AI in Moroccan education: evaluating student acceptance using machine learning classification models

Khoual Mohamed, Elkaimbillah Zineb, Mcharfi Zineb, El Asri Bouchra
IMS Team, ADMIR Laboratory Rabat IT Center, ENSIAS, Mohammed V University in Rabat, Rabat, Morocco

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ABSTRACT

Personalized learning is becoming a reality in education thanks to the rise of AI. This study investigates the possibilities of AI within the realm of education, focusing on the individualization of the learning experience. The research is based on the responses of 395 students from various faculties in Morocco. The questionnaire aimed to assess the students' opinions of AI, their level of knowledge, their previous experiences, and their perception of the application of AI within educational settings. Employing classification techniques such as decision trees (DT), multilayer perceptron (MLP), and random forests (RF), our aim was to predict the receptivity of AI in education. The findings highlight significant differences in how Moroccan students perceive AI, identifying key factors such as familiarity with the technology, ethical concerns, and perception of its potential impact on the learning experience. Classification models showed varied performance in anticipating these attitudes. This study highlights the critical importance of understanding students' perspectives on AI in education. These findings offer crucial insights for education policymakers as well as designers of educational technology solutions in Morocco. The findings can be used as a guide to adapt the incorporation of AI into the education sector with discernment, taking into account students' perceptions and preferences.

Corresponding Author:

Khoual Mohamed
IMS Team, ADMIR Laboratory Rabat IT Center, ENSIAS, Mohammed V University in Rabat
Rabat, Morocco
Email: mohamed_khoual@um5.ac.ma

1. INTRODUCTION

The educational sector is progressively incorporating artificial intelligence (AI), a technology with the potential to revolutionize both learning and teaching methods [1]. This advanced technology enables the customization of learning experiences by adjusting pedagogical techniques to meet the specific needs of each student, thereby providing more personalized and effective learning opportunities [2], [3]. Despite its considerable potential, there is a conspicuous lack of comprehensive research on the impact of AI in the educational landscape of Morocco. This data deficiency underscores the importance of understanding the distinct attitudes [4], beliefs, and preferences of Moroccan students towards AI technology.

AI in education holds great promise for personalizing learning pathways, which includes the flexible adjustment of content, teaching methods, and evaluations according to each student's progress and preferences [5]. However, the integration of AI into education presents unique challenges, making it crucial to understand students' perspectives to optimize its deployment [6], [7]. By comparing several classification methods, this study aims to address this research gap by predicting the likelihood of AI acceptance among Moroccan students. This research evaluates the opinions, knowledge, and experiences of 395 students from various faculties in Morocco regarding AI in education [8].The study utilizes classification models, including decision trees (DT), random forests (RF), and multilayer perceptrons (MLP), to forecast how students will adopt this innovative technology [9]. The goal is to determine the most accurate model by comparing their individual performances and selecting the one that provides the most precise predictions for AI acceptance.

Various studies have explored different aspects of AI in education, including academic performance, student engagement, and personalized learning. Pacheco-Mendoza *et al.* [10] utilized DT to predict academic performance, highlighting the importance of age and study habits with an accuracy of 85%. Similarly, Kabakchieva [11] applied DT to identify at-risk students based on previous results and engagement, achieving an accuracy of 87%. Aitkin and Foxall [12] employed MLP to model teacher behavioral intentions, demonstrating the ability to handle complex relationships with an accuracy of 89%. Livieris *et al.* [13] used MLP to predict student performance by identifying motivation and engagement factors, with an accuracy of 90%. Al-Rahmi *et al.* [14] integrated RF to predict student attitudes towards AI-based MOOCs, showing superior performance in user behavior modeling with an accuracy of 92%. Devasia *et al.* [15] utilized RF to predict academic performance, demonstrating high accuracy in identifying success factors with an accuracy of 91%.

Several studies have examined the integration and acceptance of educational technologies in Morocco. Ejjami [16] analyzed the impact of AI (ML and LLM) on Moroccan education, emphasizing the potential to personalize learning and reduce educational disparities. Hamdani [17] investigated students' satisfaction with distance learning, revealing dissatisfaction due to inadequate technological infrastructure and high internet costs.

These studies underscore the efficacy of different machine learning models in forecasting educational outcomes and user acceptance of technologies. However, they predominantly focus on academic performance and teacher adoption, leaving a gap in understanding AI acceptance among students in the Moroccan educational context. Despite advancements in AI-related educational research, several challenges remain: limited focus on student acceptance, geographical and cultural gaps, and a lack of comprehensive comparisons between different machine learning models to predict AI acceptance among students [18].

