the classical method of learning as it helps in reducing the carbon dioxide generation.

4 How does technology contribute to sustainable development?

Classical machine learning approaches have issues related to data privacy and security. This is why federated learning(FL) has been introduced to find solutions concerning enhancing models' accuracy, providing data privacy, and developing scalable systems. All these features offered by Federated Learning will definitely contribute to building performant models that provide solutions to complex problems related to Artificial Intelligence. In fact, federated learning was introduced to implement the General Data Protection Regulation according to the European Union Law concerning the privacy and protection of data [12].

4.1 What is FL?

Nowadays, Artificial Intelligence(AI) has become one of the most interesting and recent trends of technology. It is used in several domains and has contributed to the efficiency of many processes. In AI, one of the most faced challenges is using data from several sources to train models, while preserving their privacy according to the law of General Data Protection Regulation [12]. Here comes the introduction of the concept of federated learning [13]. This approach is about building and training machine learning models using a distributed manner, in several, remote mobile devices. Data is kept in the devices, and models are trained locally and encrypted. Later, they are aggregated and uploaded in the cloud in a centralised way. Hence, the data is kept secure [14].

For instance, let's assume having n devices{dv1,……dvn}each containing its own dataset {d1,……dn}. Using the classical methods, in order to train a machine learning model, the datasets of the n devices are aggregated and the model is trained on:

d_all=d1∗d2.. ∗dn

However, using the approach of federated learning, the federated model (Fm) is trained collaboratively, at the level of all devices containing the data, having that each device preserves its data from the rest.

4.2 The process of FL

According to figure 1, the main process of federated learning is as follows. Within the federated learning approach, there is a global machine learning(ML) model, that is first initialised, and then transmitted to local edge devices, where it will be trained. After training local ML models on edge devices' data, there will be a trained local ML model for each device. Later, the new parameters of the local model are shared with the central server so that they will be aggregated with the updated parameters coming from the rest of the nodes participating in the operation. This aggregation results in updating the global model parameters. During the aggregation step, some secure computations are done to ensure the privacy and security of the exchanged data. This approach works in an iterative manner. Hence, when the global model is updated with the transmitted parameters, a round of federated learning is executed. This new updated global model is again retransmitted back to another pool of selected nodes in order to complete another round of training. [13]

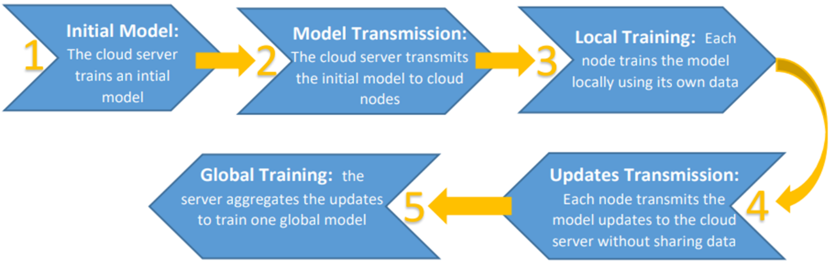

Fig. 1. Training a Model using federated learning [13]

As shown in table 1, federated learning differs from the traditional machine learning mechanisms in many ways. This is in terms of several criteria. First, the structure FL works in is a decentralised one. It trains ML models locally on edge devices, where each device does not share its data with the rest of the pool. Here, the devices' datasets are considered to be independent. Then, it communicates local updates to the central server so that it aggregates them. However, in the classical way, the training happens in the central server where the data is all stored in that server. Also, with the FL, the client model personalization is quite improved since the local training process works using unique user data. [15]

Table 1. Centralised Machine Learning Vs. Federated Learning

Characteristics	Classical Learning	Federated Learning
Training	In a centralised server	On edge devices
Model	Shared model	Personalized/shared models
Aggregation	none	Aggregation in a central server
Sharing	Sharing of datasets	Sharing of model's parameters
Target	Collect data	Distributed learning
Iterations	One time submission	Iterative process

4.3 The main advantages of federated learning

Federated Learning has brought remarkable advantages compared to the classical machine learning [14]:

- Ensuring data privacy: Federated Learning provides data privacy as it applies the General Data Protection Regulation. This is because each device or site trains the model locally using its own data and does not share it with the rest.
- Enhancing the models' accuracy: compared to the classical machine learning models, federated learning models result in a better accuracy because they are built via aggregating models trained locally using datasets from different sources.
- Decreasing the training time and cost : this is achieved thanks to, instead of training a whole global model at the central level, models are trained locally at each site and then aggregated at the central level. The federated learning approach is less time and resources' consuming and generates less latencies.
- Minimising the storage of data : at the central level, only the learned model is being processed. Once the local models are sent out of the sites, they are merged and then deleted. This is to make a performant and robust system by avoiding the storage of unnecessary data, according to the General Data Protection Regulation [12].

- Building scalable systems: this is because federated learning allows that several devices from various sites learn from one another.

4.4 Classification of Federated Learning

According to the figure 2, federated learning applications can be classified as follows:

Data partition based classification of federated learning

For the data partition based classification of FL, it can be classified as horizontal, vertical and Federated Transfer Learning. The two variants of FL which are the horizontal and vertical [15] are linked with two main use cases which are cross-device and cross-silo. In the following sections, we will explore each one of them[14].

Horizontal Federated Learning

The horizontal federated learning refers to the case where the data to be used in the edge devices, has the same features but separate samples. Here, each client device contains its own dataset, but shares the same attributes or fields' structure with the rest of the devices on the pool to be trained. Hence, in this case, the data is partitioned horizontally as it has the same structure in all devices. One of the most known examples of this kind of FL, is the predictive keyboard of the smartphones. Note that this one is among the very first applications of FL [16].

Vertical Federated Learning.

For the vertical federated learning, the datasets of the clients' devices have the same sample ID but different features, meaning different fields in the records. It means, they share common identifiers where information from both institutions come from the same user space. This approach is mainly applied in the case of data communication between several institutions. It is mainly about integrating data coming from various sources without the need to gather them in one central server. This refers to the example of a cross silo scheme where various governmental agencies share data about residents [17].

For instance, within a city, suppose we have two different institutions, which are a bank and a trading company. It is very likely that their datasets contain the same users which are the city's residents. Hence, they might have a quite large intersection in the user space. However, the features space of these datasets are different due to the difference in context of the bank and trading company. Using vertical federated learning, the aggregation of the different features is done using a privacy conserving method for building a model, and the data is used from all parties. To achieve vertical data partition, various algorithms are used: classification, gradient descent, statistical analysis, safe linear regression and data mining algorithms [13].

Federated transfer learning (FTL)

In case of having different features and samples' space among the clients' devices in the pool to be trained, the concept of Federated Transfer Learning is used [18]. For instance, the case of having a bank in Brazil and a trading company in the UK. Hence, since these two institutions are located in different places, there does not exist an interesting intersection between their users' groups. Also, they refer to two different businesses, they don't share the features' space as well. Here comes the role of transfer learning where it can be used while

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training ML models. The works presented in [19] introduced cases where Federated Learning was used in the mechanisms of transfer learning. [20]

Modelling method based classification of federated learning

The main objective of Federated Learning is to improve the efficiency of Machine Learning models in a secure way. There exist three categories of FL, decision tree based FL, statistical method and a neural network based FL. For the statistical approach, it includes mainly the logistic and linear regression, which are mostly used and considered to be easy to use, as shown in the following work [22]. For the decision tree based methods, there exist other techniques that are more accurate, stable and performant which are mainly the gradient boosting decision trees and random forest [20]. Finally, for the neural net based methods, several works have been used like recurrent neural networks and convolutional ones. Such models are considered to be performant, fault tolerant and robust. These approaches have been used in the applications of pattern recognition, and intelligent control. [13-23]

Privacy level based classification of federated learning

In fact, the main advantage of federated learning is allowing participants to have their data remain at their local level, while sharing the models' information, which may reveal some of the private data. Hence, here comes the necessity to have some mechanisms that would maintain privacy level. In fact, some of these mechanisms include model aggregation, encryption and differential privacy. For training the global model, and concerning the model aggregation, it summarises the model parameters from all the participants. In order to enhance the performance, a newer method is used which is the parameter exchange in real time, in order to achieve better results [24]. As far as privacy is concerned, the method of multitasking based local adaptation was used, to get better results and maintaining the privacy. [14]

