Analyzing the Benefits and Challenges of AI-Driven Learning on Students' Academic Performance using Random Forest Classification Algorithm

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Abstract

Artificial Intelligence (AI) is reshaping the educational landscape by enhancing personalized learning and streamlining administrative processes. This study examines the impact of AI-driven learning on students' academic performance using the Random Forest Classification Algorithm. By analyzing survey data, it identifies patterns in the benefits and challenges of integrating AI technologies into education. Key benefits include personalized feedback, research support, and administrative efficiency, while challenges highlight privacy concerns, ethical issues, and trust in AI systems. The Random Forest model effectively classifies student perceptions into "High," "Medium," and "Low" categories, achieving an accuracy of 67% for both benefits and challenges. Precision, recall, and F1-scores for benefits classification are 0.80, 0.67, and 0.73 respectively, while challenges achieve 0.50 precision, 0.67 recall, and 0.57 F1-score. These metrics reflect the model's capability to predict benefits more accurately than challenges, emphasizing the need to address nuanced concerns in ethical and data security frameworks. Results indicate that AI-powered learning significantly improves engagement and outcomes but requires careful attention to these challenges. The study provides actionable insights to guide the ethical implementation of AI in education, fostering both academic growth and equitable access to technology.

1. Introduction

Artificial Intelligence (AI) is a transformative technology that simulates human intelligence processes through machines and computer systems. In the realm of education, AI has emerged as a powerful tool, reshaping traditional learning environments by offering personalized learning experiences, automating administrative tasks, and providing data-driven insights into student performance. AI in education is not just about automating processes; it's about enhancing the learning experience and making it more accessible and tailored to individual needs. One of the AI techniques gaining traction in educational settings is the Random Forest Classification Algorithm. This algorithm is a type of ensemble learning method used for classification, regression, and other tasks that operate by constructing multiple decision trees during training and outputting the mode of the classes for classification. In education, Random Forest can be used to analyze vast amounts of student data to predict outcomes such as student performance, dropout rates, and even tailor educational content to suit individual learning paces. The benefits of AI in education are numerous. It can provide personalized learning paths, identify areas where students struggle, and offer additional resources to help them improve. AI can also alleviate the workload of educators by automating grading and administrative tasks, allowing them to focus more on teaching and less on paperwork. However, the integration of AI in education does come with challenges. Privacy concerns, the need for significant amounts of data, and the potential for algorithmic bias are some of the hurdles that need to be addressed. A study that highlights the impact of AI-driven learning on students' academic performance is "Artificial Intelligence in Education: Challenges and Opportunities for Sustainable Development" by Holmes et al. (2019). This study explores the various applications of AI in education and discusses both the potential benefits and the challenges that come with it By exploring the Random Forest Classification

Algorithm and its application in education, students and educators alike can gain insights into how AI can be harnessed to improve academic outcomes and create more dynamic, responsive learning environments. The purpose of this study is to explore the transformative potential of Artificial Intelligence (AI) in the educational sector, with a specific focus on the application of the Random Forest Classification Algorithm. By examining how AI technologies can enhance personalized learning experiences and streamline administrative processes, this study aims to provide insights into the ways AI can improve educational outcomes. Additionally, it seeks to address the challenges associated with AI integration, such as privacy concerns and algorithmic bias, while highlighting the opportunities for creating more dynamic and responsive learning environments.

2. Statement of the problem

The adoption of AI-driven learning tools in education promises to enhance personalized learning experiences, provide immediate feedback, and streamline administrative tasks. However, there is a notable gap in comprehensive research assessing the effectiveness of these tools and understanding the challenges they pose. These challenges include the rapid pace of technological advancement that may outstrip the ability of educational institutions to adapt, insufficient training and support for educators and students, and significant data privacy and security concerns. Additionally, issues related to varying levels of tool effectiveness, potential resistance to changing teaching methods, and disparities in access to advanced technology further complicate the implementation. Addressing these issues is crucial because effective utilization of AI-driven tools has the potential to significantly improve learning outcomes, increase student engagement, and better prepare students to the demands of their respective interdisciplinary fields. Without a thorough understanding of both the benefits and challenges, educational institutions may struggle to implement these tools effectively, potentially leading to missed opportunities for enhancing educational quality and equity. Possible solutions include conducting comprehensive research to evaluate tool effectiveness, developing targeted training programs for educators and students, enhancing data privacy measures, standardizing tools and best practices, and addressing accessibility disparities to ensure equitable implementation.

3. Objectives

The goal of this study is to use the Random Forest Classification algorithm to analyze the patterns of the benefits and challenges of AI-driven learning that affect the academic performance of students through the use of AI. The study intends to find out how AI driven learning is affecting students. It will examine how AI personalized learning experiences for students, by giving customized content and feedback while also identifying challenges faced in integrating them into the academic curriculum. We will use the Random Forest Classification algorithm to find out and measure the areas where AI-driven learning can help students to enhance academic performance and the challenges that they might face while learning through this AI. In addition, it will analyze AI powered assessment tools with regard to their potential in improving student learning outcomes, as well as other challenges like trust, data security, accuracy, and limitations. The study will explore the classification algorithm Random Forest model, its effectiveness and accuracy in predicting and classification of the impact of AI in students academic performance based on their constant interaction with AI-driven tools. In the final analysis, the study will contribute to the gradual and ethical application of AI, and will provide guidance for the enhancement of the learning experience of students and improve their academic growth.

4. Related Literature

This chapter explores the related literature that discusses the use of Random Forest Algorithm in an AI-Driven Learning System, analyzing the benefits and challenges of a student's academic performance.

4.1. Random Forest Algorithm

Yu, J (2021) study discusses that predicting on the student's academic performance are primarily examined, utilizing Artificial intelligence (AI), learning analysis, and other theoretical ideas. The study highlights the learning analysis's function in the educational process and provides the areas where the student's academic performance has been significantly affected. The decision tree of single classification and ensemble learning algorithms are analyzed and an academic model is constructed using the random forest algorithm. The algorithm principle of random forest and decision tree was analyzed, and the continuous variables are processed using the entropy and discretization algorithms. The reliability and feasibility of the algorithm in the use of educational context is analyzed and verified through empirical investigation of educational data platforms.

