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Collaborating Generative AI with Federated Learning to Enhance Outcome Based Education System

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Abstract

Outcome-Based Education is a student-centered educational paradigm that emphasizes students' overall development. The goal of outcome-based education (OBE) is to prepare students for life, not just for college or the workforce. It is based on concepts: a) clarity of focus (the desired objective is met by the curriculum design, instructional delivery, and evaluation). b) More opportunities (the methods and multiple opportunities for learners to demonstrate their ability) c) High standards (all learners must achieve important goals of education) d) design down (create the curriculum with the desired results in mind). By personalizing information, automating processes, and offering immediate feedback, generative AI improves learning through Outcome-Based Education (OBE), which in turn increases student's engagement and results. The creation of precise, quantifiable learning outcomes and course objectives that are in line with students' fundamental abilities in various facets of their personal and professional lives is made easier by this data-driven approach. AI helps create a comprehensive educational framework that integrates information, skills, and values into the curriculum design process, guaranteeing that students acquire not only academic understandings but also practical expertise and ethical awareness. By facilitating data analysis and model training while preserving privacy and decentralization, federated learning presents a promising way to improve outcome-based education (OBE). This paper discusses the collaboration of Federated learning and Generative AI to design a frame work based on homogenous group of students with action Plan- Do- Check-Act and heterogeneous group of learners based on Students – Division- Teams- Achievement.

Keywords: *OBE, Generative AI, Federated Learning, Distributed environment, Da8.ta privacy, Security.*

1. Introduction

The necessity for creative and effective ways to create and assess curricula has grown in importance in the quickly changing educational world. In addition to being time-consuming and labor-intensive, traditional approaches to curriculum creation and evaluation might not adequately meet the changing needs of the business and students. The use of artificial intelligence (AI) in education has become a game-changer in response to these issues, providing fresh chances to improve the caliber and efficacy of curricula. This study explores the application of artificial intelligence (AI) to the assessment and creation of an outcome-based curriculum (OBC), a modern educational approach that emphasizes reaching particular learning objectives [1]. The educational paradigm known as outcome-based education (OBE) places a strong emphasis on the intended outcomes or results-based learning process. OBE places more emphasis on what students should know, be able to do, and value after completing a program than traditional education models, which are mostly concerned with content delivery. OBE's effectiveness is largely dependent on ongoing evaluation and curriculum improvement to

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make sure it meets the established goals [2]. Nevertheless, OBE's evaluation and development procedures can be intricate and resource-intensive, necessitating the use of cutting-edge technologies to improve and expedite them. With its ability for pattern identification, data analysis, and predictive analytics, artificial intelligence offers a potent remedy for the problems encountered in curriculum development and assessment. Large volumes 9of educational data may be processed by AI technologies like machine learning (ML) algorithms and natural language processing (NLP), which can reveal insights that would be challenging to find with conventional techniques. AI can forecast future academic results, find learning gaps, and suggest individualized learning pathways by evaluating student performance data [2]. With the help of these insights, educators may make data-driven decisions that guarantee the curriculum stays successful, relevant, and in line with the intended learning objectives. Also, by automating repetitive processes related to data gathering and analysis, AI can support the ongoing enhancement of curriculum. Teachers can now devote more of their attention to instructional design and strategic planning rather than administrative duties thanks to this automation. AI-driven systems, for example, can continuously assess the efficacy of various teaching strategies and resources, giving teachers immediate feedback. A more responsive and flexible approach to curriculum development is supported by this ongoing feedback loop, which allows for proactive modifications based on empirical data as opposed to reactive ones made in response to recurring reviews [4]. AI can an equally important role in evaluation as it does in curriculum building. Summative tests, which offer a snapshot of student achievement at one particular moment in time, are frequently used in traditional evaluation techniques. On the other hand, formative evaluations made possible by AI provide continuous insights into the learning requirements and progress of students. AI can offer a more sophisticated knowledge of student learning trajectories through adaptive testing and ongoing monitoring, assisting teachers in customizing instruction to better suit the needs of each unique student. AI has enormous potential to transform curriculum development and evaluation, but its effective application necessitates careful consideration of a number of issues. These include the necessity of strong data privacy measures, the ethical ramifications of data use, and the significance of educating educators on how to use AI tools efficiently. These factors must be taken into account when we investigate the integration of AI in OBE in order to guarantee that the advantages of AI are experienced without jeopardizing the confidentiality and integrity of the educational process [3]. An important development in educational practice is the application of artificial intelligence to outcome-based curriculum development and evaluation. Teachers can increase curriculum design and assessment procedures' accuracy, efficiency, and adaptability by utilizing AI, which will ultimately result in better learning results. The purpose of this study is to investigate the several applications of AI to OBE, looking at the advantages, difficulties, and potential future paths of this cutting-edge methodology.

