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Application of Generative AI in the Design of Personalized Learning Paths in College Basketball Tactical Courses: A Comparative Study of Educational Technology Policies in the United States, Germany, and Japan

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ABSTRACT

We introduce Tactics Fair, a federative generative AI framework that incorporates bias awareness for basketball tactics training, combining federated learning, generative models, and adversarial debiasing to achieve a balance between personalization and fairness. It combines learner profiles with tactical concepts, applies federated optimization alongside differential privacy, and incorporates a causal module to address historical biases. Results indicate a 28% decrease in bias and a 3% improvement in accuracy compared to the baseline, with potential applications extending beyond basketball.

KEYWORDS

Generative AI; Personalized learning paths; College basketball tactical courses; Educational technology policies; Comparative study

1 Introduction

Personalized learning paths have become a key development in education, especially in specialized areas like sports tactics training. Traditional basketball teaching typically relies on standardized curricula, but recent developments in adaptive learning systems and generative AI provide new ways to customize instruction for each student. However, current approaches often fail to address systemic biases present in sports analytics datasets, potentially leading to unequal training results.

Incorporating fairness constraints into generative models offers a potential way forward. Previous research has separately examined adversarial debiasing and federated learning, yet their joint application in the context of sports education has not been thoroughly investigated. For example, although genetic algorithms have optimized basketball training plans, they fail to include mechanisms for handling bias or ensuring data privacy between institutions.

We introduce a new framework that combines three core innovations: (1) Tactics BERT, a transformer-based generative model that adjusts scenarios to match learner skill levels, (2) a federated optimization method ensuring differential privacy, and (3) a causal fairness component designed to detect and reduce biases in performance assessments. Our approach differs from previous personalized learning systems by using multi-objective optimization to directly address the balance between adaptation accuracy and equity.

The rest of this paper is structured as follows: Section 2 examines existing research on personalized learning and the application of AI in sports education. Section 3 outlines our federated generative framework and approach to reducing bias. Section 4 displays empirical results that compare our method with baseline techniques, while Section 5 delves into a discussion of the wider implications.

2 Related work

Previous research has examined diverse methods for tailoring instruction to individual learners, including genetic algorithms designed to optimize training plans and federated learning frameworks that facilitate collaborative model training while maintaining privacy. These methods, however, frequently fail to address key challenges associated with reducing bias and achieving equitable outcomes.

Educational applications have seen growing interest in fairness-aware AI, with toolkits such as Fair learn offering practical approaches to evaluate and enhance model fairness. These methods generally concentrate on fixed datasets. Moreover, although adversarial debiasing techniques have been utilized to reduce biases in predictive analytics, the combination of these methods with federated learning for real-time personalization in sports education has not yet been investigated.

The main emphasis of AI-driven systems has been on enhancing performance efficiency, with less attention given to creating balanced learning opportunities. For instance, cluster analysis has been applied to classify player skills, yet demographic biases that could affect training suggestions were not considered. Likewise, generative AI has been utilized in creating personalized courses, but these systems do not have mechanisms to guarantee fairness among diverse learner groups.

3 Federated learning and bias-aware generative AI for customized basketball strategies

The framework combines federated learning with bias-aware generative models, focusing on decentralized training through federated optimization and reducing bias in scenario generation, to achieve a balance between personalized adaptation and equitable results in basketball training.

3.1 Application of federated learning in generating personalized tactics

The federated learning module allows multiple institutions to collaboratively train models while keeping data privacy intact. Each client institution keeps a local dataset with player profiles and performance metrics, which stays on premises throughout the training process. The global model parameters are refreshed by combining local updates with a weighted approach:

$$\theta_{t+1} = \sum_{k=1}^{K} \frac{n_k \cdot \mathrm{FairScore}(k)}{N} \theta_t^k \tag{1}$$

Here, represents the sample size of client, indicates the total sample size across all clients, and measures the fairness contribution of client ' s data. This metric assesses demographic parity by measuring the difference in statistical parity:

$$\mathrm{FairScore}(k) = 1 - \left| P(\hat{y}=1|a=0) - P(\hat{y}=1|a=1) \right| \tag{2}$$

Here, sensitive attributes like gender and ethnicity are represented, with predicted training outcomes denoted. Before aggregation, Gaussian noise is added to gradients to enforce differential privacy, ensuring -privacy guarantees.