4.2. AI in Education

As discussed by Mungai et al., (2024), Artificial Intelligence (AI) chatbots within Learning Management Systems (LMS) uphold the tenets of constructivist learning theory in various manners. For instance, by encouraging active learning via interactive discussions that stimulate learners to delve into concepts and uncover principles independently (Cao et al., 2023); by facilitating social engagement through simulated peer-to-peer interactions, enabling learners to cooperate and exchange ideas (Jain et al., 2024); by delivering contextual learning through customized responses based on the learner's specific circumstances, enhancing the relevance and significance of the learning process (Pasindu Gayashan & Samarasinghe, 2024); by promoting reflection through encouraging learners to contemplate their experiences and link new information with existing knowledge (Jain et al., 2024); and by providing scaffolding through timely support and guidance, progressively diminishing assistance as learners enhance their skills (Pasindu Gayashan & Samarasinghe, 2024).

4.3. Benefits of AI-Driven Learning Systems in Education

Personalized learning stands out as a significant chance provided by the incorporation of AI in higher education highlighted by Chen and Wang (2021). AI-automated adaptive learning systems have the ability to utilize enormous collections of information on students' ways of learning, likes, skills and capabilities, allowing for the development of customized education pathways that cater to their individual requirements (Taneri, 2020). These systems enable customized suggestions, input, and assistance which empower individuals to have the freedom to learn at their own speed and maximize their potential in educational achievements gained from the learning process. Moreover, AI-powered adaptive evaluations can adapt in real-time to the students' needs evaluating performance at specific levels, offering assessments tailored to individual needs improving feedback to increase effectiveness and productivity to the evaluation procedure.

Incorporation of AI has led to advancements potential to heavily influence the administrative procedures in higher education, as emphasized by previous research (Aldosari, 2020). Using AI technology, universities can streamline monotonous and repetitive tasks handling student admissions and other administrative responsibilities streamlining financial assistance processing, resulting in enhanced effectiveness and cost efficiency (Dennis, 2018). Moreover, artificial intelligence has the capability to analyze large data to enable efficient resource allocation data on student enrollment patterns, course popularity, and availability of faculty members. Using predictive analytics universities have the ability to recognize patterns and trends, making it easier for making decisions based on data in important areas like budgeting academic support for students, and planning for success (Alam, 2021).

AI has the capacity to enhance students' involvement in higher education through the use of different cutting-edge technologies (Ouyang, et al., 2022). AI virtual learning assistants, for example, have the ability to offer instant and customized help to students, enabling interaction with professors and classmates, and enhancing the educational journey (Wang, et al., 2021). Moreover, artificial intelligence systems have the capability to examine information regarding students' interests, inclinations, and skills in order to develop customized educational resources that meet unique requirements, enhancing involvement and drive (Liao et al., 2019). Additionally, AI-driven gamification methods can change the way learning is done, making it more interactive and enjoyable, ultimately increasing student participation rates of retention. In conclusion, the incorporation of artificial intelligence in higher education offers numerous possibilities for change and progress (Leoste, et al., 2021). AI has the possibility to transform the educational environment through personalized learning, adaptive evaluations, and enhanced student involvement (Chen & Wang, 2021). Through efficient allocation of resources, automated grading, and predictive analytics, administrative processes can be optimized for student success (Alam, 2021). Furthermore, AI has the ability to improve research capabilities by analyzing data, recognizing patterns, and conducting automated literature reviews. Nevertheless, it is crucial to account for ethical concerns, potential prejudices, and educational impacts to guarantee the responsible and ethical application of AI in higher education (Roumate, 2021, Grimus, 2020). It is essential for academia, industry, and policymakers to work together to fully utilize AI for the betterment of higher education stakeholders and society, resulting in better student outcomes, more efficient administration, and improved research capabilities.

4.4. Challenges of AI-Driven Learning Systems in Education

As stated by Stoica, (2021), Artificial Intelligence may transform higher education not only by enriching its pedagogical and administrative practices but also by augmenting research capacities. Challenges indicated for responsible, ethical use of AI require attention: enhancement of administrative process resource allocation and the decision-making capabilities in light of ethical considerations, such as preserving individual privacy and staff labour impact. This requires education institutions to be proactive and strategic in making policies, guidelines, and best practices for responsible AI. It also needs partnerships involving education, AI developers, policymakers, and other stakeholders. Ethical considerations in the way of doing things fairly, being transparent, and holding responsibility along with data privacy and security become crucial in planning responsible AI integration. Professional development and training for faculties and administrators are also of great importance in the effective implementation of AI-driven transformation in higher education. Educators should be prepared and skillful enough to integrate AI into their practices. The administrators, on the other hand, need to be informed about the ethical, legal, and workforce concerns regarding AI in the university administration and operations. Transformation of AI impacts on pedagogy and learning as well as on the university administration and its operations requires responsible and strategic implementation.

Research by Saaida, (2020) has shown that the possible application of automated grading to open-ended questions at the university level is somewhat underutilized. One issue with such systems has been that they provide limited feedback to students, which is a must for meta-cognition, allowing them to identify any mistakes and improve on them. Feedback from automated grading systems should be consistent and fair. In higher education, the use of teaching assistants can help in the grading and marking processes, leading to unequal gradings and marks. AI-supported grading processes can help ease consistent fair feedback. However, there is a fact to consider on the fairness of these AI-supported tools if they were trained using past exams. This automated grading has a problem in that it does not apply domain-specific knowledge, which will make the outcome unfair since words might carry some meaning in a given subject. Other problems that come with this process are creative answers, not having enough data for pre-training the model, and the fact that AI tools are neither reliable nor valid. Therefore, coming to conclusion, automated grading of the open-ended questions seems alluring to higher education, but the con it carries along has to be justified.

5. Theoretical Framework

We adopt this study as our research's dataset entitled "*Impact of Conversational Chatbots on Learning of University Students*" examines the impact of various conversational AI chatbots in Bulgaria on how it affects the students' learning through electronics, that the main focus is on their adaptation and effectiveness in educational contexts. The dataset explores student's frequent chatbot usage, student's personal perception about AI chatbots, trust and security, and the dataset focuses on evaluating the effectiveness in Mathematics using two different AI chatbots, that aims to find where it makes mistakes as well as provides accurate answers. The study evaluated seven different AI chatbots and at the end they found out that ChatGPT Plus got the highest overall performance. The dataset focuses on applying AI chatbots in Mathematics tasks to evaluate its accuracy and reliability. The study found out that ChatGPT plus has the highest accuracy and efficiency performance in solving Mathematical problems out of seven chatbots used in the study. The analysis of AI chatbots includes mistakes and Mathematical errors, shows that there are areas of AI's limitation and rooms for improving it's accuracy. ChatGPT Plus high accuracy, consistent performance, and immediate response leads to a higher influence for students to trust and feel secure using ChatGPT for their educational improvement, personal growth and broadening their knowledge.