2. Role of Generative AI in Education

By presenting both opportunities and problems for teaching, learning, and evaluation, generative artificial intelligence (GenAI) has ability to transform higher education. For their assignments and projects, students can quickly and simply create essays, photos, and videos using GenAI technologies like ChatGPT or Sora. During their learning process, participants may investigate various viewpoints or finish tasks that they were first unsure they could accomplish. A research student may simply get a well-informed script from GenAI to finish a statistics study, or get several perspectives to improve their initial ideas [5]. Teachers and students have difficulties when this technology is misused or overused. Students may, for example, just come up with solutions to finish their projects rather than investigating and learning from various viewpoints. Teachers also have a hard time telling the difference between student-generated and GenAI-generated content. Students' learning processes and outcomes are greatly affected by assessment, which should be designed with feedback techniques, student involvement, and self-regulation in mind. A well-

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designed evaluation helps students identify their areas of strength and growth in addition to measuring their understanding, making the learning process more effective and efficient. GenAI has the potential to offer real-time, personalized feedback experiences that adjust to the learning style and capabilities of each individual learner. As a result, the one-size-fits-all method may be eliminated by using GenAI in evaluation, guaranteeing that all students have equal access to high-quality education [5]. However, as evaluation influences learning ways, incorporating GenAI into assessment is a novel intervention that has revolutionized earlier student learning strategies. The misalignment between the creative learning strategy and its standard assessment approaches has resulted in assessment issues.

2.1 Evaluating Learning Supported by Genai

An essential component of the educational system, student evaluation supports ongoing enhancements to instructional strategies and learning objectives. Assessment's objective is comparatively consistent: it guarantees responsibility, improves the teaching and learning process with the desired learning outcomes, and gets students ready for new challenges. For assessment practices to be very effective in supporting educational innovation, achieving high-quality assessment, and achieving student assessment goals, they must be aligned with changing educational environments.

2.2 Personalized Learning

Offering individualized learning experiences is one of the most interesting potential applications of generative AI in education. Generative AI systems can generate customized learning paths by analyzing data from student interactions. These tools ensure that learners are given the most pertinent content depending on their current comprehension by evaluating each student's progress and adjusting the content in real time. This adaptability promotes a range of learning velocities and styles, which improves student retention and engagement. For teachers, this means being able to better meet the requirements of every individual student. Teachers may use generative AI to deliver differentiated instruction and make sure every student gets the help they need to succeed, freed from the one-size-fits-all approach.

2.3 Performing Administrative Task for Educators

Many administrative duties that take time away from instruction are frequently assigned to educators. Much of this burden can be reduced for educators with the development of generative AI, which can automate processes like lesson preparation, grading, and even content production. Based on student performance in class, AI can create personalized quizzes or projects, evaluate student work fast, and give immediate feedback. In addition to increasing productivity, this change enables teachers to concentrate more on the most important component of instruction—interacting with students [6]. With AI-powered technologies handling the routine administrative work effectively, teachers can now devote more time to developing students' creativity, critical thinking, and problem-solving abilities.

2.4 Communication and Collaboration Among Students and Educators

Learning platforms that use generative AI can help students and teachers communicate more effectively. For instance, chatbots driven by AI can help students in real time by responding to their inquiries, assisting them with the course materials, or providing more resources. As a result, a smooth, round-the-clock learning environment is created where students can interact with the material even after regular class hours. Generative AI systems can assist students in brainstorming, writing drafts, and refining their work in collaborative situations. These resources serve as astute collaborators that help students develop their ideas, write better, and be more creative. Furthermore, AI's contribution to real-time language translation facilitates communication and makes learning environments more accessible and inclusive. Hence Efficiency, Personalized education, accessibility of resources and collaboration can be achieved smoothly with generative AI tools.

