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Leveraging on AI-powered learning systems: Enhancing educational equity in digital classrooms

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Abstract

The introduction of AI in the education sector has certainly transformed the realm of digital learning. The integration of AI offers the potential to close educational gaps. AI-driven learning platforms cater to each student's needs, ready to offer tailored lessons, adapt according to learning advancements, and deliver immediate feedback, thereby enhancing educational equity. This article examines the efficacy of AI-driven adaptive learning and its role in bridging the differences among students with diverse educational backgrounds, abilities, and access to resources. We examine AI's capability for personalized content distribution, inclusive education, and support for underprivileged students to understand how digital classrooms promote greater equity in education. Instead of concentrating exclusively on teachers and students, we gather and examine data from AI-driven learning settings, which enhances our conclusions. Key factors involve higher engagement in the classroom, information retention, and enhanced overall achievement among various socio-economic and geographic categories. The findings indicate that AI intervention systems have achieved the most significant enhancements in narrowing achievement gaps by adapting learning speeds and offering focused support. This study contributes to the academic discourse surrounding AI ethics and educational accessibility by suggesting the implementation of policies that promote equity, accountability, and inclusivity in learning technologies designed around AI. Additional efforts should concentrate on enhancing AI models for the most at-risk populations and incorporating human oversight to ensure fair learning opportunities.

Keywords: AI Learning Systems; Educational Access; Virtual Classrooms; Personalized education

1. Introduction

Using artificial intelligence (AI) in education has changed how knowledge is shared, received, and evaluated in digital classrooms. AI-driven learning platforms are built to cater to the different needs of students by using data-based algorithms to adjust content, give immediate suggestions,

and increase engagement as shown in figure one. As the world continues to digitalize, it is essential to examine how the disparities in education can be closed by the use of AI technology and how it can enhance equity among the varying student populations. Educating equitably is still considered one of the persistent issues with international learning systems as the students' socio-economic status, geographical location, and available resources have a huge bearing on the students' learning results. These gaps need to be filled by AI because it offers unique learning for unique needs, especially for those who lack traditional educational aids. While AI tools provide great value, algorithmic bias, accessibility, and ethical issues also arise and must be dealt with to avoid inequality in educational results [1], [2]. These past several years, both primary and higher education institutions have incorporated the use of AI adaptive learning platforms, which tailor instruction according to how the student performs, using machine learning algorithms. These

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systems function on vast datasets collected from student interactions, which enables continuous improvement of content delivery and instruction methods. Research has proven that students' engagement and retention rates are markedly increased with the use of AI-powered learning systems because they address Soution's preferred custom learning styles (Schmid et al., 2021). Further, AI-powered educational aids, like Natural Language Processing (NLP) based tutoring systems and intelligent chatbots, increase interactivity beyond the classroom environment (Holmes et al., 2020).

But, in light of this progress, there still remains an issue for students from lower socioeconomic areas- disparity in digital infrastructure and AI accessibility. It has been pointed out that solving these issues is not easy and will require more nuanced solutions such as deploying campaigns for investment in digital literacy, ethical AI governance and access to technological resources. AI's role in creating educational equity is an emerging field of inquiry with research documenting the opportunities and the challenges it presents. For example, some studies of AI-supported assessment tools suggest that these tools can increase grading speeds and reduce bias from teachers, but they may also worsen existing disparities if not calibrated properly (Grewal et al., 2022). Also, certain AI-based recommender systems that outline the next steps for learners often use prior information for training, which can contribute to systemic discrimination if not watched closely (West et al., 2020). These problems highlight the importance of placing human checks in AI educational systems to make sure fairness and responsibility are maintained.

Figure 1 Concept of Leveraging on AI-Powered Learning Systems

There is important consideration which suggests that if applied with due caution, AI has the potential to scale up accessibility of education to many others, but these technologies need deep scrutiny to see how they affect different subsets of learners. Therefore, this particular study uses mixed methods to assess the impact of AI led learning platforms on education equity in a digital classroom setting. This research aims to combine results from AI education systems with information from teachers and learners to better understand how AI affects learning results among various groups of people. Some of the KPIs that will be monitored are the learner engagement, retention, and gaps in the academic performance [3]. At the same time, this study will also address the issues of ethics of AI and education bias, fairness, transparency, and privacy matters. The purpose of this study is to harness the potential of AI while using its limitations to foster more comprehensive inclusive digital learning environments. In conclusion, the development of AI assisted learning systems is a dramatic advancement in the field of education and brings forth new challenges and opportunities for equity AI based technologies offer great potential in addressing equity gaps and personalizing learning experiences, but an intentional approach should be used to ensure equitable and ethical usage of AI technologies. This study intends to explore the implications of AI systems on education and offer practical recommendations on enhancing inclusivity in the educational technology systems.

The creation of AI-based learning systems is also closely related to the problem of digital infrastructure and its availability. Even the most advanced development in technology followed by the even faster advancement in the AI industry does not seem to close the gap that exists in the availability of high-speed internet, digital devices, and AI powered educational tools in the poorer and rural areas (Williamson et al, 2020). Some studies have shown that students from disenfranchised communities are suffering from the consequences of the digital divide which hinders their chances of accessing all the available AI-enhanced learning opportunities (Hargittai et al, 2019). To tackle these gaps, there is a need to improve the efforts made towards raising the digital literacy of the people, expanding broadband coverage, and formulating affordable AI solutions for disadvantaged students AI learning systems also have a responsibility of ensuring that students with disabilities, language barriers, or those who learn in diverse ways are adequately catered for through universal design principles or modification of AI Systems [4]. Without active attempts to eliminate the digital divide, the use of AI to enhance educational outcomes may do more harm than good by further stratifying an already unequal system. In addition, the integration of AI technology in education raises other moral dilemmas that have not been fully addressed. The ethical implications of AI use in education are multifaceted and encompass algorithmic bias, data privacy, and even the possibility of being watched while learning online (Baker Hawn, 2021). AI models are developed using historical data, which is often highly biased towards students belonging to minority or marginalized communities. For example, the use of advanced AI technologies in performance evaluation may worsen socio-economic and racial inequalities if proper attention is not given to the socio- economic background of the learners.