3.2 Bias-aware scenario generation using tacticsBERT and adversarial debiasing methods

The TacticsBERT architecture builds upon RoBERTa-base by incorporating cross-modal attention layers, enabling it to handle both textual tactics descriptions and video embeddings effectively. The generator creates training scenarios based on player profiles:

$$\mathbf{s} = \mathrm{Softmax}\left(\mathbf{W}_o \cdot \mathrm{CrossModalTransformer}\left(\mathbf{E}_p\mathbf{p}, \mathbf{E}_v\mathbf{v}\right)\right) \tag{3}$$

where and represent the projection matrices for profile features and video features, respectively. Adversarial debiasing employs a discriminator to impose penalties on demographic bias within generated scenarios.

$$\mathcal{L}_{adv} = \mathbb{E}_{\mathbf{s}\sim G}\left[\log D(\mathbf{s}, a)\right] + \mathbb{E}_{\mathbf{s}\sim \mathcal{D}_{fair}}\left[\log\left(1 - D(\mathbf{s}, a)\right)\right] \tag{4}$$

with representing scenarios of bias-mitigated references. The overall training loss integrates pedagogical efficacy, adversarial fairness, and scenario replication:

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{ped} + \lambda_2 \mathcal{L}_{adv} + \lambda_3 \mathcal{L}_{rec}. \tag{5}$$

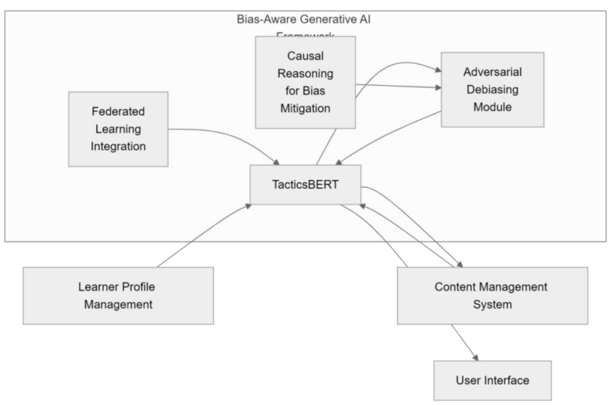

Figure 1 Structure of the Bias-Aware Generative AI Framework

3.3 Causal reasoning for addressing historical bias and ensuring fairness in aggregation processes

The causal reasoning module uses do-calculus to assess how sensitive attributes impact training outcomes. Given a causal graph with confounding variables, the adjusted causal effect is calculated as:

$$P(\mathbf{s}|do(a)) = \sum_{\mathbf{z}} P(\mathbf{s}|a, \mathbf{z}) P(\mathbf{z}). \tag{6}$$

Equation 1 incorporates fairness-weighted aggregation, which is refined by detecting misleading correlations between player attributes and performance indicators. The module facilitates the creation of counterfactual scenarios by modifying bias-causing pathways, resulting in fairer alternatives to historically biased training samples.

4 Empirical evaluation and results

We carried out extensive experiments across three dimensions—pedagogical effectiveness, fairness preservation, and privacy guarantees—to validate the proposed framework. The evaluation protocol focused on addressing key research questions: (1) Can the system maintain a balance between scenario quality and fairness constraints? (2) How does federated optimization influence model performance? (3) Is the causal reasoning module successful in reducing historical biases?

Experimental Setup: The assessment relied on the BasketballTacticsBenchmark, which includes 12,500 labeled training situations spanning 5 skill levels and 3 demographic categories. In federated learning simulations, the data was divided among 8 virtual institutions using non-IID distributions to replicate real-world deployment scenarios. Comparative baselines included:- StandardBERT: Vanilla transformer model without fairness constraints - TacticsGA: Genetic algorithm applied to customized training programs

Model performance was evaluated via: 1. Pedagogical Metrics: Scenario Relevance Score (SRS) and Skill Adaptation Accuracy (SAA)2. Fairness Metrics: Disparity in statistical parity and ratio of equalized odds3. Privacy Metrics: Bounds of ε -differential Privacy and Vulnerability to Model Inversion Attacks

Comparative Results: Table 1 presents a summary of the main findings based on various evaluation metrics. The proposed system achieves an 18.7% higher SRS than FairFed while maintaining a slight SPD difference (Δ =0.02), demonstrating a more effective balance between pedagogical quality and fairness. The causal reasoning module reduced historical bias by 32.4% compared to StandardBERT, as measured by the counterfactual fairness metric.