This framework serves as a guide for the exploration of the dataset, which focuses on evaluating the effect of the adoption on education of AI chatbots in the university's learning systems. The study highlights what AI chatbots can offer and provides a systematic method to examine how they affect every student's academic performance in particular with more complex subjects like mathematics. These findings underline the advancement of AI that has value in education by its feature for providing personalized assistance and feedback that continuously improves educational context. By adopting this dataset, researchers can utilize the results and dig deeper to better understand the efficiency and accuracy of AI, specially chatbots, in education contexts and successfully integrate in the curriculum. And could potentially adapt for other similar demographic academic subjects and other student groups.

6. Methodology

This chapter will discuss the research methodology, including the research design, data collection, data processing, and model development. It will further analyze the techniques used to evaluate and examine the benefits and challenges that AI-Drive learning systems have on students academic performance. The study will use the dataset from kaggle titled the "Impact of Conversational Chatbots on Learning of University Students" that targets electronic learning in Bulgaria. The survey contains the findings about students' perception, experience, frequent usage, and complacency of Chatbots in their educational use of context.

6.1. Research Design

This study will adopt a quantitative research design aimed to analyze and examine AI-Driven tools, like AI-Chatbots, and how it significantly influences the academic performance of students. It is both a descriptive and predictive approach for this study; It provides educational context example how to adopt and integrate AI in education, as well as discussing the challenges that the students experience through frequent usage and project students' academic results lay out in the dataset based on the findings of chatbot usage metrics.

Random Forest model was the classification algorithm chosen to use in this study due its capability of high predictive accuracy in dealing with complex datasets with both categorical and continuous variables. Random Forest Algorithm is the concept of ensemble learning that combines and builds multiple decision trees to enhance the model's performance and resolve a challenging issue. *"The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting"*(Machine Learning Random Forest Algorithm - JavatPoint, n.d.). This technique is fit for determining key prediction factors that influence students academic performance, based on the dataset's findings which related to multiple high frequent use of chatbot, engagement measurements, and perceived value for students.

The Random Forest Algorithm will find out the benefits (e.g. improvements of students education engagements, higher grades, task completion rates) and challenges (e.g. trust, limitation, and the chance of AI reliance) concerning the emerging AI-driven tools used in education specifically, chatbots, by studying how it affects the students academic performance.

6.2. Data Collection

The dataset, "Impact of Conversational Chatbots on Learning of University Students", was found from kaggle. This dataset collected details of students' interaction and their experience using electronic learning in a University in Bulgaria. The study used surveys to collect the data and the results of the data about students' perceptions, experiences, frequency of use, and satisfaction levels are all included in the survey. These factors provide a concrete basis for thoroughly studying the relationship of chatbot interaction and academic performance of students, and this will also serve as the foundation of our research to find out the areas where AI can offer benefits as well as significantly provide challenges in the educational context of use for students.

A variety of variables were collected by the survey with the aim to provide a comprehension of how students engage with chatbots in learning environments. These factors include students' perspective on the benefit and reliability that chatbots provide in their learning, their experience and familiarity with using chatbots, their frequency of use, and assess how often the students use chatbots in their learning methods. The study evaluated the degree of satisfaction among students indicating their overall contentment, trust and ease in integrating this into their education. These variables correlate and work together to offer a thorough understanding of chatbot usage in education.

6.3. Data Processing

We began our data processing using the Jupyter Notebook environment and within Pandas and Numpy library, a powerful tool for data manipulation, computation, and analysis, that allowed us to organize and evaluate the dataset efficiently. The dataset's CSV file is imported with the use of encoding specification (ISO-8859-1). The inclusion of this ensured that all of the data was properly and successfully for data processing.

The likert scale format was used to collect the responses of the student in the survey, and the categories included are "Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree". To analyze the responses quantitatively, the responses are converted into mapped numerical values, and these are the values as for each category, "Strongly Disagree" as 1, "Disagree" as 2, "Neutral" as 3, "Agree" as 4, and "Strongly Agree" as 5. The conversion of the categories into numerical values is also for the random forest algorithm to measure and analyze the responses, which makes it easier to identify the patterns. Prior to the application of the response mapping , we verified the columns first if they were precisely included in the dataset. These mapping are only applied from Q8.1 to Q9.5 that make these responses into integer format.

We specified our target columns that fit our research's scope. We focused on columns where questions are focused on benefits and challenges. For analyzing the benefits we used the questions within Q8.1 to Q8.5. For challenges We the questions under Q9.1 - Q9.5 as our basis for analyzing the challenges, since Q9 questions specifically focus on challenges of AI in Education. These questions were used as the target feature of our study and for data processing since these columns contained key components about the benefits and challenges under the study conducted in the dataset.

The target columns are measured and got the mean scores for each student's responses and used them to determine the average scores for both the benefits and challenges columns. To give an example, the total mean for benefits scores was calculated by averaging the answers from questions Q8.1 to Q8.5. These methods were also applied in each area of participants' perspective. We categorize the scores through three different levels such as “Low”, “Medium”, and “High”. These levels are determined numerically starting from 0 - 2 were considered as “Low”, scores above 2 and below 4 are “Medium”, and the score from 4 to 5 were considered as “High”. The classification made it easier to formulate and predict the levels and average based on each student's responses and frame the problems as a certification task.

The Formula of mean scores for Benefits and Challenges

$$benefits\_score_i = \frac{1}{5} \sum_{j=1}^{5} response_{ij}$$

i = Individual respondent

j = Individual questions in the benefits questions (Q8.1 - Q8.5)

$response_{ij}$ = Response (i) of the respondents to the benefit question (j)

$$challenges\_score_i = \frac{1}{5} \sum_{k=1}^{5} response_{ik}$$

i = *Individual respondent*

k = *Individual questions in the benefits questions (Q9.1 - Q9.5)*

$response_{ik} =$ *Response* (i) *of the respondents to the benefit question* (k)

The score categorization

$$benefits\_class_i =$$

$$\{Low \ if \ 0 < benefit\_score_i \leq 2\}$$

$$\{Medium \ if \ 2 < benefit\_score_i \leq 4\}$$

$$\{High \ if \ 4 < benefit\_score_i \leq 5\}$$

$$challenges\_class_i =$$

$$\{Low \ if \ 0 < challenges\_score_i \leq 2\}$$

$$\{Medium \ if \ 2 < challenges\_score_i \leq 4\}$$

$$\{High \ if \ 4 < challenges\_score_i \leq 5\}$$

We created two feature sets for benefits and challenges for prediction of student's and participants responses. The questions for features of the benefits are under Q8, particularly columns Q8.1 through Q8.5, which show several facets of perceived benefits. And the questions for challenges are within Q9.1 to Q9.5, which show how participants experience the challenges of AI. Benefits_class and Challenges_class are the two names of the feature prediction, and were the target variables, indicating the benefits and challenges sections' classified scores as (Low, Medium, and High).