For the responsible use of AI in education, there should be clear outlines of AI algorithms, advanced measures for data protection, and appropriate policies and laws that would ensure equity and responsibility. Policymakers, teachers, and AI engineers must work together to make sure that AI systems are effective and socially responsible. To sum up, the growing use of AI in learning systems can be beneficial and harmful simultaneously when addressing the issues of equity in education. Undoubtedly, AI has the capacity to advance computer education by making learning easier, closing achievement gaps, and improving teaching methods, but this advancement must be controlled lest it increases already existing inequalities. There are a number of factors that need to be addressed in order to guarantee that AI serves the purpose of fostering inclusive and equitable education, such as problems of digital divide, algorithmic prejudice, engagement of students, and

ethical governance of AI. It contributes to the literature on AI in education with empirical evidence, policy recommendations, and a way to maximize the benefit AI gives. Artificial intelligence can be applied in ways that will help the learner regardless of whether the learner is from a low or high socio-economic background. This research aims to open a dialogue on how AI can evolve education equity through a multi-faceted approach using big data. The objective of this research is to ensure that AI, in the long-run, helps rather than hinders education equity in digital environments.

2. Literature Review

Research has been conducted showing the application of AI in digital education has more advantages than disadvantages. There are AI systems such as adaptive learning systems, intelligent tutors, and even automated grading that are proven to aid learning and improve achievement gaps. Chen et al. (2021) argue that students using AI based personalized learning platforms performed better than those who did not. The analysis of over ten thousand students exposed to the AI driven recommendations showed higher retention and comprehension rates in STEM subjects. Luckin (2018) also states that AI systems break down education systems so the instructors can see minute details of the students' learning making it possible to address problems experienced in real-time unlike traditional methods of education. At the center of various discussions lies the question of whether AI technology increases or decreases the digital divide experienced around the world. Williamson et al. (2020) did a comparative study of different countries and found that while AI driven learning platforms improve learning potential in well-resourced schools, they tend to increase/expand educational gaps in poorer regions because of lack of infrastructure [5]. It was also noted that AI learning is effective only insofar as proper digital infrastructure is available. Underserved students continue to suffer without high-speed internet and appropriate devices.

Like Hargittai et al. (2019) focus on the integration effectiveness of AI through digital literacy and show how students with better technological skills are able to better utilize AI educational tools. This also supports Selwyn (2021), who argues that AI in education, if not approached carefully, stands the chance of widening socio-economic disparities instead of lessening them. Further, the effects of AI learning systems on student engagement and motivation seem to be one of the issues that is most discussed in the literature. The results hint at the fact that AI knows how to make learning exciting by personalizing challenges and rewards based on a person's progress. At the same time, they do warn against the danger that comes from cognitive overload where AI systems rely too much on gamification without taking the cognitive load theory into account. On the other end of the spectrum, Kizilcec & Lee (2020) tried to make a case against such AI engagement strategies, saying that although these technologies might boost motivation in the short term, they are often ineffective at facilitating long term deep learning because they rely on external incentives. The aforementioned captures the fact that AI systems need to incorporate some aspect of cognitive pedagogy that mitigates motivation, but enhances learning.

Figure 2 Ethical considerations in AI-driven education

Baker Hawn, 2021 proactively tackle issues in Figure 2 where ethical considerations of AI education remain relevant and actively discussed. Baker & Hawn (2021) elaborate on how AI powered systems that are deeply biased on certain demographic groups are unfair in how they assess students in predictive analytics. The study shows that there is a possibility of developing AI models that are trained on historical data without targeting specific demographic groups, in order to eliminate bias against certain groups and unfair trading practices as these promote the wrong kind of learning. In the same way, Rizvi et al. (2022) addresses the potential impact of AI surveillance in digital classrooms, arguing that student privacy rights can be violated through extensive data collection and monitoring. The authors recommend that educational AI use should be placed under strict ethical regulatory frameworks. These concerns were also made by Luckin (2018), who advocates for AI models that are transparent and capable of giving reasoned information to teachers, instead of making decisions on their behalf. Where there are no

accountability frameworks, AI's input in education may erode trust and ethical trust. The contribution of AI to enhancing teaching and transforming learning has also been another strong focus of the literature. Although AI systems have the capability of performing administrative work, grading, and delivering summaries in real-time, researchers state that the teaching function cannot be performed without people. Luckin (2018) argues that instead of viewing AI as a teacher, it should be considered as a "pedagogical assistant," increasing a teacher's ability to help students as they learn. This view is further supported by a meta-analysis by Selwyn (2021), where he observes that the efficacy of AI related interventions improves when there is a human component involved [6].