3. Introducing Federated Learning in Education System

Enhancing student learning, optimizing classroom environments, and improving institutional policy optimization and decision-making are all benefits of integrating AI and machine learning into the

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educational ecosystem. When centralized machine learning techniques are used in education, machines are trained with data that is unique to a given institution. When training the AI/ML model, a centralized approach lacks data diversity because it is unable to access shared data across collective datasets from several institutions. These statistics do not account for the underrepresented students at each university and are skewed toward the majority of the population. The abundance of dispersed data that is accessible across various educational institutions is not fully utilized by such solitary training approaches. Data privacy may be compromised if these data are made available to cloud servers [7]. Federated Learning is a ground-breaking technology that uses distributed data from various educational entities while preserving the locality of their collected data to achieve high performance machine learning models, thereby resolving the issue of data privacy and security across cloud servers. This method processes data in two phases. a) Local Model Training: To create a local machine learning model (usually a neural network), local data sets are trained on local servers within the organization. b) Global data modeling: a central server retrieves and aggregates these local models to create a global model, which is then disseminated to all local servers for additional improvement. Federated Learning prevents sensitive data from being shared with other organizations by utilizing only the data model that is supplied by the local server. Federated learning technologies have been successfully applied in the fields of social science, communication, and health care, but they still require extensive implementation in the educational system. In a number of outcome-based educational domains, it has the potential to improve AI-based educational systems. By providing each student with individualized education support and impartial, equitable opportunities, it can greatly improve the educational experience. It helps teachers make evidence-based decisions, improving curriculum creation and allocating and using resources as efficiently as possible.

4. Collaborating Generative AI and Federated Learning

Without compromising with students and educational institute sensitive and private data, Federated learning in collaboration with Generative AI can be used in education system in following domain.

4.1 Personalization of Education with Maintaining Student's Privacy

Offering students individualized learning opportunities is one of the main advantages of the generative AI educational paradigm. By utilizing the curriculum's outcome-based learning pattern, generative AI technologies can assist students in adhering to learning psychology. 1) involving them in their field of interest; 2) helping them to overcome difficulties by giving them advice, feedback, and mastery-based problem solving; and 3) periodically planning, observing, and assessing them.

Although centralized machine learning has been successful in improving student learning outcomes and experiences, its scalability and reliability have been constrained by bias and privacy concerns surrounding student data. Using a federated AI platform, which allows each student profile to independently modify student models based on individual learning interactions without sharing raw data globally, can help overcome this problem.

4.2 Improving Class Room Environment

Although the behavior patterns of students in a classroom may be similar, each course has distinct traits that help differentiate successful from struggling learners. Using generative AI assessment tools, federated AI may identify shared behavior patterns with global model individual patterns. By integrating federated learning into an LMS, educators can receive real-time feedback on a collaborative, private, and objective model that predicts students' performance across many courses [7]. Depending on each learner's unique learning style, it can also recommend study sessions, resources, and techniques.

4.3 Improving Institutional Strategic Decision System

Federated AI with GenAI may create AI models that reduce biases by exposing users to a variety of dispersed and varied data. This makes it possible for the university to come up with ways to retain students, especially those who struggle academically and tend to drop out. The institution can create a

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strategy plan for students and teachers as well as an objective policy for all students. Institutions can improve their policies to improve the educational system by processing various data models.

5. Federated -Generative AI Enabled Data Analytic Framework for Education

The fundamental idea behind federated learning is that, with the coordination of an aggregate server, numerous servers cooperatively train a shared model using their own local training data. The risk of privacy exposure is reduced because these servers do not share or exchange data.

