Revolutionizing AI-Assisted Education with Federated Learning: A Pathway to Distributed, Privacy-Preserving, and Debiased Learning Ecosystems

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Abstract

The majority of current research on the application of artificial intelligence (AI) and machine learning (ML) in science, technology, engineering, and mathematics (STEM) education relies on *centralized model training* architectures. Typically, this involves pooling data at a centralized location alongside an ML model training module, such as a cloud server. However, this approach necessitates transferring student data across the network, leading to privacy concerns. In this paper, we explore the application of *federated learning (FL), a highly recognized distributed ML technique,* within the educational ecosystem. We highlight the potential benefits FL offers to students, classrooms, and institutions. Also, we identify a range of technical, logistical, and ethical challenges that impede the sustainable implementation of FL in the education sector. Finally, we discuss a series of open research directions, focusing on nuanced aspects of FL implementation in educational contexts. These directions aim to explore and address the complexities of applying FL in varied educational settings, ensuring its deployment is technologically sound, beneficial, and equitable for all stakeholders involved.

Introduction

The integration of artificial intelligence (AI) and machine learning (ML) in the educational ecosystem marks a significant shift from traditional teaching methods. This technology offers substantial benefits for the entire educational ecosystem: it enhances student learning experiences (Dillon et al. 2022), optimizes classroom environments (Pham et al. 2023), and improves institutional policy optimization and decision-making (Brdesee et al. 2022). Nevertheless, advancing educational systems with AI/ML models face significant challenges at the student, classroom, and institution levels. A paramount challenge stems from using *centralized ML techniques* in STEM education, where individual AI/ML models are trained using data exclusive to each educational entity, e.g., an institution (Jalil, Hwang, and Dawi 2019).

Firstly, centralized ML approaches cannot access the patterns shared across collective datasets from different institutions, leading to a lack of data diversity when training the AI/ML models. Such a lack of diversity results in ML-driven student models that are biased toward the majority population at each institution, failing to meet the needs of underrepresented students. Additionally, such isolated training methods fail to capitalize on the wealth of distributed data available across different educational entities. A seemingly straightforward solution to these issues would be to aggregate data of educational entities to a centralized location (e.g., on a cloud server) and then use the aggregated data for training ML models. However, this approach raises significant data privacy concerns: transmitting student data away from their home institutions threatens the confidentiality of their sensitive information. *Distributed ML techniques* have the transformative potential to address these challenges: they enable the obtaining of ML models using the distributed data without the need for cross-institutional data sharing.

This visionary paper explores the potential of an emerging distributed ML technique, *federated learning (FL)*, within the educational ecosystem. FL's implementation signifies a potential breakthrough in achieving high-performance ML models by utilizing distributed data across educational entities yet maintaining the locality of their collected data. The general training architecture of FL, illustrated in Figure 1, consists of two key operations: *(i) Local Model Training:* In this phase, each training unit (e.g., a local server at an institution) independently develops a local ML model, typically a neural network, using its own dataset. *(ii) Global Model Aggregation and Broadcast:* Following local training, a central server periodically pulls and combines these local models into a comprehensive global model, which is then broadcast back to the units for further refinement. This step helps achieve a coherent global model that leverages learnings from all participating units. FL's architecture maintains data privacy by solely relying on the transfer of model parameters, preventing data transfers across the network.

