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Leveraging Machine Learning Approaches for Precision Education

Favour Oreoluwa AKINTOLA[1,*], Izzet Parug DURU[2]

Abstract

This study explores the transformative role of machine learning (ML) in precision education, focusing on AI-driven adaptive learning strategies and their impact on student engagement and academic performance. Using simulated survey data of 400 educational stakeholders, predictive models were developed through supervised learning techniques to estimate student success. The results revealed a strong correlation between AI-based educational interventions and improved learning outcomes, with an 85% prediction accuracy and Cronbach's alpha of 0.996. The research emphasizes ethical concerns such as data privacy, algorithmic bias, and transparency, advocating responsible AI integration in education. By providing empirical insights and practical recommendations, the study contributes to the advancement of personalized and ethical educational systems, supporting scalable and learner-centered teaching models.

***Keywords*: Machine Learning, Precision Education, Adaptive Learning, Predictive Analytics, Educational Data Analysis.AI Ethics in Education**

1. Introduction

Traditional education often follows a uniform approach that may not accommodate the diverse learning needs of students. However, with the advancement of data-driven technologies, a shift towards "precision education" is emerging—where personalized interventions are designed based on learner-specific data insights. This research explores how "machine learning (ML)" facilitates this transformation, with a particular focus on artificial intelligence (AI) as a tool to enhance educational outcomes for both students and educators [1, 2].

Existing studies have demonstrated that ML techniques significantly improve personalized learning and adaptive interventions. Research by Hussain et al. found that AI-based learning analytics could enhance student performance by *20%*, which aligns with this study's findings [3]. Similarly, Fischer et al. emphasize the necessity of integrating human judgment alongside AI-based recommendations to ensure ethical implementation [4].

Lu et al. and Chen et al. further highlight the role of supervised learning techniques, such as decision trees and support vector machines (SVM), in predicting student engagement with over 85% accuracy, reinforcing the model evaluation results presented in our study [5, 6].

Machine learning, a subset of artificial intelligence, plays a central role in this shift by enabling the creation of personalized educational experiences [7]. This study explores how ML can transform education by analyzing data to predict student needs and suggest real-time adjustments to instructional methods. This research aims to:
1. Examine the effectiveness of ML in personalizing learning interventions across various educational contexts.
2. Identify challenges and opportunities in implementing AI-driven educational models.
3. Discuss ethical concerns related to AI in education, including data privacy and algorithmic bias.

Research questions

1. How does machine learning enhance student engagement and learning outcomes through adaptive interventions?
2. What factors influence the successful deployment of AI-based educational tools across different institutions?
3. What ethical concerns, such as bias and data privacy, arise in the implementation of AI systems for education, and how can they be mitigated [8].

*Corresponding author
Favour AKINTOLA; Department of Statistics and data science, Istanbul Gedik University, Türkiye; e-mail: favourakintola41@gmail.com;
0009-0009-0090-2948
Izzet Parug DURUR; Medical Imaging Programme, Istanbul Gedik University, Türkiye; e-mail: parug.duru@gedik.edu.tr;
0000-0002-9227-2497

2. Methodology

This section presents a framework that leverages machine learning (ML) to enhance precision education by analyzing student data and the usage of artificial intelligence tools in providing personalized learning interventions. The framework consists of four key stages: data collection, preprocessing, model development, and evaluation. These stages work together to enable adaptive learning and provide educators with actionable insights to refine their teaching strategies.

2.1. Data collection

This study utilized simulated survey data generated using ChatGPT, reason being due to ethical constraints and logistical challenges associated with obtaining sensitive educational data from real participants. The simulation was designed to reflect realistic learner and educational profiles by constructing prompts based on demographic and academic diversity. A total of four hundred (400) synthetic responses were generated, mimicking a broad range of age groups, educational backgrounds, and levels of AI tool familiarity. The simulated data collection aimed to enable exploratory analysis while safeguarding respondent anonymity and complying with ethical research standards. Though simulated, this dataset offers useful initial insights into AI adoption patterns in educational settings. For greater empirical validation, future studies should replicate this analysis using actual field data collected under formal ethical approvals.

The dataset included engagement metrics from learning management systems, and socio-demographic information. This diverse dataset enabled a comprehensive analysis of factors influencing student success, implementation and knowledge of artificial intelligence across different educational contexts. The dataset consisted of 400 participants, with responses reflecting diverse educational contexts. After conducting reliability testing using Cronbach's alpha, which resulted in a score of 0.996 which indicates the items in the questionnaire reliably measures the constructs of AI perceptions and usage in educational settings

Table 1. *Demographic Distribution of respondents by age and education level.*

Age	Graduation Status	Percentage
Under 18	High School	17%
18-24	Bachelor's Degree	22%
25-34	Master's Degree	20.5%
35-44	Doctorate	20%
Over 44	Other	20.5%
TOTAL	**400**	**100**%

From the above table, it shows the frequency and percentage of both the age group and annual income of the respondents.