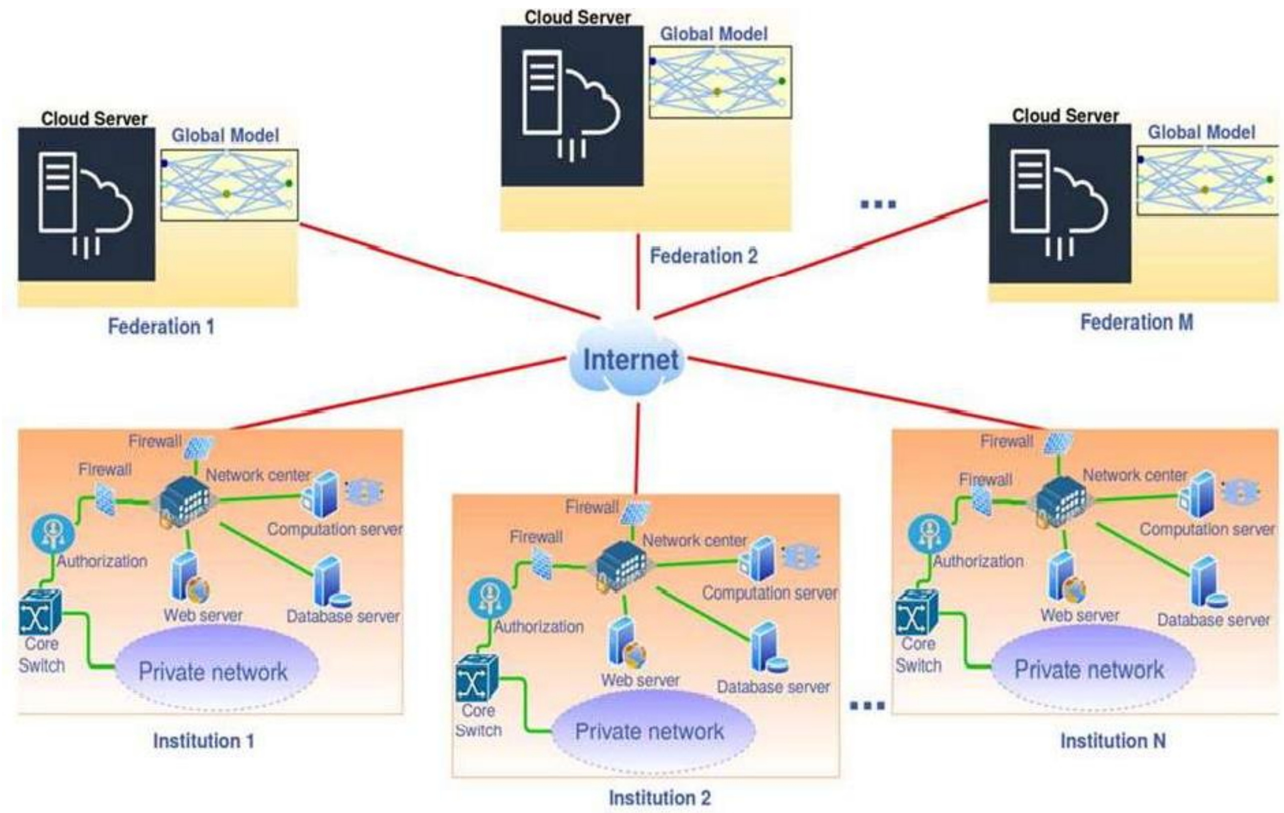

Figure 1 **Federated Learning Architecture with Gen AI**

An overview of our framework's design is shown in Figure 1. Since each educational institution just needs to construct a local federated learning server and connect to a recently installed aggregation server, it is clear that there is no detrimental alteration to the information system currently in use at some of these institutions [8]. The others, such as the Web server, local database server, local private network, etc., are all preserved. Consequently, we prefer to think of FEEDAN as an advancement of the existing education information management system. It is healthy and natural. A federation is a collection of organizations working toward a shared objective. For instance, a lot of institutions are interested in learning how different factors impact students' performance. By providing data from their own students for a single model training, they may create a federation. As a result, every educational establishment inside the federation might be considered a participant. A participant may take part in more than one federation [9]. Next, we provide a quick overview of the main elements of our system that pertain to privacy protection and the use of federated learning.

5.1 Generative Data Server or Computation Server

Instead of just a single server, generative data servers are typically clusters of servers or small datacenters used as private clouds. Existing education information systems already have generative data servers that handle a wide range of compute activities, such as financial accounting,

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office automation, and student performance analysis. Some processing power must be devoted to the federated learning task in order to support federated learning. The widespread use of virtualization technologies has made it simple to set up a federated learning environment and allocate the necessary processing capacity for federated learning training and derivation operations. Each educational institution in the system must implement a federated learning environment in addition to providing processing power. The choices for creating a federated learning environment are numerous. For instance, Google created the open source TensorFlow Federated (TFF) framework for decentralized data computation, including machine learning [10]. The Webank AI team created the industry-level federated learning platform FATE, which allows businesses to work together on AI while maintaining data protection and privacy [] In addition to offering a wide range of algorithms in the fields of computer vision, natural language processing, and recommendation, PaddleFL primarily concentrates on deep learning design [11]. There is also NVIDIA's Clara Federated Learning for distributed collaborative federated learning training [12]. Since various federations may use different environments to train their models, it might be necessary to implement numerous federated learning environments on an educational institution's computing server in order to let it to participate in many federations. It is desirable that all participants in a federation use one uniform environment.