FL has demonstrated success in applications within the healthcare (Thwal et al. 2021; Ng et al. 2021; Lee et al. 2021; Kumaresan, Kumar, and Muthukumar 2022; Lu et al. 2022; Linardos et al. 2022; Adnan et al. 2022; Oldenhof et al. 2023; Wu et al. 2023) and social science/communication domains (He et al. 2019; Shen, Gou, and Wu 2022; Salim et al. 2022; Khelghatdoust and Mahdavi 2022); however, its impact is still underexplored in education domain. In particular, FL holds the potential to enhance AI-assisted education in several critical domains. It can contribute significantly to *student* experiences by delivering personalized educational

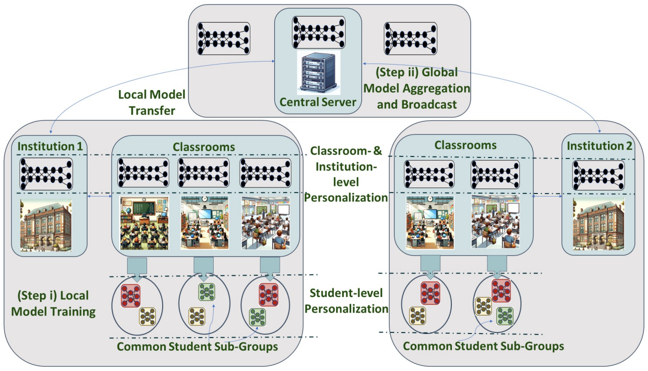

Figure 1: FL's distributed training architecture in education. Local models are (i) trained at three different levels, (ii) aggregated to a global model at the server, and broadcast across the network to initiate the next local training round.

support that is both equitable and unbiased. In *classrooms*, FL enables educators to make informed decisions based on evidence, enhancing curriculum development and optimizing resource allocation. Finally, by delving into data-driven insights, FL becomes instrumental in shaping policies and guiding decision-making processes within educational *institutions*, particularly in the pursuit of improving student success and retention rates. This paper inspects such unique advantages and potential of FL in this ecosystem. Discussing the challenges introduced by implementing FL in education, it proposes a series of open research problems, serving as a roadmap for future research in this emerging field.

Related Work

The prevalence of AI/ML applications in education has been increasing in recent years (García et al. 2007; Zawacki-Richter et al. 2019; Williamson and Eynon 2020; Holmes and Tuomi 2022). Over time, AI-assisted learning has introduced various AI/ML models of students' learning trajectories crucial in developing educational tools. For example, *open learner models* (Hooshyar et al. 2020; Susnjak, Ramaswami, and Mathrani 2022; Shahbazi and Byun 2022; L. Leite et al. 2022; Ramaswami et al. 2023) can track and represent learners' progress effectively (Bull and Kay 2010) and improve metacognitive activities, fostering self-monitoring (Bull and Kay 2007), which is referred as *self-regulated learning* (Corno 1986; Henderson 1986; Zimmerman and Martinez-Pons 1988; Zimmerman 1990, 2015). AI-assisted learning has also been shown to be capable of adapting to educational and pedagogical approaches to each student, referred to as *personalized learning*, which is an effective strategy for improving students' learning experiences and outcomes at the classroom and institutional level (Jiang et al. 2019; Intayoad, Kamyod, and Temdee 2020; Fallah, Mokhtari, and Ozdaglar 2020). Despite the benefits of AI/ML for education, the conventional centralized ML training methods (Rastrollo-Guerrero, Gómez-Pulido, and Durán-Domínguez 2020; Albreiki, Zaki, and Alashwal 2021; Kotsiantis, Pierrakeas, and Pintelas 2004; Su, Lin, and Liu 2022) – commonly pursued to obtain AI/ML models to enhance educational systems – encounter three notable challenges. First, the *distributed nature of data* and frequent data insufficiency across educational entities (Kuleto et al. 2021) can limit the effectiveness of AI/ML models when trained on the data available to each education entity, e.g., an institution. Second, the persistent problem of *unbalanced data*, even in the presence of large student datasets, increases the risk of bias towards majority groups (Dablain, Krawczyk, and Chawla 2022; Sha, Gašević, and Chen 2023; Pagano et al. 2023; Zhang et al. 2023). This can potentially undermine the effectiveness of AI/ML models, especially in addressing underrepresented student minorities, such as women in STEM fields. Lastly, *data privacy* (Boulemtafes, Derhab, and Challal 2020; Tungar and Patil 2023; Svendsen et al. 2023), particularly when data from different sources are aggregated and used for ML model training, sensitive student data may get exposed.