This study aims to bridge these gaps by conducting a comparative analysis of various classification models to predict AI acceptance among Moroccan students. By examining the responses of 395 students from different faculties across Morocco, the research assesses their perceptions, knowledge, and experiences with AI in education. Employing classification models such as DT, MLP, and RF, the study endeavors to forecast student adoption of this innovative technology. The goal is to identify the most accurate model by evaluating their respective performances and selecting the one that provides the best predictions for AI acceptance. Contributions of the study:

- Comparative analysis of classification models: evaluate and compare the performances of DT, MLP, and RF models in terms of accuracy for predicting students' receptivity to AI in education.
- Understanding student perceptions: provide a detailed analysis of Moroccan students' attitudes, perceptions, and concerns regarding AI in education.
- Recommendations for policymakers: offer insights to guide educational policies and the integration of AI in the Moroccan educational sector, considering students' preferences and perceptions.
- Implications for educational solution designers: propose guidelines for developing AI-based educational tools tailored to the needs and expectations of students.

2. METHOD

2.1. About the dataset

2.1.1. Sampling methodology and data collection process

In our research, we opted to conduct an online survey using Google Forms as the primary data collection tool. The survey consisted of 20 detailed questions, which are listed in Table 1. All written in French-the primary language of instruction in Morocco. This approach allowed us to engage a diverse group of respondents and effectively gather their insights. By thoughtfully designing the questions, we aimed to explore various aspects of AI integration in education. Choosing Google Forms ensured ease of participation for respondents while streamlining data collection for researchers. Overall, our strategy emphasized efficiency, accessibility, and cultural sensitivity, enabling us to gather valuable information on Moroccan students' attitudes toward AI in education.

From February to May 2023, 395 students voluntarily participated in this survey while maintaining the anonymity of their responses. No personal information was requested or collected as part of this data collection process. The questions included in the survey were meticulously designed to encompass both quantitative and qualitative aspects. Quantitative inquiries focused on measures such as the frequency and duration of using AI tools, overall satisfaction ratings, and the perceived impact on academic outcomes. Simultaneously, qualitative questions explored students' individual perspectives, their autonomy in learning, the reliability of information provided by AI tools, and concerns associated with their usage [8].

Table1. Student-related survey questions

Survey questions	
Have the use of AI technologies helped you in consolidating your acquired data memory?	Have you noticed an improvement in the quality of your education and learning skills with the use of AI technologies?
Do you think that the use of AI technologies has influenced your ability to independently solve problems?	Are AI technologies sufficient in effectively answering your queries?
Do AI technologies contribute to better understanding of complex concepts?	Do you frequently rely on AI technologies to complete your university assignments?
Is the potential dependence on AI technologies for your studies a source of concern for you?	Have you noticed an improvement in your academic performance since you started using AI technologies?
Has the adoption of AI technologies affected your independence in acquiring knowledge?	Are the solutions provided by AI technologies consistent with those from other verified sources?
In your opinion, are AI technologies an asset to your learning process?	Are you comfortable using AI technologies in your studies?
Has your understanding of the subjects you studied been enhanced by integrating AI technologies?	Has your approach to information search changed with the introduction of AI technologies into your routine?
Are you satisfied with the accuracy of the information provided by AI technologies?	Have you seen an increase in your efficiency in educational activities due to the use of AI technologies?
Have you ever encountered inaccurate information provided by AI technologies?	Have AI technologies ever provided you with outdated information?
Did you solely rely on AI technologies for information reproduction?	On average, how much time do you spend using AI technologies?

2.1.2. Personal information and demographic data about students

A thorough examination of the participants' personal and demographic traits is shown in Figure 1. Notably, most of the participants have attained a high degree of education and possess a substantial number of university degrees. To be more precise, 80% of participants said they had earned a bachelor's degree, 15% said they had a master's degree, and 5% said they had a doctorate, demonstrating the range of academic levels represented. This inclusive group includes students of various ages and academic backgrounds. Among them, 94% were aged between 18 and 38, while the rest were over 39 years old. Additionally, an analysis of gender distribution reveals that 56% of participants were female, while 44% were male [8].