5.2 Collaborative or Aggregation Server

An education federation's global model is updated and maintained via a collaborative or aggregation server. The collaborative server is in charge of combining the learned results from various educational institutions in the given network after each computing server runs the federated learning training algorithm locally and sends the trained results to it. In fact, for a federated learning job, this is the only thing that any educational institution needs to communicate with outside parties. The aggregation server will update the global common model and use an aggregation technique (such as federated average) after receiving training results from several institutions [12]. The freshly acquired global model is then distributed by the collaborative server to the participating educational institutions, allowing them to train their local models using the updated global model. Students' privacy is ensured since the collective server and local computation server only share weight and loss values. Thus, there must be an aggregating server for every federation. Additionally, it is not necessary for an aggregation server to be in hardware form. An aggregation server may also be a public cloud virtual computer.

5.3 Data Privacy through Authentication and Authorization

Data privacy protection and data value mining are always at conflicts position. Regardless of whether federated learning-based data analysis is implemented or not, unrestricted access to student data exposes privacy. Authentication and permission are the two primary components of data access control, just like in any other information system. Authorization is the process of granting access privileges to various data, whereas authentication is the process of confirming that a legitimate user is gaining access to framework. Certain, but not all, data can only be accessed by an authenticated user. The authorization results dictate which data can be accessed. Changing the authentication and permission policy is the primary step in implementing the framework proposed. Although it is not required, a new user must be added to the authentication policy if they are specifically chosen to administer federated learning tasks. However, the user executing the federated learning task must be given access privileges to the data required for federated learning.

5.4 Cloud Computation Server or Web Server

The "MVC" (Model, View, and Controller) architectural structure is now commonly used in many information systems, with Web servers offering cross-platform user interfaces (i.e., View). Current educational information systems also make extensive use of web servers. Authorized users can view their desired and granted data in various visual representations through a web browser. Since the advent of federated learning, Web servers have also become crucial since they can provide users with both the visualization of the training process and the outcomes of the derivation. As was previously mentioned, a number of federated learning solutions (like TFF) currently offer a web browser access portal for tracking the training process. The results of the derivation can be freely visualized in a web browser, depending on the requirements of system development.

5.5 Working of the Federated -Generative AI Enabled Data Analytic Framework

After the formation of a federation, the participants can begin working together to train their shared model using the subsequent stages. The collaborative server receives the participants' initial notification of their interest in taking part in the model training, after which it initiates the training and oversees the participants during its duration. Federated training is carried out iteratively, just like centralized training, until the predefined criterion is met, or converged. The aggregation server picks a number of participants for training in the current iteration at the start of each iteration based on the participants' statuses (such as liveness and available computation capability) [12]. Each participating educational institution's compute server begins training the model using its local data as soon as it receives the global model. As long as everyone uses the same approach, our FEEDAN architecture has no restrictions on local training techniques. In other words, one federation will employ the same training algorithm while other federations may use different ones. For instance, a federation can mandate that players use an SGD-style method to train the model. The local training outcomes (such as weight and loss values) will be communicated to the aggregation server after a predefined amount of time or when specified local requirements are satisfied. The aggregation server can use a variety of aggregation techniques, including federated average, to combine the training data from the participants into the global model. Additionally, the aggregate algorithm is unrestricted by the framework. A federation is able to select the collaborative algorithm that best suits its requirements. Once the results from the chosen participants have been aggregated, the collaborative server will assess whether or not the predefined convergence condition has been satisfied. The training process might end if certain requirements are met [13].

6. Challenges in The Collaboration of Federated AI with Generative AI in Education System

We must take into account challenges that educational institutions face while implementing GenAI in conjunction with federated learning. Among the difficulties that various institutions are facing are:

- **Computational Inequalities:** For local training on devices or servers, generative AI and federated learning demand a specific amount of processing power. Model performance may be impacted by heterogeneous data processing environments with varying computational speeds, particularly for institutions with limited resources.
- **Data Heterogeneity:** Distributed data, frequently generated in several contexts. It causes notable differences between various partitions. Data heterogeneity results from this. The demographics, regional details, and educational methodology of educational statistics vary widely. Due to the data's non-independent and irregular distribution, model training may be skewed, which could result in an ineffective or inefficient model.
- **Lack of User Interfaces:** There is no interactive User interface for educational system to operate federated learning education system enabled with generative AI. This leads to the performance while using the framework for education system.

Conclusion

Education systems with outcome-based learning can be improved to new heights by utilizing generative AI and federated learning technologies. The suggested architecture emphasizes the use of generative AI and federated learning to develop privacy-preserving machine learning models with distributed data from the educational system. The application of these technologies at various educational levels, involving various stakeholders such as students, classrooms, and institutions, was examined in the article. These applications show how to improve educational systems while protecting data privacy by utilizing FL and GenAI.

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