To address these challenges, there have been some recent efforts in exploring the use of *distributed ML approaches*, particularly FL, in the education ecosystem (Wu et al. 2021; Bhattacharya et al. 2023; Sengupta et al. 2024). Despite these emerging contributions, applying FL in education is still relatively in its infancy. A comprehensive and visionary work that sums up the application of FL across various levels of the education ecosystem, its adoption and adaptation challenges, and the future opportunities it presents for enhancing AI-assisted education is noticeably absent. This paper aims to fill this gap and further presents future research avenues that enable the ubiquitous adoption of FL in education.

Potential Use Cases of FL in Education

In this section, we discuss the practical implementations that can harness the full potential of FL in the education sector.

FL for Students: Personalization and Privacy: One of the key benefits of AI-assisted educational tools is their ability to provide students with *personalized learning* opportunities. This includes supporting students with regard to three main constructs of learning psychology: (i) *affective* (i.e., increasing engagement and reducing frustration), (ii) *cognitive* (i.e., individualized hint, feedback, and mastery-based problem-solving), and (iii) *meta-cognitive* (i.e., planning, monitoring, and evaluating) (Azevedo and Strain 2011). While centralized ML has achieved notable successes in enhancing students' experience and outcomes regarding each psychological construct, the bias and privacy concerns regarding students' data have limited their scalability and reliability. FL alleviates these major limitations by enabling a distributed ML training platform in which each student's device independently refines a model of the student based on unique learning interactions, like completing exercises and time spent on tasks, without sharing raw data with the central server. Periodically, insights from these local models are aggregated on a central server through FL, creating a global model that combines knowledge shared across students without compromising privacy.

FL for Classrooms: Improving Learning Environments: Even though students in a classroom exhibit common behavioral patterns, each course presents unique characteristics for distinguishing successful from struggling students. FL can simultaneously capture shared behavioral patterns with a global model and individual nuances through locally tailored models (e.g., through meta-learning approaches (Chu et al. 2022)). For instance, integrating FL into the *learning management system (LMS)* can enable a collaborative, private, and unbiased model training to predict students' performance across courses with real-time feedback for educators (Rubin et al. 2010). It can also offer tailored suggestions for study sessions, materials, and strategies based on each student's evolving learning patterns. Insights derived from FL can further inform the development of culturally responsive curricula and teaching methods, fostering environments where all students have equal opportunities for success.

FL for Educational Institutions: Strategic Insights and Decisions: Through exposure to distributed and diverse data, FL can build ML models that mitigate biases. This enables institutions to devise student retention and success strategies, particularly for minority students. Accurately identifying factors influencing retention and success can further refine the institutions' informed decision-making capacity (Aljohani 2016). As a result, educational institutions will immensely benefit from the unbiased policy-making and equitable strategic planning enabled by implementing FL.

Challenges of FL in Education

As we advocate for implementing FL in education, we must consider the challenges educational institutions might face with its deployment. Below, we highlight several of such challenges, understanding of which is essential to move this promising research avenue forward.

Network Infrastructure Limitations: As FL relies on the extensive transfer of models between a central server and distributed nodes (e.g., students' devices or school servers), the process requires a robust and reliable network infrastructure (Konečný et al. 2016; Li et al. 2020). Institutions with inadequate network facilities might experience delays or interruptions, impacting the efficiency and effectiveness of the model training process.

Computational Disparities: FL requires a certain level of computational power for local training on devices/servers. This can create a divide between well-resourced and under-resourced institutions, where the latter might struggle with insufficient computational abilities. Such heterogeneity may lead to uneven participation of institutions, impacting model performance, especially for under-resourced institutions.