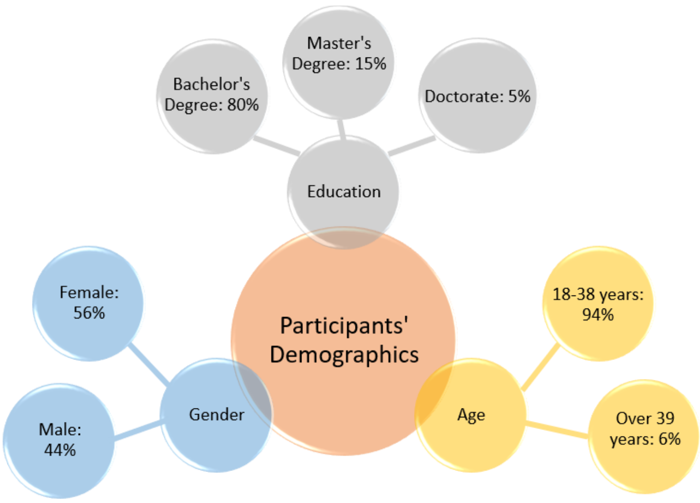


Figure 1. Students' personal information/demographic data

2.2. Methodology

To assess and compare the results of classification models in predicting the acceptance of AI among Moroccan students, a rigorous methodology was established. This methodology unfolded through several key stages, as depicted in Figure 2.

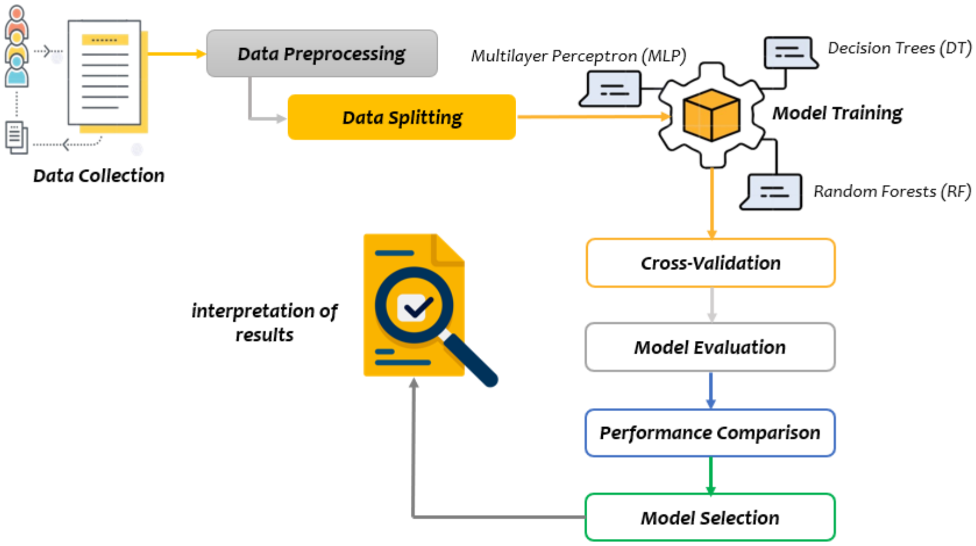


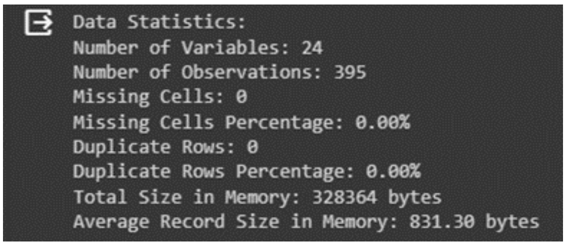
Figure 2. Proposed methodology

2.2.1. Data collection

This process involves gathering relevant information from a diverse group of students across various faculties and universities in Morocco. We will utilize multiple channels such as university mailing lists, social media platforms, and student clubs to ensure broad participation. The primary tool for data collection will be a multiple-choice questionnaire, designed to elicit detailed and structured responses. This data will provide crucial insights into Moroccan students' acceptance of AI in education, forming the foundation for further analysis and interpretation in our study.