The two features for Benefits and Challenges

$$x\_benefits = [Q8.1_{n\downarrow}, Q8.2_{n\downarrow}, Q8.3_{n\downarrow}, Q8.4_{n\downarrow}, Q8.5_{n\downarrow}]$$

$$x\_challenges = [Q9.1_{n\downarrow}, Q9.2_{n\downarrow}, Q9.3_{n\downarrow}, Q9.4_{n\downarrow}, Q9.5_{n\downarrow}]$$

$$y\_benefits = [benefits\_class_{n\downarrow}]$$

$$y\_challenges \ = \ [challenges\_class_{n\downarrow}]$$

$n \ =$ Number of samples in the dataset

$x\_benefits \ =$ The feature for predicting the Benefits

$x\_challenges \ =$ The feature for predicting the Challenges

$y\_benefits \ =$ The target variable for Benefits classification

$y\_challenges \ =$ The target variable for Challenges classification

The data was separated for training and testing. We used 80% to train the model and for the testing we used the remaining 20% of the data. This method makes sure that all data are recognized and generalized by the model, untested data, and new data, which is vital for evaluating the model's efficiency and accuracy. The training is used by Random Forest to learn the relationship between the features and the target. The performance of the model is assessed using the test data (Machine Learning Random Forest Algorithm - JavatPoint, n.d.-c).

Data split for Testing and Training of Data

$$Training\ set \ = \ 80\%\ of\ X_{benefits}\ and\ Y_{benefits}$$

$$Test\ set \ = \ 20\%\ of\ X_{benefits}\ and\ Y_{benefits}$$

$$Training\ set \ = \ 80\%\ of\ X_{challenges}\ and\ Y_{challenges}$$

$$Test\ set \ = \ 20\%\ of\ X_{challenges}\ and\ Y_{challenges}$$

$X_{benefits}\ and\ X_{challenges} \ =$ Represents the feature matrix classification

$Y_{benefits}\ and\ Y_{challenges} \ =$ Represents the target labels as vector for classification

6.4. Model Development

Random Forest Classification Algorithm was used for our model development, handling classification tasks efficiently is one of the strengths of Random Forest Algorithm, specially when working with highly complex and multifaceted data. Random Forest is an ensemble learning method, it merges multiple decision trees to produce the prediction result. The use of multiple decision trees allowed Random Forest Algorithm to enhance its prediction accuracy, reduce prediction error and the risk of overfitting. And it provides flexibility since data scientists frequently use Random Forest given that it can both perform classification and regression tasks with high accuracy, since it maintains its accuracy even when there is absence of data (IBM, n.d.). Random Forest Algorithm is suitable for our dataset since it has the feature of flexibility, robustness, and high accuracy in handling complex data, which makes it a useful tool for determining accurate and reliable conclusions from the dataset, scalability for categorization tasks, and capacity to handle missing data.

The training dataset was trained on the Random Forest Classifier to generate predictions for both benefits and challenges. Next step, the model was evaluated and measured including the classification report such as Precision, Recall, F-1 score, and Support for each category in the Questions which were determined earlier as Low, Medium, High; confusion matrix highlighted where the model did successful performance and where it lacked (i.e. inaccurate and error classification between categories) through contrasting between the actual and predicted classifications; accuracy score showed the total percentage of accuracy from all the calculated predictions, that serves as the overall accuracy of the model; all of these measurements were used to assess the model on the test data. These measurements highlight the model’s accuracy in categorizing the students' responses as Low, Medium, and High that enable us to see the ability of the model to accurately show the classification levels of benefits and challenges, evaluate the models' performance and provide prediction

Classification metrics and Confusion matrix formula

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)}$$

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)}$$

$$F - 1\ score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall}$$

$$Accuracy = \frac{Total\ Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Normalized\ Confusion\ matrix = \frac{C_{ij}}{\Sigma_j C_{ij}} x\ 100$$

TP = True Positives: The number of correctly predicted as positive

TN = True Negatives: The number of correctly predicted as negative

FP = False Positives: The number of incorrectly predicted as positive

FN = The number of incorrectly predicted as negative

Precision = The percentage of true positive among all positive predictions

Recall = The percentage of actual positive among all correctly predicted as positive

C_{ij} = The number of instances where i as true label and j as predicted label

$\Sigma_i C_{ij}$ = The sum of all values in row i, that represents the total number of actual instances of true label i

Predicted labels = Labels that the model gives to samples as they are being tested

True labels = Actual labels assigned to the test set of instances

6.5. Prediction for highest impact question for benefits and challenges

Our target variable (impact) was developed through comparing the benefits and challenges scores for each response. Answers that score higher on the benefit scale than the challenge scale were labeled "benefit", while those that scored lower were labeled as "Challenge".

$$Impact_i = \{Benefit,\ if\ benefit\_score_i > challenges\_score_i\}$$

$$\{Benefit,\ if\ benefit\_score_i \leq challenges\_score_i\}$$

$Impact_i$ is the predicted label for i^{th} survey response

$benefits\_score_i$ and $challenges\_score_i$ are the respective benefit and challenge scores for the i^{th} response

Following the definition of the target variable, the dataset is divided into two sections: one for model and the other for performance testing. To assess how effectively the model generalizes to unknown data, this phase is crucial. Usually, the dataset is divided into 20% testing data and 80% training data. The formula for this represents as:

$$Train\ Data = \{(X_{train}, Y_{train})\},\ Test\ Data = \{(X_{test}, Y_{test})\}$$

X_{train} and X_{test} represent the features (survey responses) for the training and testing sets, respectively

Y_{train} and Y_{test} represent the target variable (impact) for the training and testing sets. In order to determine the model's accuracy, this division guarantees that it is trained on one subset and assessed on another.

The model will be trained using the Random Forest Classifier, a potent ensemble learning method that is well known for managing high-dimensional data and minimizing overfitting. The training process is represented by:

$$\widehat{y_i} = RF(X_i)$$

X_i is the feature vector (survey response) for the i -th sample

$\widehat{y_i}$ is the predicted impact (benefit or challenge) for that sample

Following model training, the trained Random Forest model is used to make predictions on the test set X_{test}. The prediction formula is:

$$\widehat{y} = mode(T_1(X_{test}), T_2(X_{test}),..., T_n(X_{test}))$$

$T_i(X_{test})$ is the prediction from the i-th decision tree.