Data Heterogeneity: Distributed data, often produced in diverse contexts, leads to significant variations across different partitions, a phenomenon referred to as *data heterogeneity* (Zhao et al. 2018; Hsieh et al. 2020). Educational data varies greatly in demographics, regional specifics, and educational approaches. This non-independent and identically distributed (non-IID) nature of data leads to potentially skewed model training that can affect generalization across diverse educational landscapes. For instance, when collaborating institutions aim to create ML models for personalized learning, variations in course structures, teaching styles, and student demographics may lead to locally biased models, limiting the effectiveness of the aggregated global model.

Interactive User Interfaces (UIs): Currently, there is no interactive UI for teaching the stakeholders how to operate FL-based approaches. Training staff and educators to use these systems effectively can be resource-intensive.

System Performance Maintenance: Regular updates and maintenance of the FL system require continuous resource allocation, leading to high costs over time. Institutions with no access to high-performance computing (HPC) hardware might struggle with limited resources and the financial burden (e.g., caused by excessive energy consumption) of FL.

Privacy and Ethical Considerations: Using student data in ML models requires careful attention to ethicality, consent, and transparency. Moreover, models can become susceptible to unauthorized access if the central server is compromised in FL settings. This could lead to data inference attacks, where private data can be recovered through model exploitation. Applying *differential privacy* techniques can hinder attackers' ability to recover genuine information from the models to some extent (Dwork 2006). However, generative adversarial networks (GANs) can still use the compromised ML models to generate synthetic data identical to the training data (Hitaj, Ateniese, and Perez-Cruz 2017).

Evaluation and Benchmarking: Due to the diverse educational settings and goals across institutions and classrooms, establishing effective benchmarks and evaluation metrics (e.g., ML model accuracy, ML model fairness, ML model false positives/negatives) for FL models in education is challenging. While benchmarking measures and techniques have been proposed in other domains (Taïk and Cherkaoui 2022; Wu et al. 2022), the issue remains persistent in the education domain.

Future Opportunities

Despite its challenges, integrating FL into the educational landscape presents exciting opportunities for groundbreaking research and exploration in previously understudied areas. Some of these opportunities are highlighted below.

Blockchain-Assisted FL: Blockchain-assisted FL represents an emerging and promising field of research in education, having already sparked interest in other domains, e.g., wireless communications (Alghamdi et al. 2022; Jaberzadeh et al. 2023; Billah et al. 2022; Chhetri et al. 2023; Salim, Turnbull, and Moustafa 2021; Li et al. 2024). Combining FL's distributed learning framework with blockchain's robust, immutable ledger system can increase accountability in managing student records, improve resource sharing across institutions, and foster trust in handling student data. However, the inherently resource-intensive nature of FL and blockchain technologies can lead to *substantial computational power requirements*. This could be a concern for educational institutions, especially regarding the financial and environmental impacts.

Multi-Modal FL over Unbalanced Modalities: Research in domains like medicine and wireless networks have demonstrated the potential of multi-modal FL, which enables using different types/modalities of data during ML model training (Xiong et al. 2022; Lin et al. 2023; Che et al. 2023; Borazjani et al. 2024). Similarly, educational data, which encompasses a variety of modalities, e.g., text, audio, video, and interactive activities, is inherently multi-modal. Multi-modal FL can thus offer a promising solution to take advantage of the available data in the educational context. However, the *heterogeneity of data modalities* (e.g., some classrooms may only have text and audio data, while others have video and audio) presents a significant challenge for implementing multi-modal FL in the education context. When integrating unbalanced and diverse data types, there is a further risk of introducing biases into the models. These biases can arise from the unequal representation of different data types across various classrooms and institutions.