Communication architecture based classification of federated learning

Even though the federated learning approach is based on a decentralised architecture, it still needs the intervention of a central/main node. That central server would take care of managing the collection of data from the participants, and the aggregation of the local models in order to build a global one that would be shared back with the pool. To support this, a one central server with multiple participants architecture is used. The central node's main role is considered to be the manager of the learning process, and the controller of the updates coming out from the different participants. Here, several issues might arise including: the differences between the several participants and the possibility of having malicious updates. To handle these issues, Google has introduced solutions. First, the clustering algorithm, where participants in the pool with similar data are grouped into clusters. They act as central subsystems, and each one of them submits its updates to the main central server, which aggregates them. This makes the overall performance faster. To build these clusters, several works have been presented in the literature including the local model's cosine similarity. Other works have shown interesting results including the Iterative Federated Cluster Algorithm- IFCA framework and Federated Stochastic Expectation-Maximization- FedSEM. [13-21]

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Data availability based classification of federated Learning:

federated learning can be classified in two types: Cross-silo and Cross-device based on the availability of data and the number of participant nodes. For the cross-silo federated learning, usually, there are hundred devices that are used for training. They are used within an institution and the data can be partitioned either vertically or horizontally. The most current trend in this sense is the FATE framework, which reduces the communication cost through the batch encrypt algorithm. As far as the cross device federated learning, the number of clients' nodes is enormous given that they belong to the same domain and interests. In this case, the task of maintaining entries for each transaction is challenging, as the number of clients is large. Such approach is suitable for domains especially the IoT applications. [13]

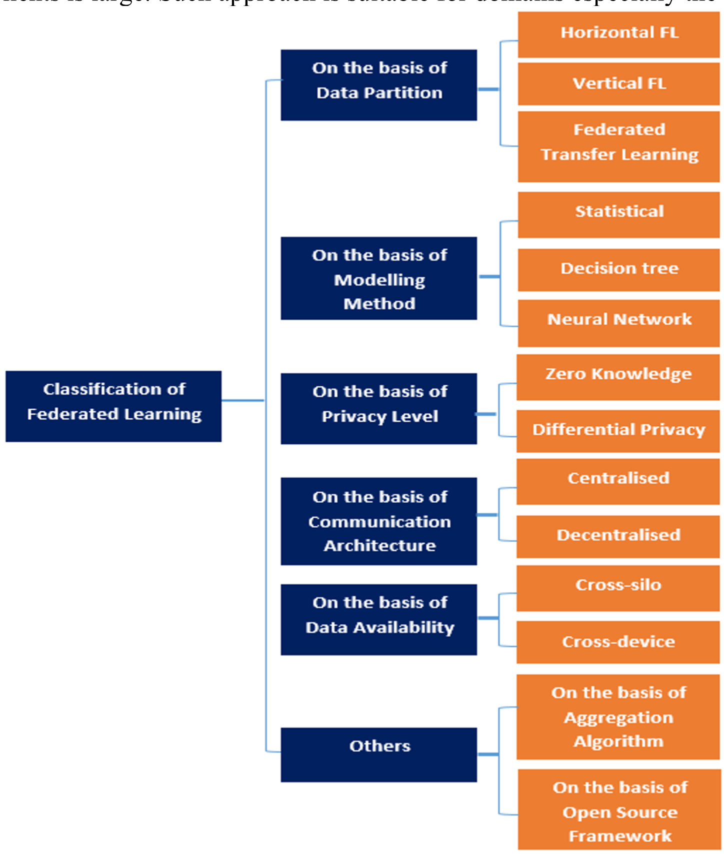

Fig. 2. Classification of federated learning approaches

5 The Application of Federated Learning to the field of eLearning

In the literature, several applications of eLearning were built based on the concept of Federated Learning. They are helpful and beneficial because they allow privacy preservation of data at the level of each educational institution, and hence, no need to store all data in one central server [16].

Table 2. Overview of the most recent FL approaches in eLearning.