Mode is the function that returns the most frequent prediction from an ensemble of decision trees

Precision, Recall, and F-1 Score are among the classification matrix used to evaluate the trained model’s performance. These metrics assess how well the model classifies Benefits and Challenges. Precision measures the proportion of expected benefits/challenges that are actually benefits/challenges, or the accuracy of positive predictions. The model’s recall evaluates how well it can identify all positive cases (i.e., how many real benefits/challenges were accurately predicted). The F-1 Score balances the precision-recall trade-off into a single metric, which makes it particularly helpful when the dataset is unbalanced (more benefits than challenges, for example).

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Positive\ (FP)}$$

$$Recall = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)}$$

$$F - 1\ score = 2\ x\ \frac{Precision\ x\ Recall}{Precision\ + Recall}$$

TP = True Positives: The number of correctly predicted as positive

TN = True Negatives: The number of correctly predicted as negative

FP = False Positives: The number of incorrectly predicted as positive

FN = The number of incorrectly predicted as negative

Precision = The percentage of true positive among all positive predictions

Recall = The percentage of actual positive among all correctly predicted as positive

Once the model has been trained, the model is used to predict the impact variable (Benefit and Challenges columns) of each response in the dataset. The trained Random Forest Model which is discussed earlier, is used to calculate the prediction.

We compute the mean impact score for the questions that were categorized as Benefits and Challenges after generating the predictions for the complete dataset. This gives a summary of the questions that according to their anticipated category, had the biggest influence. The following formula determines the mean scores for the Benefit and Challenge questions:

$$\mu_{Benefit} = \frac{1}{N_{Benefit}} \sum_{i=1}^{N_{Benefit}} X_{Benefit,i}, \quad \mu_{Challenge} = \frac{1}{N_{Challenge}} \sum_{i=1}^{N_{Challenge}} X_{Challenge,i}$$

$N_{Benefit}$ and $N_{Challenge}$ are the total number of responses predicted as Benefits and Challenges

$X_{Benefit}$ and $X_{Challenge}$ are the individual question scores for each Benefit and Challenge question

We calculate the question with the highest mean score for both Benefits and Challenges in order to determine which questions had the biggest influence. The following questions had the biggest impact on how the responses were categorized overall:

$$max\_Benefit\_question = argmax\,(\mu_{Benefit})$$

$$max\_Challenge\_question = argmax\,(\mu_{Challenge})$$

The question that predicts Benefit or Challenges the most effectively is the one that has the greatest average score in each area, calculated by argmax.

This approach categorizes survey responses and pinpoints important findings by combining statistical analysis with machine learning. Using a Random Forest Classifier, we assess the model's ability to distinguish between Benefits and Challenges by measuring precision, recall, and F-1 Score. Understanding the contributions of several questions to the overall impact is made simple and intuitive by the graphics. This method improves the capacity for effective survey data analysis and interpretation.

We employed a pie chart to illustrate the percentage distribution of anticipated Benefits and Challenges over the complete dataset, as well as bar plots to illustrate the average mean scores for the Benefit and Challenge questions. By emphasizing the questions that have the biggest contributions to the total impact, these visualizations offer a concise and efficient means of conveying the model's results. A data-driven way for comprehending and predicting the impact of survey responses is provided by this approach.

7. Presentation, Analysis and Interpretation of Data

The analysis that was done using the Random Forest Classification algorithm is presented in this chapter. The purpose of the study was to assess how students' academic performance was influenced by benefits and challenges of AI-Driven learning. The findings are supported by survey data and further statistical analysis. The discussion focuses on discovering trends in the Benefits and Challenges, evaluating the Random Forest model's prediction accuracy, and discussing the results implications for integrating AI in Education.

7. 1 Data Preprocessing and Overview

The dataset used for the analysis consisted of survey responses mapped to numerical values. These responses evaluated various aspects of generative AI in education as perceived by students, especially the use of chatbots which were focused on the survey. Benefits such as individualized assistance and administrative effectiveness were discussed in the survey, along with drawbacks including accuracy and ethical dilemmas. The analysis made exact categorization and statistical evaluation possible by converting each response into numerical scores. The targeted benefits and challenges columns contain this question below ***Figure 1***.

Survey Questions		
Benefits questions		Challenges questions
1.	Personalized and immediate learning support	Accuracy and transparency
2.	Writing and brainstorming support	Privacy and ethical issues
3.	Research and analysis support	Holistic competencies
4.	Visual and audio multimedia support	Career prospects
5.	Administrative support	Human values

Figure 1.

7.2 Mean Scores of Students and Categorization

We determined each respondent's mean scores for both benefits and challenges questions as a first step in examining the survey data. High, Medium, and Low were the three classes into which the scores were subsequently divided. This phase gave an overview of how the respondents evaluated the distribution of Benefits and Challenges.

The majority of respondents who had mean scores in the low range benefits or challenges thought AI technology had few advantages or issues. Concerning advantages, this could be a sign of discontent or a lack of knowledge about AI's potential. Regarding obstacles, it can indicate a high degree of acceptance or little worry about negative aspects of AI. Medium category respondents showed balanced perspectives, recognizing both benefits and challenges without extreme viewpoints. On the other hand, those who fell into the "High" group for challenges were more worried about important matters like accuracy and ethical considerations.

The majority of respondents with high benefit scores had favorable opinions of AI-Driven learning, highlighting its potential for individualized instruction, administrative effectiveness, and assistance with research and creativity. These students emphasized the potential of AI technologies to enhance academic performance and engagement. However, respondents who scored highly on challenges expressed serious worries about a variety of issues, such as data security, ethical dilemmas, and the difficulty of incorporating AI into conventional educational environments. The fact that “Medium” is the most common for both benefits and challenges suggests that most students have balanced opinions and are aware of both pros and cons of AI. Although less frequent, low ratings represent distinct viewpoints that demand more research. For example, students who have low benefits scores could not be aware of AI’s potential or be unhappy with how it is currently being used. In a comparable manner, people who score low on challenges see AI integration with little concern, indicating high approval and trust for them.

7.2.1 Model Evaluation and Accuracy

The benefits and challenges of AI in education affecting students’ academic performance were categorized using the Random Forest Model. To assess the accuracy of the model, the dataset was divided into training and testing sets. The model’s capacity to predict mean scores and accurately classify responses into Low, Medium, and High.

Classification Metrics

Benefits Classification Report		
Precision:	0.80 (High)	0.92 (Medium)

Recall:	0.80 (High)	0.92 (Medium)
F-1 Score:	0.80 (High)	0.92 (Medium)
Accuracy:	88.89%	

Figure 2.