2.2.2. Data preprocessing

Data preprocessing involves cleaning the data, processing missing values, coding categorical attributes and normalizing the data where necessary. At this stage, the data is checked for duplicates and missing values. As shown in Figure 3, there are no missing values in this dataset, so there is no need to remove gaps or duplicates [19].



```
Data Statistics:
Number of Variables: 24
Number of Observations: 395
Missing Cells: 0
Missing Cells Percentage: 0.00%
Duplicate Rows: 0
Duplicate Rows Percentage: 0.00%
Total Size in Memory: 328364 bytes
Average Record Size in Memory: 831.30 bytes
```

Figure 3. Data statistics

2.2.3. Data splitting

This procedure entails dividing the dataset into three separate subsets for the purpose of training, validating, and testing the machine learning model, as shown in Figure 4. The goal is to guarantee that the model exhibits good generalization to new data, hence preventing overfitting:

a. Training set: the model is trained on this subset in order to help it identify patterns and modify parameters in order to reduce prediction mistakes.
b. Validation set: this subset is utilized in the training phase to optimize hyperparameters. It offers an immediate and impartial assessment of the model's performance, aiding in the choice of the most effective model.
c. Test set: once the model has undergone training and validation, this subset is used to evaluate the model's capacity to apply its knowledge to fresh, unfamiliar data. It provides an impartial assessment of the model's real-world performance [20].

By carefully splitting the data, the process ensures that the machine learning model can effectively balance underfitting and overfitting, leading to a robust and reliable predictive performance.

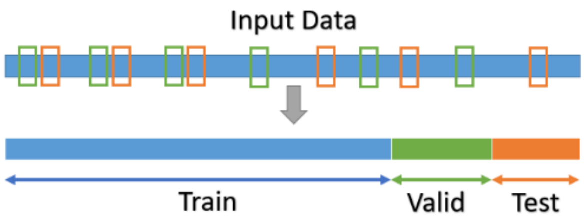


Figure 4. Data splitting

2.2.4. Model training

In this study, we employed three machine learning models to predict AI acceptance among Moroccan students: MLP, DT, and RF. Each model was selected for its distinct strengths and suitability for various data types and analytical tasks [21]. Below is a detailed explanation of the training process for each model utilized in this study.

A. Multilayer perceptrons

MLP are sophisticated feedforward artificial neural networks composed of multiple interconnected layers of nodes, often known as neurons. The network is structured in a way that each layer is fully connected to the next, allowing it to effectively capture and understand intricate, non-linear patterns in the data by utilizing activation functions, as depicted in Figure 5.

The training procedure of a MLP consists of the following steps:

1. Initialization: the network's weights and biases are randomly set at the beginning of the learning process.
2. Forward propagation: the input data is sequentially processed via the network, one layer at a time. Every individual neuron use an activation function to process its input and produce an output.
3. Loss calculation: the model's prediction error is assessed by comparing the expected output with the actual output using a loss function, such as cross-entropy for classification tasks.
4. Backward propagation: the backpropagation technique is used to compute the gradients of the loss function with respect to the weights and biases, enabling error correction [22].
5. Optimization: using optimization methods like Adam or stochastic gradient descent (SGD), the weights and biases are modified to minimize the loss.
6. Iteration: the parameters are continuously improved to increase prediction accuracy and decrease errors. This cycle of forward propagation, loss calculation, backward propagation, and optimization is continued for a predetermined number of epochs or until the model converges.

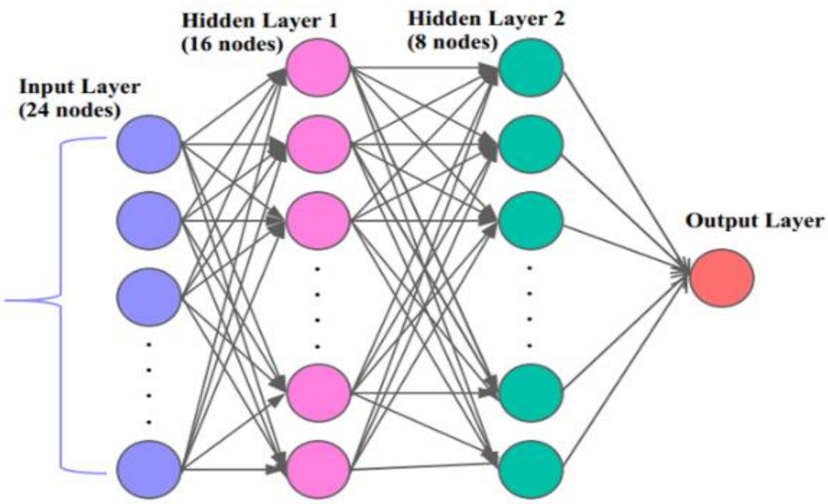


Figure 5. MLP structure with 24 inputs, 2 hidden layer and 1 output

B. Decision trees

DT are non-parametric algorithms used in supervised learning for both classification and regression tasks. They operate by iteratively dividing the dataset into smaller groups based on feature values [23], resulting in a hierarchical structure where each node corresponds to a decision point, as depicted in Figure 6.