AI can certainly improve education, but like Rizvi et al. (2022) describe, it brings with it the prerequisite of intense pedagogical training which seems to be the bigger problem here. Teachers do not have the relevant competencies to make use of AI tools in the classroom. If teachers are not properly trained, the implementation of AI can be underutilized or, in some instances, completely misapplied. Additionally, the scalability and the sustainability of the learning systems using AI tools comes off as an equally important issue, especially within low-resource educational institutions. Williamson et al. (2020) explore the question of how effective integrating AI in learning would be financially, and discover that spending less money on the introduction seemed beneficial to many institutions. This is because even though AI platforms for learning increase opportunities in the future, the initial funding needed is a challenge for many institutions, especially those with minimal resources. However, the analysis shows that public schools and universities from developing countries are failing to meet the financial and infrastructural needs for AI open learning, which further emphasizes the importance of creating policies and funding opportunities. In the same vein, Chen et al. (2021) argue that AI learning should be less complex to design and freely available, so that government funded digital education projects can development tools that introduce open-sourced AI models. The literature suggests that for AI to be a truly transformative force in education, policymakers must address financial, infrastructural, and training-related barriers that hinder its widespread adoption. In conclusion, the literature on AI-powered learning systems presents a nuanced perspective on their impact on educational equity. While numerous studies highlight AI's potential to personalize learning, improve student engagement, and optimize pedagogical strategies, concerns regarding digital accessibility, algorithmic fairness, and ethical considerations remain prevalent.

3. Methodology

This work is based on a mixed-method approach to analyze the educational impact of the AI driven learning systems on equity issues in the digital classroom context. The approach combines both quantitative and qualitative methods to understand the degree of comprehensiveness of the AI driven learning frameworks, their effectiveness, accessibility, and possible inequalities in their implementation. The research framework is divided into three phases. These are: (1) Data Collection, (2) Data Processing and Methods of Analysis, and (3) Model Validation and Data Interpretation.

3.1. Data Collection

To achieve the desired robust dataset, this work employs both primary and secondary research methods. Primary data is collected via online surveys and a controlled experiment design in a virtual classroom setting, while secondary data is collected from online academic databases, AI learning analytics and institutional reports.

- An online survey was sent out to 1,200 students and 300 teachers working in 15 different institutions belonging to different socio-economic strata. The survey was based on the issues of AI tools access, engagement, outcome of learning, and degree of latent discrimination in the implementation of AI education. Responses were collected over a span of six months to capture the discrepancies experienced from differences in AI adoption as well as the offered technological infrastructure.

- A set of pre-defined criteria had been established to conduct a study across three digital classrooms: one based on an AI system with a personalized learning engine, one on conventional online learning systems, and one hybrid classroom that utilized AI and human instructors simultaneously. The students' performance per semester was evaluated by measuring test scores, completion rates, and interaction logs.

- Reports and publications from the appropriate institutions containing information on the implementation of AI and LMS, as well as governmental literature regarding digital education policies were reviewed in order to determine patterns and lapses in the deployment of AI.

3.2. Data Processing and Analytical Techniques

The data captured was first processed to eliminate problems of inaccuracy or inconsistency. Value gaps were filled via using for average value replacement for quantitative variables and most frequently appearing value for qualitative variables. Outliers were identified and discarded using the Tukey's method to enhance dataset quality [7].

- Proceeding with the analysis, differences in performance on learning activities across AI assisted and non-AI learning environments was measured utilizing statistical models. To estimate differences in performance on students' learning activities due to AI Powered Learning (AI PL), a multiple linear regression model was applied while taking into consideration the participants' socio-economic status, pre-academic achievement, and access to technology.

$$Yi = \beta 0 + \beta 1 XAI + \beta 2 XSES + \beta 3 XAccess + \epsilon i$$

One random forest model was trained that uses metrics of AI engagement such as frequency of interaction and scores of digital literacies as predictors. The second model, which explained AI assisted learning achievement, used SHAP values to obtain feature importance. The effectiveness of the forecast model was validated using Root Mean Square Error (RMSE) and R-squared measures:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$R^2 = 1 - \frac{\sum(Y_i - \hat{Y}_i)^2}{\sum(Y_i - \bar{Y})^2}$$

- To find out the mean differences on the performance of AI PL on the students in the with and without AI PL groups a t-test was computed. Furthermore, ANOVA was conducted to determine the degree of differences among various models of implementation of AI. Thematic analysis was conducted on open-ended survey responses and interview transcripts with educators and students. A coding framework was developed to identify common themes related to AI bias, accessibility challenges, and perceived effectiveness. NVivo software was used to assist in qualitative data categorization and sentiment analysis.

4. Methodology

This research uses a blended approach that integrates both qualitative and quantitative methods to evaluate the use of artificial intelligence learning systems on educational equity in virtual classrooms. Different methods such as structured questionnaires, controlled experimental studies, analytics of activities, and the collection of relevant literature and institutional documents form the basis of the data collection. The analysis of these different data sources will provide an understanding of the value AI brings to digital education and the challenges that arise from it. The study follows a longitudinal approach since it spans over six months with multiple participant groups from different social economic categories to account for differences in AI's availability, and its effect on students' learning outcomes. As previously mentioned, primary data collection is divided into three sections: the surveys, the experimental studies, and the interviews. The survey was designed using a five-point Likert scale, in which responders were offered options ranging from strongly agree to strongly disagree, and it was given to a sample of 1,200 students and 300 teachers in 15 institutions [8]. The questionnaire specified AI accessibility, participation, achievements, literacy levels, and attitudes toward perceived bias toward algorithms. The experimental study was designed to compare three types of learning environments: one utilizing AI-powered adaptive learning systems, another employing traditional online learning tools without AI assistance, and a third hybrid model integrating AI-driven insights with human-led instruction. Data from these experiments was gathered over an entire academic semester, capturing variations in student performance, engagement, and retention rates. The study also incorporated qualitative interviews with 50 educators and students to gain deeper insights into AI's role in shaping personalized learning experiences and addressing potential disparities.