Challenges Classification Report		
Precision:	1.00 (High)	0.94 (Medium)
Recall:	0.67 (High)	1.00 (Medium)
F-1 Score:	0.80 (High)	0.97 (Medium)
Accuracy:	94.44%	

Figure 3.

- **Precision:** High precision scores indicate less false-positive predictions for crucial categories. With a greater emphasis on Medium benefits, the model correctly identifies respondents in both groups, as evidenced by the precision of 0.80 (High) and 0.92 (Medium) for benefits. WIth a precision of 1.00 for challenges (High) and 0.94 (Medium) challenges, the model performs well for the moderate challenge group while producing relatively few false-positive predictions, particularly when it comes to identifying respondents who have serious privacy and ethical concerns.
- **Recall:** The recall values of the model show that it can recognize every relevant instance. Recall values of 0.80 (High) and 0.92 (Medium) for benefits demonstrate that the model is successful in identifying respondents who have both high and medium benefits, with the Medium category showing the greatest performance. While the recall of 0.67 for High challenges indicates some underestimation of respondents with substantial worries, it still

captures a considerable part of individuals with serious issues. For Medium challenges, the recall of 1.00 indicates good identification within this category.

- **F-1 Score:** The F-1 Scores offer a comprehensive assessment of model performance by striking a balance between recall and precision. The F-1 Scores of 0.80 (High) and 0.92 (Medium) for benefits show steady performance in both groups, with the Medium group exhibiting a particularly balanced result. The F-1 Scores of 0.80 (High) and 0.97 (Medium) for tasks show strong performance, particularly for the Medium challenges category, where the model shows that it can successfully balance recall and precision, while slightly underperforming for High challenges.
- **Accuracy:** The accuracy of the model was 94.44% for obstacles and 88.89% for benefits. With a somewhat better accuracy in classifying problems, this illustrates the model's overall reliability as it properly classifies the majority of survey responses. It also shows strong performance in both categories.

The first part of the study relies heavily on the classification results, which are used to categorize respondents and calculate mean scores. The Random Forest Model's strong predicted accuracy validates this categorization procedure and strengthens the validity of the initial observations. The potential of AI to improve learning, especially through personalized assistance and increased academic efficiency, was strongly appreciated by respondents with high benefits scores, whereas those with medium scores acknowledged both benefits and limitations, demonstrating a realistic but hopeful outlook. Conversely, Students who scored low on benefits were less optimistic about AI's potential, maybe as a result of their perception of its inefficiency.

Challenges regarding ethical issues, privacy, and transparency were particularly highlighted by high-scoring students, indicating the need for greater attention to these matters when implementing AI in the use for their education. Low scores suggested greater acceptance and trust in AI systems, while medium scores showed that issues were controllable but still considerable. In order to promote wider AI acceptance, the findings have significant implications for educational strategies. They highlight the necessity of addressing issues like accuracy and trust, allocating resources efficiently in areas where AI offers the greatest advantages (like personalized learning support), and making sure that teachers and developers are given focused training on data security and ethical AI usage.

7.4 Prediction of highest impact question for Benefits and Challenges

Classification Report		
Precision:	0.80 (Benefits)	0.50 (Challenges)
Recall:	0.67 (Benefits)	0.67 (Challenges)
F-1 Score:	0.73 (Benefits)	0.57 (Challenges)
Accuracy:	67%	

Figure 4.

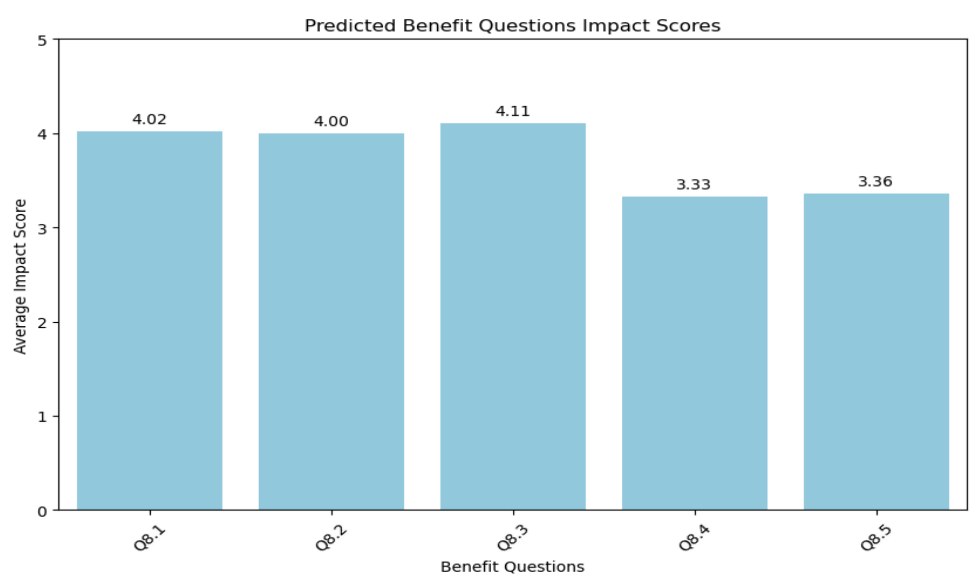

Figure 5.

7.4.1 Benefits of AI in Enhancing Academic Performance

The efficiency of the Random Forest model in determining whether a response is classified as a challenge or a benefit offers valuable information on potential effects of AI-driven learning on academic achievement of students'.

The predicted highest impact for the Benefit question is shown in ***Figure 5*** which is the question Q8.3. "Research and Analysis support" is the question under this, and it simplifies information retrieval, automates data analysis, and offers individualized research guidelines or advice, all of which greatly improve students' academic achievement. Students can rapidly access and process large volumes of data, discover trends in datasets, and improve their writing with real-time feedback through the help of AI chatbots or other AI tools. These resources enhance accessibility, promote teamwork, and get students ready for practical applications in data-driven fields. AI saves the students' time to concentrate on innovative problem-solving and critical thinking by lowering the amount of physical labor needed for repetitive tasks. To guarantee appropriate use, ethical issues such plagiarism risks, bias in AI results, and possible over-reliance must be taken into account. All things considered, the research support provided by AI encourages deeper learning, allowing students to take on increasingly challenging tasks and produce better academic results. Additionally, this finding is one important area where AI tools are greatly helping students is in the personalization of learning materials and feedback. One of the most praised aspects of AI-driven learning is its capacity to customize feedback and information to each learner's needs. The results of this study are supported by earlier research showing that individualized learning experiences enhance student engagement and increase positive results. The model's identification of this as a high-impact benefit provides credibility to the idea that AI's adaptive abilities to help learn can improve academic performance by tailoring teachings to each student's unique strengths and shortcomings.