The training procedure for DT comprises several essential steps:

1. Root node creation: using parameters like information gain or Gini impurity, the dataset is examined to identify the feature that offers the best split.
2. Splitting: the dataset is separated into subsets depending on the selected feature values.
3. Recursive splitting: this method of splitting divides each subset repeatedly, producing new nodes and branches each time, until the stopping requirements are satisfied (such as obtaining a minimum number of samples per leaf or a maximum tree depth).
4. Leaf node creation: the last leaf nodes are formed, which contain the model's predictions, such as the class labels for classification tasks.

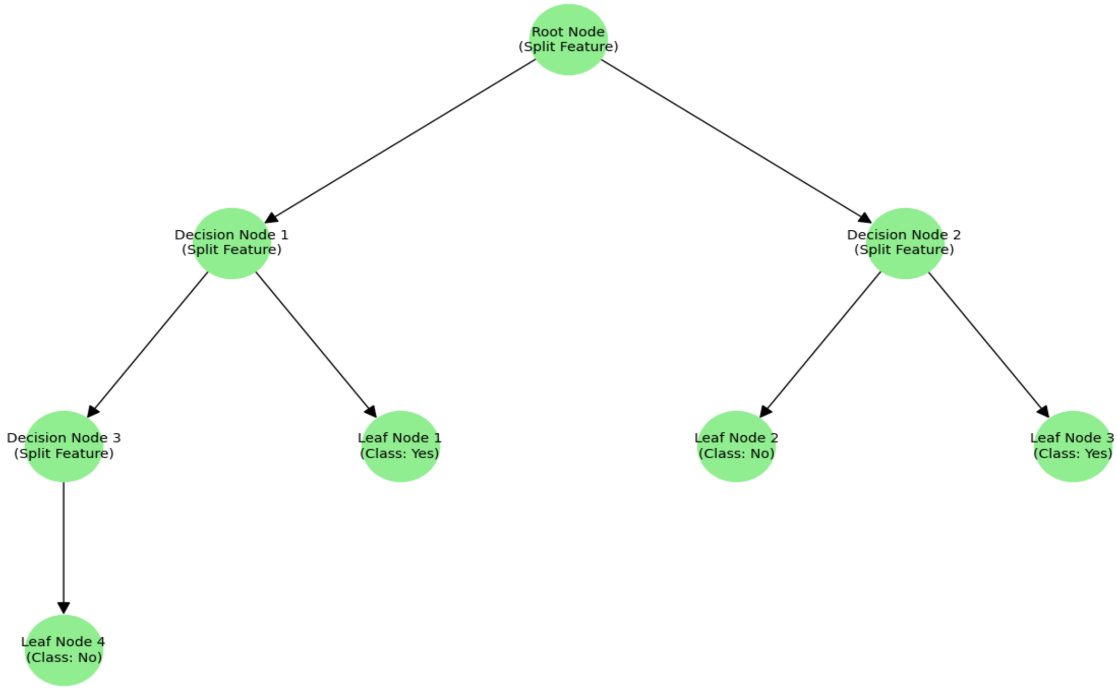


Figure 6. Structure of a DT

C. Random forests

Overfitting is avoided and prediction accuracy is increased via RF, a kind of ensemble learning technique. This is accomplished by generating multiple DT and combining their outcomes. Each tree is grown using a bootstrap sample of the data and utilizes a randomly selected subset of attributes to make divisions, as depicted in Figure 7.

The training procedure for RF comprises the subsequent steps:

1. Bootstrap sampling: multiple bootstrap samples are generated from the original dataset to produce varied training sets for each tree.
2. Tree training: every DT is trained using a distinct bootstrap sample. At every node, a random subset of characteristics is taken into account for division, which brings in variety and diminishes correlation among the trees.
3. Aggregation: the ultimate result of the model is achieved by combining the predictions made by each individual tree. For classification tasks, the usual approach is to choose the outcome based on a majority vote. In contrast, for regression tasks, the predictions are often averaged to get the final result.

By following this comprehensive training process, each model is effectively trained to understand and predict AI acceptance among Moroccan students, ensuring robust and reliable outcomes. This multi-model approach allows for a thorough evaluation of different predictive techniques, enhancing the overall reliability and accuracy of the study's findings.