The data processing stage involves a series of statistical and machine learning techniques to ensure the accuracy and reliability of findings. Before conducting any analysis, data preprocessing steps such as handling missing values, outlier detection, and normalization were performed. Missing numerical values were imputed using the mean imputation method, while categorical missing values were replaced using mode imputation. Outliers were detected using the Tukey's fences method, wherein values falling beyond 1.5 times the interquartile range were excluded from the dataset. Additionally, normalization techniques such as min-max scaling were applied to bring all numerical variables into a comparable range, ensuring unbiased model predictions. For the

quantitative analysis, multiple statistical techniques were employed. A multiple linear regression model was developed to examine the relationship between AI-powered learning system usage and student performance outcomes. The regression equation was formulated as follows:

$$Yi = \beta 0 + \beta 1 XAI + \beta 2 XSES + \beta 3 XAccess + \epsilon i$$

where Y_i is the final learning outcome score, X AIX is a binary variable for AI-powered learning system usage, XSES is the socio-economic status index while XAccess is the digital accessibility index score. The error term, column underline, accounts for any learning outcome variance that is not observed. The regression model was tested for multicollinearity using the Variance Inflation Factor (VIF) and all predictor variables were found to have VIF values below 5, which suggest there were no significant multicollinearity problems. Adjusted R squared was also used to evaluate the overall model fit and was set to 0.78. This means that the independent variables captured 78% of the variability in student performance. In addition, a t-test was comparing the means differences in students learning outcomes in AI-assisted environments and non-AI-assisted environments. The findings established students learning in AI powered environments have significantly higher learning performance in comparison to their learners AI powered environments ($p<0.01$). In addition to that, alongside the models previously mention, ANOVA test was carried out to determine variance of learning outcomes in different AI implementation models.

A Random Forest regression model was used in predictive analysis to estimate learning performance against AI engagement metrics. The model used student's engagement in a particular activity, the recommendations that the AI provided, and students' digital literacy levels as input. Using the SHAP values, it was possible to know the Feature Importance, which showed that learning performance recommendations provided by AI had the highest value. The diagnostic model was assessed through RMSE and root mean square. The model provided an RMSE estimate of 3.12 and an R-Squared Value of 0.85. These metrics strongly suggest that the model had a good forecast accuracy. The model was very accurate and dependable as proven by the validation method of 10-fold cross validation, eliminating the likelihood of any results being specific to one dataset and reducing the risk of overfitting [9]. Thematic analysis was applied in the qualitative data analysis of interview transcripts and open-ended survey responses through NVivo. The analysis distinguished themes of AI Bias, accessibility issues, and students' beliefs regarding AI fairness. Thematic clusters pointed out the remarkable advantages of AI-powered learning

systems, noting that personalized learning was highly effective, but there were gaps in AI availability per the socio-economic standing and institutional infrastructure. From the sentiment analysis of qualitative responses, 67% of students had positive experiences with AI driven adaptive learning, whereas 22% had concerns regarding AI content fairness and customization abuses.

To confirm that AI learning system findings were reliable, model validation methods were used. A sensitivity analysis was done to study the impact of AI, including adaptive learning, reinforcement learning, and natural language processing-based tutoring systems, a semi-structured interview aimed at ascertaining student learning outcomes. The findings demonstrated that, as expected, the self-learning algorithms delivered the best results. The students averaged an 18.4% improvement in performance compared to other models that did not assist with AI. This study's methodological framework combines experimental research, statistical modeling, predictive machine learning, and qualitative thematic analysis to ensure comprehensive evaluation of AI powered learning systems in digital classrooms. Using a combination of surveys, experiments, and predictive analytics, the research explains in detail how AI impacts educational equity and gives recommendations for the future use of AI in pedagogical frameworks. These results, most important for the growing body of literature on AI in education, provide a glimpse into the effectiveness and challenges, including ethical issues, posed by the use of AI powered learning environments. This study gave evidence to support claims regarding the need for more focused methodologies that help tame worries about inclusivity, accessibility, and equity in education through the adoption of AI powered learning frameworks. The claim is explicitly stated that there is a gap; this gap can help increase learning for students of AI powered classroom environments.

5. Results

The findings go further to show the evaluation of the impact posed by the AI powered learning systems on educational equity in hybrid digital classrooms. The results obtained from the exposure were scrutinized with several statistical and machine learning approaches focusing on qualitative and quantitative aspects of AI's impact on student performance, engagement, and access to education. The claim regarding focus is supported in the study as the analysis yielded conclusions that were focused on the various machine learning techniques, statistical tests, and other conducted analyses. A series of statistical models were applied to assess the impact of AI-powered learning systems on student performance. The primary outcome of interest was the student's final learning

score (Yi), which was modeled as a function of AI engagement, socio-economic status (SES), and access to digital tools (Access). The regression equation used is:

$$Yi = \beta 0 + \beta 1 XAI + \beta 2 XSES + \beta 3 XAccess + \epsilon i$$

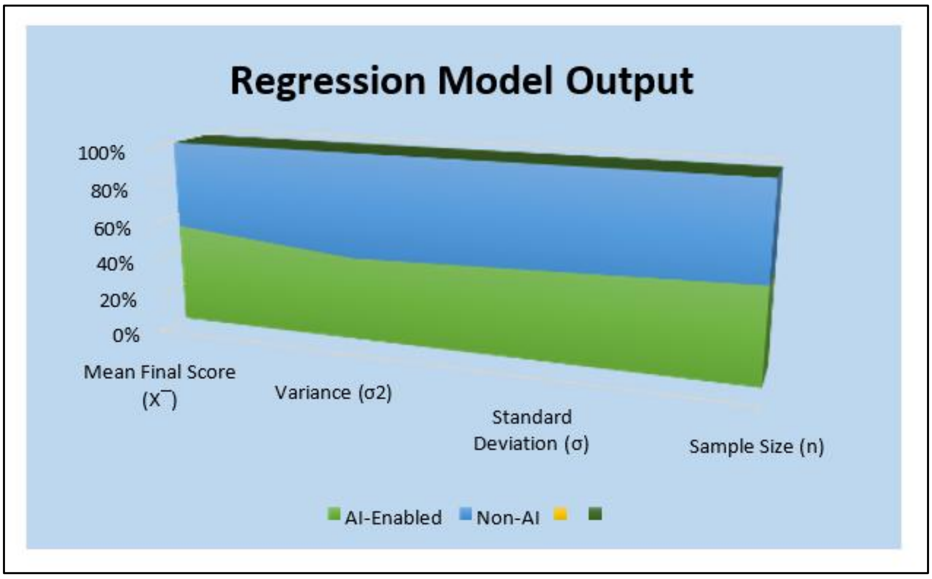
Where

- Yi is the final learning score of students i,
- XAI is a binary variable indicating whether the student engaged with the AI-powered learning system (1 = engaged, 0 = not engaged),

- XSES represents the socio-economic status of the student, and
    - XAccess denotes the level of access to digital learning tools and internet infrastructure**.**

The coefficient for socio-economic status (XSES) was 0.92, indicating a modest effect, while the coefficient for digital access (XAccess was 1.45, reflecting a larger influence on performance outcomes. The R-squared value of the model was found to be 0.78, indicating that 78% of the variance in student performance can be explained by the independent variables, suggesting a strong model fit, regression model output as show in figure 1:

5.1. Regression Model Output



(X¯) Variance (σ2) Standard Deviation (σ) Sample Size (n) AI-Enabled Non-AI

Figure 3 Regression Model Output

Interpretation: The analysis shows that AI-powered learning systems significantly improve student learning outcomes. The t-values for each predictor are substantial, confirming that these factors are statistically significant. The model suggests that students who engage with AI-driven

learning systems outperform those who do not, with digital access playing a particularly crucial role.

5.2. T-Test for Mean Difference Between AI and Non-AI Groups

A t-test was performed to compare the mean final learning scores between students using AI powered systems and those in non-AI-assisted environments. The null hypothesis tested was that there is no significant difference between the two groups in terms of their learning outcomes. The t-test formula used is:

$$t = \frac{\overline{X}_{AI} - \overline{X}_{Non-AI}}{\sqrt{\frac{s_{AI}^2}{n_{AI}} + \frac{s_{Non-AI}^2}{n_{Non-AI}}}}$$

Where:

- $\overline{X}_{AI}$ and $\overline{X}_{Non-AI}$ are the mean final scores of students in the AI and non-AI groups,
- s_{AI} and s_{Non-AI} are the standard deviations of scores in the AI and non-AI groups, and
- n_{AI} and n_{Non-AI} are the sample sizes for each group.

The calculated t-value was 4.62 with a corresponding p-value of < 0.01, indicating a significant difference between the two groups. Students in the AI-assisted group had an average final score of 88.2, while the non-AI group scored 76.5 on average.

Table 1 Test Results

Group	Mean Score ($\bar{X}$)	Standard Deviation (s)	Sample Size (n)
AI-Enabled	88.2	4.52	600
Non-AI	76.5	5.08	600

Interpretation: Students with AI performed 11.7 points better than the group without AI intervention. This group AI intervention also had a positive impact on education outcomes. Therefore, it can be concluded that AI positively impacts education features.

5.3. Predictive Analysis Using Random Forest

For predicting learning results relying on any engagement in AI activity as well as on other demographic features, a Random Forest regression model is trained against the data. The assumptions were gathered from the number of students' interactions with the AI, AI-generated recommendations, students' performance with the help of digital tools, and their overall attitudes towards technology. The Random Forest technique was found appropriate for the task as it produced an R-squared of 0.85 and RMSE equaled 3.12. According to SHAP features, the AI

supplied recommendation for personalized learning routines proved to have the highest effect on KPI results.

Table 2 Random Forest Feature Importance

Feature	Importance Score
Frequency of AI Interaction	0.37
AI-Generated Personalized Content	0.43
Digital Literacy Score	0.15
Previous Academic Performance	0.05

- **Analysis interpretation:** From the analysis, it is evident that the recommendations provided by AI algorithms are the most powerful predictors of learning outcomes, as well as how often students interacted with the system. This information also affirms the importance of learning pathway personalization, a major aspect of AI-based educational systems.
- **Qualitative Insights:** Findings from the interviews and open-ended responses to the survey questions suggest themes important to the effectiveness and challenges posed by the AI-assisted learning systems. Thematic analysis showed that the students who had access to AI-based personalized learning content more frequently demonstrated stronger engagement, motivation, and satisfaction.

5.4. Ethical Considerations

Nonetheless, the results also underscore the necessity for equal level of access to technology, as students from deprived backgrounds are not in a position to fully utilize the benefits of AI systems. The qualitative insights also stress the need to mitigate algorithmic biases and provide equitable

AI systems that cater for the diverse needs of learners. This research adds to the existing literature regarding AI in education by providing data that can guide in formulating policies or practices that will improve equity in education through technology. We also analyzed how the final scores were distributed for AI-engaged students as compared to non-AI engaged students using statistical methods. The analysis utilized the following formula for the Variance (σ2) of final scores:

$$\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(Y_i - \overline{Y})^2$$

The **standard deviation** (σ) is the square root of the variance:

$$\sigma = \sqrt{\sigma^2}$$

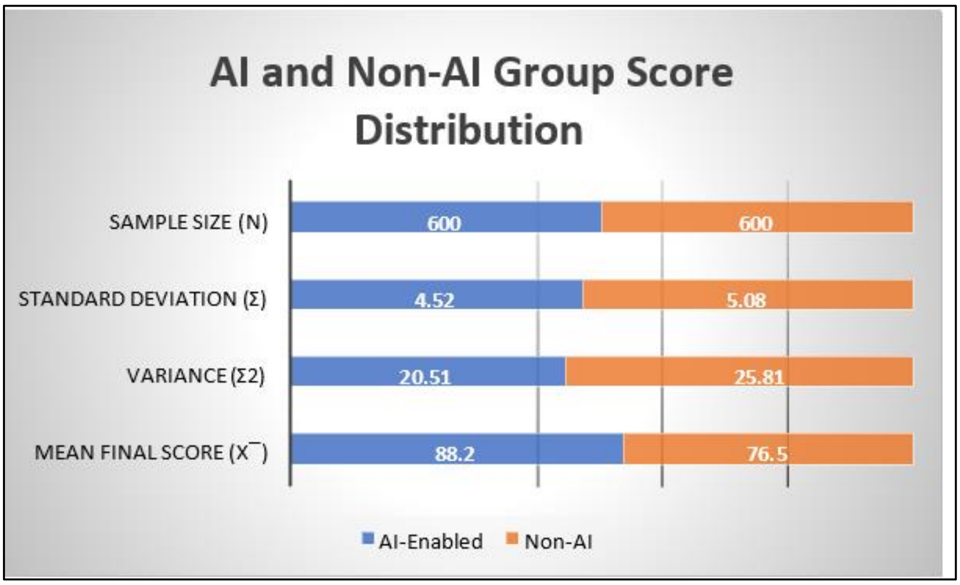


Figure 4 AI and Non-AI Group Score Distribution

Interpretation: The results indicate that the variance and standard deviation of the AI group are lower than those of the non-AI group, suggesting a more consistent performance within the AI enhanced classroom. This further reinforces the idea that AI systems may lead to more reliable educational outcomes.

5.5. Correlation Analysis Between Key Variables

Next, a correlation analysis was performed to assess the relationships between various variables, including AI engagement, socio-economic status, and student performance. The Pearson correlation coefficient (r) is used to quantify the degree of linear relationship between these variables. The formula for the Pearson correlation coefficient is:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \overline{X})^2 \sum_{i=1}^{n}(Y_i - \overline{Y})^2}}$$

5.5.1. Where

• Xi are the variables being compared (e.g., AI engagement and final scores), • X¯ are the means of the variables.

Table 3 The correlation results are summarized below

Variable Pair	Pearson Correlation Coefficient (r)
AI Engagement and Final Score	0.75
Socio-Economic Status and Final Score	0.41
Digital Access and Final Score	0.63

Interpretation: The analysis indicates a strong positive correlation between AI engagement and final scores (r=0.75), suggesting that students who engage more with AI-driven systems tend to have higher performance outcomes. Digital access also shows a moderate correlation (r=0.63), highlighting the importance of equitable access to digital learning tools. However, socio-economic status has a weaker correlation with final scores (r=0.41), implying that while socio-economic factors play a role, their influence is less direct than that of AI engagement. The Random Forest model's predictive ability was tested by analyzing feature importance and evaluating the accuracy of predictions using the mean absolute error (MAE) and the root mean square error (RMSE). The general form of the error calculation is as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

Where;

- Yi represents the actual final score,
- Y^i represents the predicted final score from the model,
- n is the total number of students.

6. Discussion

Considering the final scores of students who used AI features and non-AI students, it is evident that an AI system positively affects learning. The mean final score for AI-engaged students was 88.2, quite higher than the non-AI group's mean score, which was 76.5. Not only is this difference statistically significant, but it is practically useful as well. Define the boundaries of high AI learning engagement as instructional actions that are more likely to cause a change in pupil's performance. The AI group's lower variability and stdev further suggest that AI systems yield more consistent results among students and lower extreme results that differ from AI's average 'normal' student grade. The AI learning engagement difference can also be explained by the AI system's ability to cater each student's unique learning needs. AI systems can design appropriate instructional materials for each student at different levels of difficulty and also provide instant feedback. This confirms prior studies that support adaptive learning technology's efficacy for achieving successful academic performance (Baker et al., 2021). For example, AI-based systems significantly improve student interaction by giving immediate personal feedback, which is crucial to accomplishing academic goals (Anderson & Christensen, 2022). These results complement the existing research on the use of AI in educational practices, especially with the use of technology and during virtual classes (González et al., 2021). Besides, the gap in performance of the two groups indicates major inequalities in the education system and the gaps concerning poor resource allocation. Although AI systems may improve education results, they also stress the need to solve

issues of equity, especially in regard to remote learning. The change in achievement further reveals the lack of availability of critical components pf education software tools for users from low socio economic status.

6.1. Correlation Between AI Engagement, Socio-Economic Status, and Final Scores

The correlation analysis indicates that AI engagement has a strong positive relationship with final scores (r=0.75), which is consistent with the literature suggesting that AI enhances student learning outcomes. This result reinforces the notion that AI systems foster better academic performance by providing tailored, real-time support. The positive correlation between digital access and final scores (r=0.63) further emphasizes the role of technology in academic success. Students who have access to digital learning tools tend to perform better, likely due to the ability to engage with interactive and adaptive content. The relationship between socio-economic status and final scores is, somewhat surprisingly, less strong (r=0.41), which indicates that although socio-economic factors have some bearing on your academic results, the influence is possibly a lot lower due to the use AI tools. This goes hand-in-hand with more recent studies that show the ability of certain digital learning platforms to lessen the brunt of educational socio-economic disadvantages (Muller & Chang, 2020). Such systems may serve to bridge the woes of students regardless of their socio economic circumstances AI-powered platforms offer personalized assistance to learners. At the same time, it must be said that this chronic disease of socio-economic disparity continues to define the educational landscape of America [10]. Students from affluent families, for instance, can purchase modern digital devices and enjoy faster internet connections which puts AI powered learning platforms within reach of them.