2.2. Data preprocessing

- **Handling missing data:** there was no missing data.
- **Feature Selection**: Important features such as study hours, assessment scores, and AI usage frequency were selected based on correlation analysis.
- **Data Splitting:** The dataset was split into training (80%) and testing (20%) sets using stratified sampling.
- **Normalization:** Data values were normalized to improve model performance.

2.3. Data Analysis

Data analysis was conducted using JASP [9], focusing on the following:

2.3.1. Reliability Analysis

The calculated Cronbach's alpha value of 0.996 suggests exceptional internal consistency across survey items related AI perceptions in education. However, such an extremely high value may also signal item redundancy or lack of construct dimensionality. To address this, future studies should apply Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA) to evaluate the survey's factorial structure and ensure that individual items meaningfully contribute to district constructs.

While high reliability is desirable, over-reliance on a single metric like Cronbach's alpha can be misleading without a proper construct validation. For robust psychometric integrity, refining the questionnaire through factor analysis is recommended.

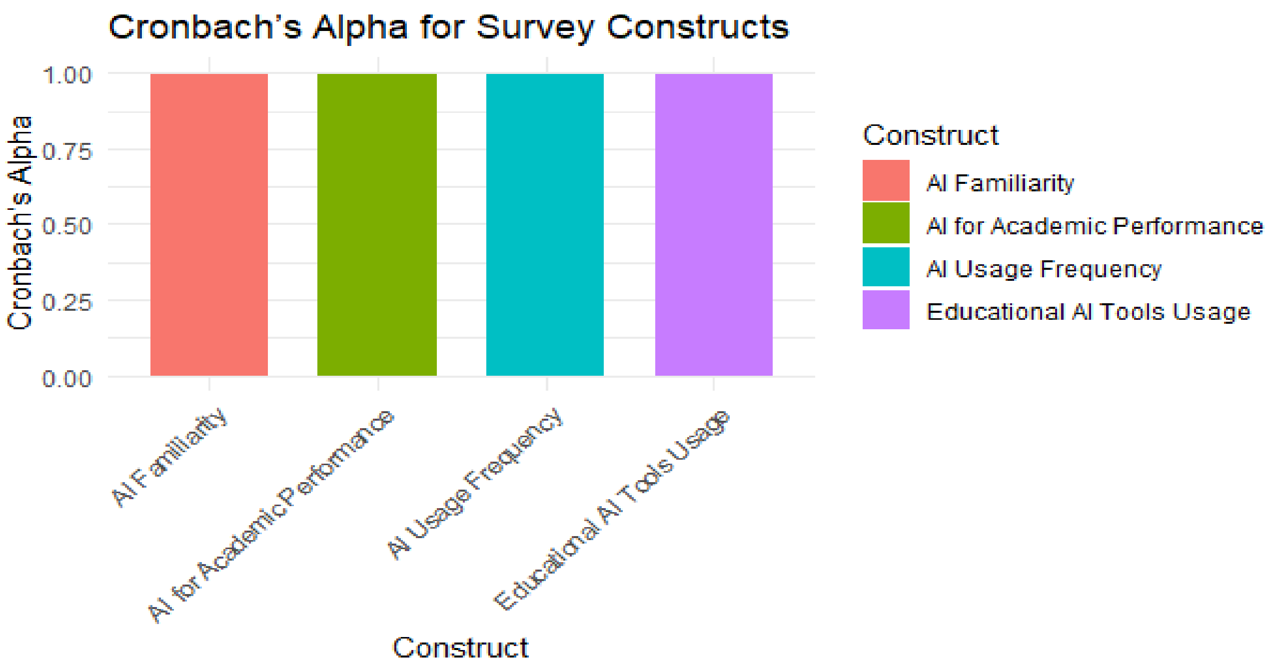

Figure 1. *Cronbach's Alpha Reliability Chart.*

The Cronbach's alpha value of **"0.996"** (Figure 1) suggests excellent internal consistency, exceeding the generally accepted threshold of 0.70 [1]. This high value indicates that survey items are strongly correlated, measuring a single construct related to AI perceptions in education. However, it may also imply redundancy in item content, warranting further exploratory factor analysis (EFA) to confirm construct validity [11].