Article	Description	Approach
Mitigating Biases in Student Performance Prediction via Attention-Based Personalized Federated Learning [25]	Predicting students learning performance according to their activities.	Applied FL method on students' subgroups in order to predict their learning outcomes. They were defined by their demographic variables.
Federated Learning for Data Analytics in Education[17]	This paper presents the application of federated learning techniques to a well-known learning analytics problem: student dropout prediction.	Learning analytics problem: student dropout prediction. This work uses horizontal FL techniques to apply LA to data distributed across different educational institutions by preserving the data privacy.
Towards Decentralised Learning Analytics[26]	Predictive analytics	1) Data owners control who legitimately has access to data pertaining to them. 2) Federated Learning, where the data remains on the data owner's device and/or the data is processed by the data owners themselves. 3) Graph Convolutional Networks for Heterogeneous graphs, which are examples of knowledge graphs
Pedagogical Data Federation toward Education 4.0 [27]	Achieving the Pedagogical data analysis	This article proposes a Federated Education Data Analysis (FEEDAN) framework by applying the advanced federated learning. It could achieve the privacy guaranteeing analysis, with even higher performance in certain cases, in comparison with traditional centralised machine learning paradigm.
Privacy-Preserving On-Screen Activity Tracking and Classification in E-Learning Using Federated Learning [28]	Detecting the on-screen activity of students	A privacy-preserving architecture based on federated learning is introduced in order to determine whether students are utilising their time to study or not.
A Federated Learning Method for Real-time Emotion State Classification from Multi-modal Streaming [29]	Students in online learning: Emotion state recognition	This paper presents Fed-ReMECS, a federated learning framework for real-time emotion state classification from multi-modal data streaming.
Predictive Analysis and Simulation of College Sports Performance Fused with Adaptive Federated Deep Learning Algorithm [30]	Student performance prediction method	This paper uses an adaptive federated learning method and a personalised federated learning algorithm based on deep learning and then proposes a student performance prediction method
A Federated Transfer Learning Framework Based on Heterogeneous Domain Adaptation for Students' Grades Classification [31]	Students' grades classification	This paper proposes a framework based on federated transfer learning for students' grades classification with privacy protection.

Research on Online Teaching Emotion Detection based on Federated Learning [32]	Online teaching emotion recognition detection for teachers	This work proposes a Federated-learning system based on online teaching emotion recognition detection for teachers. Through the recognition of teachers' teaching emotion, it can realise the auxiliary analysis of the teaching level of teachers, help to find the problems in the process of online teaching and improve the teaching level of teachers.

The table above shows a variety of applications of federated learning in the eLearning field. They tackled some important issues like the emotion detection for students and teachers, grades prediction and classification, and detection of the onscreen activity. All these concepts were implemented in a decentralised manner. This means that the built models were trained across decentralised devices on local datasets, and there was no need to exchange them. These models are more performant and grant privacy for users especially when they do not wish to share their data. Combining eLearning with federated learning can offer a personalised learning experience for learners while keeping the privacy of data, which is a very interesting added value.

6 Conclusion

In fact, sustainable development has been the concern of all nations all over the years. It is a challenging mission as it includes several aspects that are interrelated. It combines economic, ecological and social aspects all together. Decisions makers and communities must be able to balance all these factors to achieve a sustainable world. The main objective is to satisfy the needs of present nations without compromising the needs of future generations. eLearning is one of the illustrations of sustainable development. Adopting it has several positive consequences on the ecosystem, energy saving and the wise usage of resources. Nations have diverged towards the eLearning concept widely especially after the pandemic. In order to achieve this, they have exploited technology. Many advances in technology have served distant learning, especially the artificial intelligence ones. Here comes the objective of this article. Throughout this work, we have explained how eLearning can achieve the sustainable development of nations in several aspects. We moved to explaining the link between technology and eLearning, and how they can serve each other. We talked about how artificial intelligence facilitates eLearning processes, and we tackled one of its latest techniques. It is federated leaning. We included its definitions, along with its types and approaches. We presented a general overview of the most recent, and successful applications of the federated learning method to the domain of eLearning. We have examined several databases to achieve this work including IEEE, Springer, and Scopus. We have filtered the articles through Zotero and kept the most relevant ones. As future work, we believe that it would be interesting to examine the effectiveness of FL on other well-known domains like the tourism and health domains.

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