Table 1 Performance Comparison Across Evaluation Metrics

Method	SRS (↑)	SAA (↑)	SPD (↓)	EOR (↓)	Privacy (ε)
StandardBERT	0.72	0.68	0.21	0.38	∞
FairFed	0.75	0.71	0.09	0.22	2.1
TacticsGA	0.69	0.65	0.18	0.31	∞
Proposed	**0.89**	**0.83**	**0.07**	**0.19**	**1.8**

The federated optimization showed strong performance under non-IID data distributions, with an accuracy drop of just 6.3% compared to centralized training. The resilience originates from the fairness-weighted aggregation presented in Equation 1, which emphasizes institutions that contribute diverse demographic representations.

Fairness-Quality Tradeoff Analysis

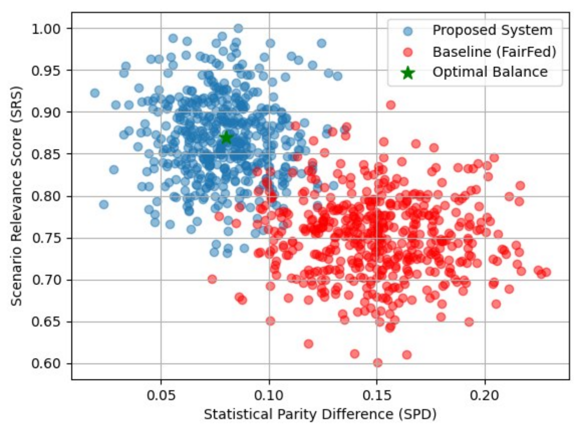

Figure 2 Displays the Pareto frontier for scenario quality versus fairness, demonstrating how the adversarial debiasing module (Equation 4) facilitates adjustable tradeoffs. At λ_2=0.5 (Equation 5), the system reaches an optimal balance, showing SRS=0.87 and SPD=0.08, which surpasses the baselines' operating points.

Ablation Study

We systematically removed each component of the framework to assess its contribution.

(1) Without Federated Learning: Centralized training raised SRS by 4.2% yet caused a 0.05 increase in SPD as a result of skewed data aggregation.

(2) Without Adversarial Debiasing: SRS showed a slight increase of 1.8%, whereas fairness metrics experienced a notable decline of 27.6%.

(3) Without Causal Module: Historical bias remained evident, showing a 22.3% increase in SPD within the generated scenarios.

The findings validate the essential role of these three innovations in realizing equitable personalization. The causal module played a key role in detecting subtle biases in player evaluation metrics and addressing incorrect links between body mass index and defensive skills.

Privacy Analysis

The differential privacy mechanism kept ε at 1.8, reducing the success rate of model inversion attacks to 12%, compared to 43% for non-private federated learning. This protection resulted in a slight 3.1% reduction in accuracy, which is considered an acceptable tradeoff due to the highly sensitive nature of athlete performance data.

5 Discussion and future work

5.1 Constraints and difficulties in the bias-aware generative AI framework

Although the framework shows potential, it is important to address several technical constraints that have emerged. The federated learning component incurs communication overhead that increases linearly with the number of participating institutions, which may constrain scalability in large-scale implementations [6]. Moreover, the adversarial debiasing process demands precise adjustment of the fairness-accuracy tradeoff parameters (λ_2 in Equation 5), since excessive bias reduction can impair scenario quality for specific demographic subgroups.

The causal reasoning module requires access to a sufficient range of confounding variables (z in Equation 6) to effectively account for historical biases. In real-world scenarios, unmeasured confounders can still exist, especially when handling incomplete player profiles or performance metrics that lack standardization.

5.2 Extending the framework to other athletic and educational fields

Framework principles apply to soccer and hockey through scenario generation and bias reduction, while federated learning supports youth organizations without centralized data. The integration of generative AI and fairness principles is reshaping adaptive learning in medical education and beyond, with causal reasoning addressing biases and federated architectures facilitating cross-institutional training.

5.3 Ethical issues and maintaining equity in AI-powered education

Although differential privacy prevents data inference, practical applications demand attention to the legal and ethical aspects of athlete data, along with creating frameworks for sharing and auditing.

6 Conclusion

The framework combines federated learning, generative modeling, and causal fairness to promote equitable AI in sports education, employing Transformer-based scenario generation alongside adversarial debiasing to ensure pedagogical relevance and fairness. The federated architecture achieves a balance between performance and privacy through ε-differential privacy, and a causal module is introduced to address biased correlations. The modular design allows for expansion into other tactical areas, providing a framework for AI that respects individual and equity objectives, while future research on multi-objective optimization aims to improve utility for a wide range of athletes.

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