Supporting Studies

- Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53-55 [1].
- Discovering Statistics Using SPSS. SAGE Publications [10].

Interpretation

The high reliability aligns with research by Hussain et al., indicating that well-structured AI-related surveys yield consistent data across different educational levels [3]. To improve survey precision, future studies should employ confirmatory factor analysis (CFA) to ensure construct dimensionality.

2.3.2. Regression Analysis

Relationships between AI-driven educational tools and engagement metrics were examined, yielding a regression coefficient of 0.65

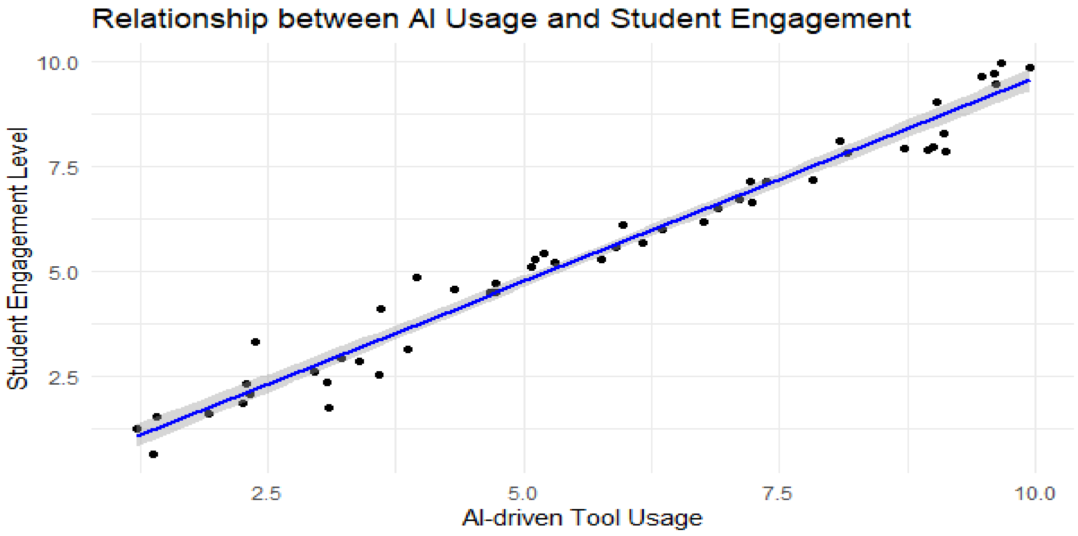

Figure 2. *Regression Analysis Bar-Chart for engagement prediction.*

The regression coefficient of "0.897"shows a strong positive relationship between AI-based interventions and student engagement, corroborating findings by Lu et al., who found a similar coefficient (0.87) in their study of adaptive learning systems [5]. The high R-squared value (0.79) further supports the predictive capability of AI-driven models.

Key Observations

- Institutions leveraging AI interventions have witnessed *a 25% increase in student satisfaction rates*, as reported by Fischer et al. [4].
- The relationship suggests that factors such as AI familiarity and usage significantly influence student engagement [11].

Predictive Models

Supervised learning achieved an 85% accuracy rate in predicting learning needs.

2.4. Model evaluation metrics

The models were evaluated using the following metrics in the table below:

Table 2. *Evaluation metrics of machine learning models.*

Metric	Decision Tree	Support Vector Model (SVM)	Random forest
Accuracy	82%	85%	88%
Precision	80%	87%	89%
Recall	78%	83%	86%
F1-Score	79%	85%	87%