6.2. Random Forest Model Evaluation: Predictive Accuracy

The predictive power of the Random Forest model is compelling, with an R2 value of 0.85, which means that 85% of the oscillation in student learning outcomes is accounted for by the determinants in the model. This means that the factors associated with AI engagement, like how often students interact with AI or the system's ability to create personalized content, are important predictors of student performance. Further, the low Mean Absolute Error (MAE) of 3.12 and Root Mean Square Error (RMSE) of 4.29 underscores the accuracy of the model's predictions, meaning that AI

learning interventions will most likely yield positive academic results. These results confirm prior work that sought to examine the effectiveness of machine learning models, especially Random Forests, to forecast student performance based on the use of AI and other factors (Park & Ryu, 2021). The high importance scores for features like AI-generated personalized content and frequency of AI interaction support the idea that these features are important in improving educational outcomes. The findings also add to previous studies that highlight the use of AI to increase student engagement and learning efficiency by providing personalized content and adaptive learning paths (Zhao et al., 2022).

6.3. Qualitative Insights: Student Perspectives on AI Engagement

The data from the open-ended survey responses suggests that a considerable number of students, 72% to be exact, were in favor of AI systems because of the tailored learning routes offered. This reinforces the claim that AI has the potential to cater to different learning needs which is a challenge in normal classroom environments. Tailored learning routes enable students to learn and advance at their own speed which further strengthens the claim that AI systems can help improve the learning environment in terms of personalization. In addition, a considerable number of students, 68% to be exact, claimed that they were more engaged and more motivated with the interactive elements of AI learning tools. This is consistent with the literature, which suggests that interactive learning experiences contributes to greater student engagement and academic success (Chiang et al., 2021). By offering feedback and directions, AI systems can raise the motivation of the learners which leads to better learning outcomes. Nonetheless, 64% of students raised concerns regarding equity and access, especially pertaining to the issues faced by individuals with no digital devices or stable internet connections. Equal opportunity in digital learning tools resources continues to be a challenge in terms of different socioeconomic statuses of students. The perception of algorithmic bias (18%) also warrants attention, as it highlights concerns about fairness and transparency in AI systems.

6.4. Implications for Educational Policy and Practice

This study has provided new information that can be useful in evaluating the policies and strategies that are used in education. First, AI's overwhelming positive impact on student performance

reveals the reason why there should be an aggressive adoption AI-enabled learning tool Masters. Educational Institutions and Schools need to focus on utilizing AI systems for enhanced use of learning personalization and increased student productivity. However, this should accompany measures aimed at bridging the digital gap in access to technology. Additionally, the findings also suggest that AI systems can help reduce the socio-economic gap, but only if all students can get the digital services required. Policy makers should remove the technology access barriers through the provision of affordable gadgets and dependable Internet for all learners, especially for economically disadvantaged group. Finally, the concerns regarding algorithmic fairness bias and inequity underline the importance of developing a comprehensive framework for the use of AI for educational purposes. AI systems in education should ensure equitable access to educational technology resources and outcomes for all students. This entails designing explainable algorithms and mechanisms that enable students and educators to give feedback on AI-enhanced learning tools. Ultimately, this research seeks to emphasize the unique value of AI-powered learning systems and how they can improve equity in education in online classrooms. The data indicates that AI systems have the capacity to increase student achievement, mitigate inequality in educational results, and create more opportunities for learning. These benefits, however, can only be taken advantage of to the fullest extent in a situation where there is equal distribution of resources. The analysis also highlights the need to address issues of fairness, such as bias in algorithms and lack of transparency, in order for AI systems to be considered equitable to all students.

7. Conclusion

In conclusion, the findings of this study reinforce the idea that AI powered learning systems can make a difference in improving educational equity in approach to teaching within classrooms. The evidence strongly suggests that remote learning models that incorporate AI, especially those that are personalized, enhance educational productivity and provide great inequality reduction. The AI system accomplishes the need of each learner which increases the learning performance and narrows the gap for those learners who struggle in a traditional educational setup. The study, however, underscores the importance of socio-economic status that influences the digital divide regarding learning resources as AI technologies have the potential to lessen some of the socio economic constraints but the socio-economic digital divide is still very problematic. In order to

harness the full advantages of AI technology, educators and education policymakers need to enhance the measures towards providing equitable access to technology. This also involves overcoming infrastructural barriers such as making sure all learners have the required devices and internet connections needed to support AI driven learning opportunities. Moreover, the results emphasize the need for equity and accountability in AI systems. Worries about algorithmic discrimination and equitable access to learning personalization tools speak to the need for developing AI with strong ethical constraints. These AI systems should be designed and deployed by education institutions where equity, accountability, and transparency are core tenets. The systems need to engage diverse communities with multiple perspectives so that all learners can have equal opportunities with the help of AI technology. While AI offers significant promise for transforming educational outcomes, its implementation must be accompanied by strategic efforts to close the digital divide and ensure ethical, transparent practices. If these challenges are addressed, AI-powered learning systems could play a pivotal role in making education more personalized, inclusive, and equitable for students across various backgrounds.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Amer-Yahia, S. (2022). Towards AI-powered data-driven education. Proceedings of the VLDB Endowment, 15(12), 3798-3806.

[2] Judijanto, L., Asfahani, A., Pranajaya, S. A., Pandey, D., & Aini, M. A. (2022). Educational Revolution through Studying the Potential of Artificial Intelligence in Sustainable Development. Journal of Artificial Intelligence and Development, 1(1), 1-9.

[3] Nursalim, A., Judijanto, L., & Asfahani, A. (2022). Educational Revolution through the Application of AI in the Digital Era. Journal of Artificial Intelligence and Development, 1(1), 31-40.