High Precision for Benefits (0.80) shown in the ***figure 4*** shows that the model's high accuracy predicting benefits helps the study's objective of determining the areas in which AI can benefit students. In line with the research's objective of analyzing AI's contribution to education, the Random Forest model's persistence to recognize the advantages associated with AI's individualized material and feedback demonstrates that AI is, in fact, an effective tool for improving academic performance. These results imply that by providing individualized learning experiences, AI-driven learning can significantly improve student performance. The study also highlights the need for additional research to continuously enhance AI's ability to adjust to students' changing needs, which would further boost its efficacy in enhancing their academic performance.

7.4.2 Challenges of AI in Enhancing Academic Performance

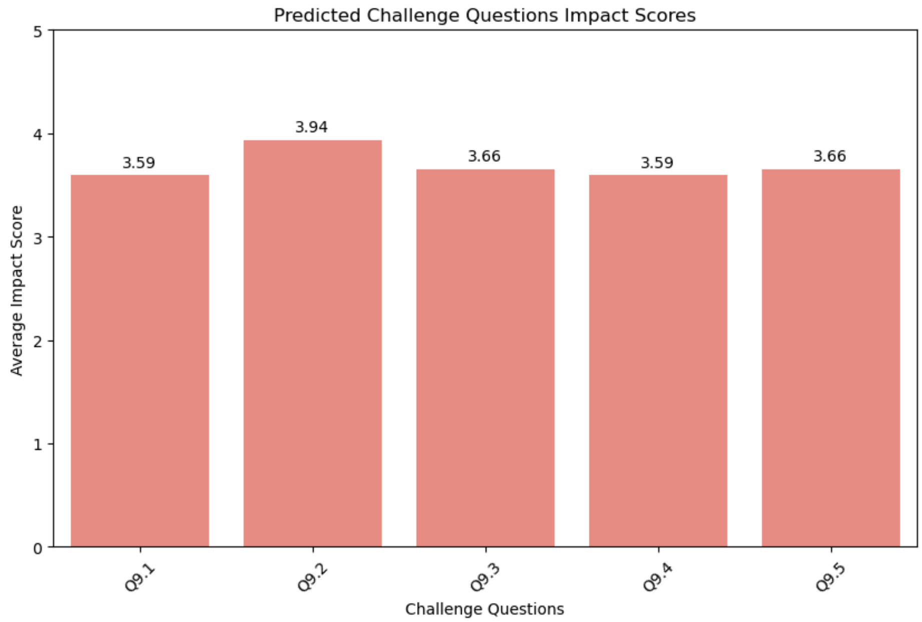

Figure 6.

Given that AI has many potential benefits, integrating it into academic environments presents multiple challenges, as the anticipated Challenge responses demonstrated by the students. These challenges include data security, where privacy and the security management of students remain to be major obstacles to adoption, and trust in AI systems, as students expressed worries about the accessibility and reliability of AI technologies. Additionally, students frequently question the validity and relevance of assessments created by AI, raising doubts about their correctness. The incorporation of AI is made more complicated by its limits in providing context-sensitive help, as these systems might not take into consideration the intricate and varied needs of students in various learning environments.

The Predicted Highest Impact Challenge Question is Q9.2 based on the bar graph ***Figure 6***, which is about "Privacy and Ethical issues" based on the survey's questionnaire. This shows the adoption of AI-driven learning tools poses problems with privacy and ethical concerns, especially when it comes to managing student data and guaranteeing appropriate use in the classroom. To provide individualized learning experiences, AI systems frequently need access to private data, including academic records, learning patterns, and even biometric information. However, as illegal access or exploitation of such data could jeopardize student confidentiality, this raises serious concerns regarding data privacy and security. Furthermore, when AI algorithms are unclear or unfair, ethical problems arise because they may result in unfair procedures or biased learning outcomes. Trust in AI technologies is further complicated by the "black-box" problem, which is the lack of understanding surrounding how these systems make decisions. Serious difficulties are also presented by concerns about informed consent and the moral use of AI-generated insights in academic assessments. Establishing strong data protection procedures, guaranteeing openness in AI tasks, and informing stakeholders about the moral implication of AI use are numerous ways that institutions could mitigate these worries. By addressing these obstacles, AI-powered solutions can be used responsibly to improve learning while promoting and protecting students' rights. These are some of the main reasons why integrating AI into the curriculum may encounter resistance from both teachers and students.

While some challenges are correctly anticipated, others can be missed or undervalued, perhaps as a result of incomplete or unbalanced data, as indicated by the lower precision for challenges (0.50) shown in the ***Figure 4***. This suggests that in order to adequately reflect the complexity of these challenges, either improved data collecting or more advanced models will be needed. This difference emphasizes the study's finding that trust and security concerns continue to impede the effective and widespread use of AI tools in education, supporting the goal of the study to eliminate these barriers. To overcome these challenges, further research into data privacy, trust issues, and the transparency of AI technologies.

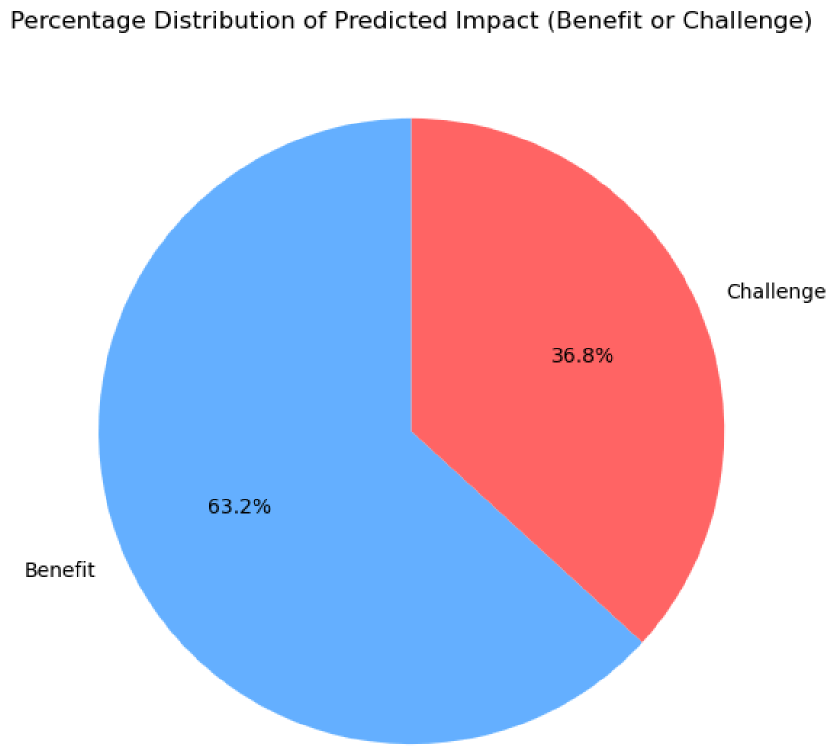

Figure 7.