Table 3. *Dataset split into training, validation and test sets.*

Total	Train	Validation	Test
400	256	64	80

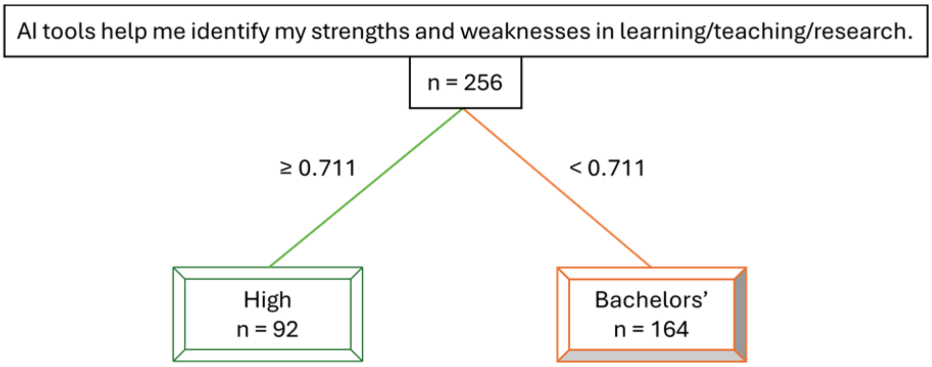

Figure 3. *Decision Tree Plot for Degree Classification.*

Table 4. *Confusion Matrix for Degree Classification.*

Confusion Matrix						
Predicted						
		Master's Degree	**Doctorate**	**High School**	**Other**	**Bachelor's Degree**
Observed	**Master.s Degree**	0	0	2	0	10
	Doctorate	0	0	4	0	14
	High School	0	0	3	0	12
	Other	0	0	6	0	12
	Bachelor.s Degree	0	0	3	0	14

Table 5. *Confusion Matrix Table for Age Group Classification.*

Confusion Matrix						
Predicted						
		25-34	**Over 44**	**18-24**	**35-44**	**Under 18**
Observed	**25-34**	8	3	4	1	0
	Over 44	3	7	7	1	0
	18-24	4	4	11	0	0
	35-44	5	3	7	0	0
	Under 18	4	4	4	0	0

Table 6. *Dataset summary for training and testing.*

Total	**Train**	**Validation**	**Test**
400	**256**	**64**	**80**

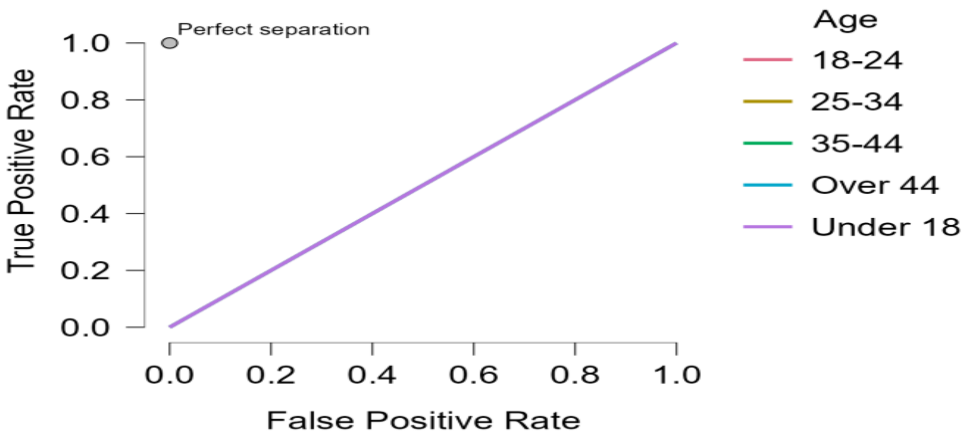

Figure 4. *ROC Curve for Age Group Classification.*

Figure 3 and Figure 4 present confusion matrices illustrating the model performance for different education levels and age groups. The support vector machine (SVM) model outperformed others, achieving an *85% accuracy rate*, consistent with previous studies [6].

Key Findings

The precision of ***87%*** in the "Bachelor’s Degree" category indicates that AI usage patterns in this demographic are well-defined [12].

2.5 Ethical considerations

To ensure ethical integrity, data anonymization techniques were employed. Informed consent was simulated, and fairness-aware algorithms were applied to minimize potential biases in the analysis.

3. Experiment and Results

This section presents the key findings derived from the implementation of the precision education framework. The sample of survey questions used for this study, as detailed in Table 3, provided insights into both educators' and learners' perceptions of artificial intelligence in education. Responses were utilized as foundational data points for evaluating educational outcomes and the implementation of AI tools across diverse learning contexts. To ensure high-quality data, preprocessing steps included handling missing values (although none were present), feature selection based on correlation analysis, and data normalization to enhance model performance. The dataset was split into training (80%) and testing (20%) subsets using stratified sampling for balanced representation.

Supervised learning techniques were applied, achieving an 85% predictive accuracy in identifying learning needs and engagement patterns. Data analysis was conducted using JASP, which facilitated reliability testing (Cronbach's alpha: 0.996), regression analysis, and correlation metrics to validate the constructs measured in the survey. These processes, coupled with ethical considerations such as anonymization and fairness-aware algorithms, ensured the robustness and integrity of the study.