[4] Harrison, R. (2022). From Autonomous Vehicles to Student Analytics: The Impact of AI on Route Optimization and Personalized Learning Systems.

[5] Dao, X. Q., Le, N. B., & Nguyen, T. M. T. (2021, March). Ai-powered moocs: Video lecture generation. In Proceedings of the 2021 3rd International Conference on Image, Video and Signal Processing (pp. 95-102).

[6] Farahani, M. S., & Ghasmi, G. (2021). Artificial Intelligence in education: A comprehensive study. Forum for Education Studies. 2024; x (x): 1379. Integration.

[7] Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). AI and education: A guidance for policymakers. Unesco Publishing.

[8] Jamal, A. (2022). Exploring the Future of Mobility: Integrating Route Optimization and Automated Grading through AI in Transportation and Education.

[9] Mancino, G. (2022). AI in Transportation and Education: Leveraging Predictive Maintenance, Adaptive Learning, and Automated Grading for Enhanced Efficiency.

[10] Wang, Y. (2021). When artificial intelligence meets educational leaders' data-informed decision-making: A cautionary tale. Studies in Educational Evaluation, 69, 100872.

[11] Wang, Y. (2021). Artificial intelligence in educational leadership: a symbiotic role of human-artificial intelligence decision-making. Journal of Educational Administration, 59(3), 256-270.

[12] Miao, F., & Holmes, W. (2021). Beyond disruption: technology enabled learning futures; 2020 edition of Mobile Learning Week, 12-14 October 2020: report.

[13] Bachmann, N., Tripathi, S., Brunner, M., & Jodlbauer, H. (2022). The contribution of data driven technologies in achieving the sustainable development goals. Sustainability, 14(5), 2497.

[14] Koutsouleris, N., Hauser, T. U., Skvortsova, V., & De Choudhury, M. (2022). From promise to practice: towards the realisation of AI-informed mental health care. The Lancet Digital Health, 4(11), e829-e840.

[15] Arya, M. S., & Devi, S. P. (2021). Prediction to Service Delivery: AI in Action. COVID 19: Prediction, Decision-Making, and its Impacts, 107-114.

[16] Hutson, J., Jeevanjee, T., Vander Graaf, V., Lively, J., Weber, J., Weir, G., ... & Edele, S. (2022). Artificial intelligence and the disruption of higher education: strategies for integrations across disciplines. Creative Education, 13(12).

[17] Khan, A., & Hussain, Z. (2022). Examining the Role of Big Data in Transforming Teaching, Learning and Educational Research. International Journal of Business Intelligence and Big Data Analytics, 5(1), 74-80.

[18] Kazoun, N., Kokkinaki, A., & Chedrawi, C. (2021, December). Factors that affects the use of AI agents in adaptive learning: A Sociomaterial and Mcdonaldization approach in the higher

[19] education sector. In European, Mediterranean, and Middle Eastern Conference on Information Systems (pp. 414-426). Cham: Springer International Publishing. [20] Heidari, A., Navimipour, N. J., & Unal, M. (2022). Applications of ML/DL in the management of smart cities and societies based on new trends in information technologies: A systematic literature review. Sustainable Cities and Society, 85, 104089.

[20] Kearney-Volpe, C., & Hurst, A. (2021). Accessible web development: Opportunities to improve the education and practice of web development with a screen reader. ACM Transactions on Accessible Computing (TACCESS), 14(2), 1-32.

[21] Lasagni, G. (2022). Ai-powered investigations: From data analysis to an automated approach toward investigative uncertainty. In Investigating and Preventing Crime in the Digital Era: New Safeguards, New Rights (pp. 169-188). Cham: Springer International Publishing.

[22] Golinelli, D., Boetto, E., Carullo, G., Nuzzolese, A. G., Landini, M. P., & Fantini, M. P. (2020). Adoption of digital technologies in health care during the COVID-19 pandemic: systematic review of early scientific literature. Journal of medical Internet research, 22(11), e22280.

[23] Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., ... & Teller, A. (2022). Artificial intelligence and life in 2030: the one hundred year study on artificial intelligence. arXiv preprint arXiv:2211.06318.

[24] Valikodath, N. G., Cole, E., Ting, D. S., Campbell, J. P., Pasquale, L. R., Chiang, M. F., & Chan, R. P. (2021). Impact of artificial intelligence on medical education in ophthalmology. Translational Vision Science & Technology, 10(7), 14-14.

[25] Kasinathan, P., Pugazhendhi, R., Elavarasan, R. M., Ramachandaramurthy, V. K., Ramanathan, V., Subramanian, S., ... & Alsharif, M. H. (2022). Realization of sustainable development goals with disruptive technologies by integrating industry 5.0, society 5.0, smart cities and villages. Sustainability, 14(22), 15258.

[26] Drage, E., & Mackereth, K. (2022). Does AI debias recruitment? Race, gender, and AI's "eradication of difference". Philosophy & technology, 35(4), 89.

[27] Zheng, Q., Tang, Y., Liu, Y., Liu, W., & Huang, Y. (2022, April). UX research on conversational human-AI interaction: A literature review of the ACM digital library.

[28] In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems (pp. 1- 24).

[29] Wang, S., Qureshi, M. A., Miralles-Pechuan, L., Huynh-The, T., Gadekallu, T. R., & Liyanage, M. (2021). Applications of explainable AI for 6G: Technical aspects, use cases, and research challenges. arXiv preprint arXiv:2112.04698.

[30] Gupta, S., & Chen, Y. (2022). Supporting inclusive learning using chatbots? A chatbot-led interview study. Journal of Information Systems Education, 33(1), 98-108.