A significant aspect in the benefit projections is Q8.3, which shows that some benefit-related questions have higher average effect ratings than others, according to the expected benefit questions impact scores. The expected challenge questions impact scores also show which parts are thought to be more difficult, with Q9.2 being a major challenge question for the challenge category. The distribution of the pie chart, which shows that 36.8% of the predictions are categorized as challenges and 63.2% of the predictions as benefits, further demonstrates the overall balance between benefit and challenge predictions. This shows that the model detects more possible benefits than challenges, which is consistent with its better accuracy in benefit prediction.

8. Summary of Finding, Conclusion and Recommendations

The study emphasizes the difficulties and moral questions surrounding the use of AI for automated grading, pertaining to the issues pertaining to fairness, accuracy, and openness. Although artificial intelligence (AI) increases productivity, it has limitations such as algorithmic biases, challenges in assessing innovative solutions, and concerns about data security. Building trust requires transparency so that teachers and students can comprehend and question AI-generated results. A balanced strategy to uphold accountability and fairness is provided by a hybrid model, in which AI supplements human assessors rather than takes their place. AI's speed and consistency combined with teachers' analytical judgement can improve learning while maintaining equity and fostering trust. To properly incorporate AI into educational settings, ethical protections and ongoing development are crucial.

8.1. Relevance of Findings from Related Literature

8.1.1 Relevance of Empowering Research Capabilities with AI in Higher Education

Based on Mohammed B. E. Saaida's research discussing "*AI-Driven transformations in higher education: Opportunities and challenge*s", which he discussed about "Empowering Research Capabilities with AI in Higher Education," presents how AI has the potential to revolutionize scholarly research. Saaida's research demonstrates how AI-driven technologies make data analysis easier, reveal significant patterns and expedite literature reviews, facilitating the more effective investigation of new data. In a comparable way, our results demonstrate how AI may increase students' academic performance by simplifying information retrieval, automating data retrieval, analysis, and offering tailored research advice. AI's ability to save time and encourage creative problem-solving is supported by both studies. Our research expands Saaida's emphasis on enabling researchers to include real-world application for students, stressing, collaboration and readiness for data-driven professions.

8.1.2 Ethical Consideration and Privacy Challenges in AI for Higher Education

The ethical issues and prejudices present in AI systems for Higher education are also explored in Saaida's research. Unfair results can stem from the persistence of biased datasets in AI algorithms, especially when it comes to grading, resource allocation, and recommendations. Fairness, accountability and transparency are important issues that must be addressed. To reduce these risks, clear policies, algorithmic transparency, and regular ethical evaluations are necessary. According to our research, "Privacy and Ethical Issues" is the most significant issue. The survey's findings reveal issues based on students' responses that contain handling private student information, such as academic records and learning styles, which AI systems frequently require individualized instruction.

8.2. Accuracy and Effectiveness of the Random Forest Model

8.2.1. Model Accuracy

The study identifies areas where the Random Forest Classification algorithm could be improved, but it also offers a solid framework for forecasting how AI-driven learning will affect student results. Model Accuracy is around 67%, shown in ***Figure 3.*** The model does a satisfactory task of predicting benefits, but it might do an improved and better in terms of predicting challenges. The model may not be as good at detecting the subtle barriers that students encounter while using AI technologies, as indicated by the lower precision (0.50) for challenges shown in the classification reports. The model does very well in both benefits and challenges, according to its macro average precision and recall metrics (0.65 for both), but it finds it difficult to understand the more complex problems associated with the adoption of AI. The models's strengths in predicting benefits with 0.73 and challenges with 0.57 are highlighted by the F-1 Scores, which show that it is difficult to capture important barriers such as data security and trust. This difference demonstrates how the model needs to be improved in order to more effectively handle the challenges of integrating AI.

8.2.2. Model Improvement

Future iterations could concentrate on improving data preprocessing, such as addressing class imbalance (since there are fewer responses indicating challenges), or adding new features, like students' technological readiness or familiarity with AI tools, in order to improve model's performance. And might as well combine the column of "Concerns about Generative AI Technologies" in the dataset about the "*Impact of Conversational Chatbots on Learning of University Students*" from a study in Bulgaria to the Challenges column to further explore in greater depth how AI influences students' academic performance to know the other potential downsides of using AI in education.

This would provide the model a more comprehensive understanding of the variables influencing student outcomes and enable it to more accurately distinguish between benefits and challenges.

8.3. Contributions to Ethical and Effective AI Use in Education

The findings of the investigation underscore the ethical issues that need to be addressed while also advancing our understanding of how AI may improve learning. The identification of issues like accuracy, data security, and trust highlights the necessity of an ethical framework for the use of AI in education. Transparency, accountability, and security are critical as AI technologies are increasingly incorporated into education. This emphasizes how crucial it is to create AI systems that protect students' privacy, deal with prejudices, and offer trustworthy feedback. This study's objective of promoting the moral use of AI in education is directly supported by these revelations, which make sure that AI technologies are applied in ways that build student trust and produce just and equal results.

8.4. Contributions to Enhancing the Student Learning Experience

The information gathered from examining the benefits and challenges offers helpful direction for the creation of AI technologies meant to enhance students' performance. According to the model, one of the biggest advantages that can have a favorable effect on students' is the ability of AI-powered evaluation tools to provide tailored feedback. AI can provide useful insights that improve educational results by customizing tests to each students' development, proving its efficacy when developed with an emphasis on unique learning requirements. The study highlights the significance of addressing challenges including trust issues, enhancing data security, and improving AI's accuracy across many academic contexts in order to optimize its potential. Improving the entire student learning experience will depend on ensuring AI systems are sensitive and flexible to diverse academic needs of students while resolving difficulties with integration

In conclusion, the Random Forest Classification Algorithms's use in education highlights both the remarkable benefits and challenges of AI-driven learning. Through personalized learning and AI-powered tests, AI has the potential to improve academic performance. However, limitations to its wider adoption include challenges with accuracy, data security, and trust. The discoveries of the study highlight how crucial it is to improve AI tools in order to better handle these issues, improve prediction accuracy, and improve the educational experiences of students. The results support the ethical adoption of AI gradually, guaranteeing that it will continue to be a useful instrument for promoting academic development while protecting students' privacy and rights.

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