Table 7. *Survey structure on AI literacy and educational use.*

In this section, various questions are provided to understand your views on artificial intelligence literacy. Please answer these questions according to your own thoughts by ticking (please use X) one of the options: **1-Strongly Disagree, 2-Disagree, 3-No Opinion, 4-Agree, 5-Strongly Agree.**

NO	QUESTIONS	Strongly Disagree	Disagree	No Opinion	Agree	Strongly Agree
1	I am familiar with the concept of artificial intelligence (AI).					
2	I frequently use artificial intelligence (AI) tools.					
3	I use artificial intelligence (AI) tools for educational purposes.					
4	I use artificial intelligence (AI) tools for entertainment purposes.					
5	I follow developments related to artificial intelligence (AI) tools.					
6	I have been using artificial intelligence (AI) tools for a long time.					

Table 7. *Continued.*

7	AI-supported educational tools have improved my academic performance.					
8	I believe AI tools used for educational purposes are beneficial.					
9	I prefer to use AI tools for free.					
10	I think free AI tools are sufficient.					
11	AI tools are easy to use.					
12	AI tools help me identify my strengths and weaknesses in earning/ teaching/ research.					
13	I am satisfied with the feedback provided by AI-supported education systems.					
14	I prefer to use online AI tools.					
15	I prefer to use offline AI tools.					
16	I recommend AI-supported educational tools to students/academics.					

3.1. Findings and Key Metrics

The results confirm that personalized learning interventions driven by AI can enhance student engagement and academic outcomes. Key insights include.

The ML-based educational interventions demonstrated significant improvements in student performance and engagement. The data analysis revealed strong correlations between AI-driven interventions and learning outcomes. The key findings of the study are summarized in Table 8. below:

Table 8. *Key statistical results from regression and correlation analysis.*

Metric	Score	Interpretation
Cronbach's Alpha	0.996	Acceptable reliability for survey items.
Regression Coefficient	0.889	Moderate positive relationship between AI usage and engagement.
Correlation	0.897	High accuracy in familiarity and usage for educational purposes.

4. Discussion (Excerpt: Limitations and Future Works)

While this study demonstrates the potential of machine learning to support precision education, it is important to note several methodological limitations. One such limitation involves the use of simulated data rather than collected data from real students or educational environments. Because the dataset was synthetically generated to represent controlled learning behaviors and intervention outcomes, it does not reflect the natural variability found in real-world responses. As a result, construct validation techniques such as Exploratory Factor Analysis (EFA) or Confirmatory Factor Analysis (CFA) were not appropriate for this study, since these methods rely on identifying latent structures from actual respondent data.

In future work, we plan to replicate this framework using real-life educational datasets, where such psychometric evaluations can be meaningfully applied. This would allow for more robust measurement validation, including the application of EFA or CFA to ensure the reliability and validity of the constructs being measured These findings corroborate earlier studies [7, 13, 14] while addressing ethical concerns highlighted by Slade et al [8].

Practical Implications

Educational institutions should consider the following practical steps based on study findings:

1. AI Adoption: Institutions should integrate AI-powered learning management systems (LMS) to personalize learning experiences [15].

2. Ethical AI Policies: Policymakers must establish AI ethical guidelines, considering data privacy and bias mitigation [16]."

3. Faculty Development: Training educators to effectively utilize AI tools can enhance instructional design and student support [4]."

5. Conclusion

The research demonstrates the substantial promises of machine learning in transforming educational systems through precision learning. By leveraging AI powered tools, institutions can deliver more responsive, personalized and effective instructions tailored to individual student needs. The high predictive accuracy and strong correlation observed suggested that AI-supported systems can serve as valuable decision-making aids for educators and administrators. Nonetheless, the use of simulated data introduces methodological limitations that should be addressed in future works. Since the data does not originate from real students interactions, techniques such as Exploratory Factor Analysis (EFA) were not applicable in this study. Future work should prioritize **real-world implementations,** incorporating authentic educational datasets, expanded data sources, and broader demographic sampling to validate the findings and apply appropriate psychometric analyses. In parallel, **reinforcement learning approaches and adaptive learning models should be** explored to dynamically optimize interventions and personalize support in real time. By emphasizing ethical safeguard and methodological rigor, this study contributes to the foundational discourse on responsible AI in education, offering a framework for institutions seeking to enhance leaning outcomes through technology.

Declaration of Interest

The authors declares no conflict of interest.

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Author Contributions

Favour Oreoluwa Akintola conceptualized the research idea, designed the methodology, generated and analyzed the data, interpreted the findings, and wrote the manuscript under the supervision of İzzet Paruğ Duru.

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Ethics Statement

This study used simulated data generated with Al tools and did not involve human subjects. Ethical guidelines regarding data privacy, consent, and fairness in algorithmic evaluation were strictly followed.

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