FL for Large Language Models (LLMs): Integrating LLMs within the FL framework represents an enticing research area that has recently gained significant attention (Ezzeldin et al. 2022; Yu, Muñoz, and Jannesari 2023; Ju et al. 2023; Fan et al. 2023). The FL approach to LLM training proves advantageous by leveraging diverse data sources (Yu, Muñoz, and Jannesari 2023), supporting optimization tasks like fine-tuning, prompt tuning, and pre-training. In the education sector, this methodology can allow for the development of comprehensive LLMs, enriched with a wide array of linguistic inputs and learning contexts, making them highly adaptable to different educational needs, including enhancing interactive learning tools and providing personalized assistance in adaptive learning environments. However, this innovative approach faces a significant challenge beyond the hurdle of existent heterogeneous data: the *resource-intensive* nature of training LLMs. In particular, LLMs require significant computational resources for training. This burden is further distributed across multiple educational entities in an FL setup, which may not have enough or uniform computational capabilities.

Internet of Things (IoT) System Integration: Recent advancements in FL have extended its application to IoT networks (Şahinbaş and Catak 2021). This integration is particularly promising in the educational sector, where many IoT devices, e.g., smart whiteboards and student tablets, can collect diverse data in a distributed manner. This results in allowing real-time data processing across the education ecosystem. For example, FL can optimize the learning environment by adjusting conditions or tailoring content based on student engagement levels captured through student-to-device interactions. This approach enables responsible use of the vast amounts of data generated by IoT devices and supports the creation of a reciprocal educational system. Such a system can adapt to the evolving needs of students and educators, offering a more interactive and tailored educational experience. However, establishing such a system requires further attention to address data inference attacks to ensure using dispersed student data without compromising the leakage of private information in such data.

Mental Health Benefits: FL has recently found its application in mental health research (Pranto and Al Asad 2021; Khalil, Tawfik, and Spruit 2024). Applying FL also holds a notable promise for improving student mental health awareness in the education sector. For instance, educational institutions can use the ML models developed via FL to identify patterns indicative of mental health concerns. In particular, FL can obtain ML models that track students' progress, online behaviors, engagement levels, and stress state. FL insights can subsequently guide the development of personalized ML-driven interventions, including mental health resources and counseling services, fostering supportive learning environments. However, the *interdisciplinary nature of research* at the intersection of education, mental health, and ML presents complexities. More precisely, integrating insights from psychology is critical to understanding and addressing students' sensitivity to the interventions proposed by ML models.

Explainable AI (XAI): Recent explorations in XAI have shown its utility in decision-making within FL systems for a variety of domains, such as social media (Salim, Turnbull, and Moustafa 2021; Liu et al. 2022; Chen et al. 2022; Huong et al. 2022; Arisdakessian et al. 2022). Applying XAI in FL also holds substantial potential for the education sector, particularly in enhancing transparency and understanding of AI-driven decisions. One practical implementation of XAI in education is through online student/instructor dashboards. These dashboards are interfaces for educators and decision-makers to analyze, understand, and refine ML-based student models. XAI, combined with FL, can also have a nuanced role in education by revealing biases in decisions at both the classroom and institutional levels. This can be achieved by comparing ML models trained on skewed datasets (e.g., predominantly featuring data from the majority of student groups inside an institution) against models specifically designed for underrepresented groups that can be obtained via personalized FL approaches (Chu et al. 2022). Despite these enticing applications, the integration of XAI within FL in education is largely overlooked, making *interpreting model-generated insights challenging* for various educational stakeholders.

Conclusion

In this visionary paper, we explored the potential impact of federated learning (FL) in education, emphasizing its capacity to revolutionize the educational landscape. We highlighted the opportunities FL presents in creating privacy-preserving ML models using the distributed data available across the educational ecosystem. We revealed how FL can be applied beneficially at different levels of the educational system, including students, classrooms, and institutions. These applications showcase FL's versatility and potential to enhance educational processes and outcomes while maintaining data privacy. We then provided a series of open problems, laying out potential avenues for future research. These problems, when addressed, could further solidify the impact and efficiency of FL in education, paving the way for a more innovative and supportive educational landscape.

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