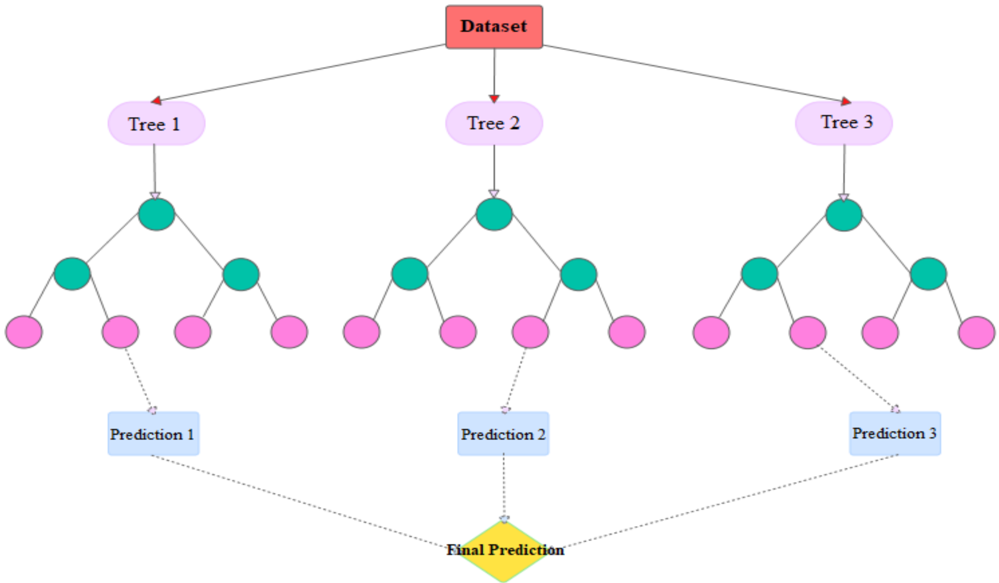


Figure 7. Structure of a RF model

2.2.5. Interpretation of results

The final step involves analyzing the outcomes from the selected model to derive meaningful insights and conclusions. This includes understanding the implications of the model's predictions and how they can be applied in real-world educational settings.

Interpretation steps:

1. Analyze predictions: examine the predictions made by the selected model to identify patterns and trends.
2. Identify key factors: determine which features are most influential in predicting AI acceptance among students.
3. Draw conclusions: summarize the key findings and their implications for integrating AI in education.
4. Provide recommendations: offer practical recommendations for policymakers, educators, and technology developers to enhance AI acceptance in the educational sector.

A visual representation of the detailed model training and evaluation process described above, as depicted in Figure 8. We'll break down the methodology into a clear and structured diagram.

Figure 8. Visual representation of the detailed model

3. RESULTS AND DISCUSSION

The question "Are you comfortable using AI tools for your studies?" serves as the target variable for our classification analysis. This crucial question underpins our predictive models, including RF, DT, and MLP [24]. By focusing on this question, we aim to predict and understand the acceptance of AI among Moroccan students in their educational journey. This specific question reflects students' comfort levels with AI tools, allowing us to employ machine learning algorithms to discern patterns, categorize students based on their responses, and conduct a comparative analysis of model performance in predicting student acceptance of AI in education.

– Student comfort levels with AI tools: the findings, illustrated in Figure 9, indicate that 64% of Moroccan students feel comfortable using AI technologies for their studies, whereas 23% of participants expressed either less comfort or reluctance in using these tools. This highlights the need for further investigation into the factors influencing students' attitudes towards AI in education and emphasizes the importance of addressing potential barriers to acceptance.

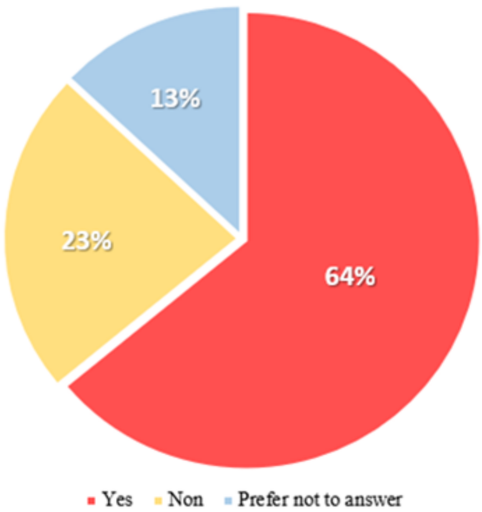
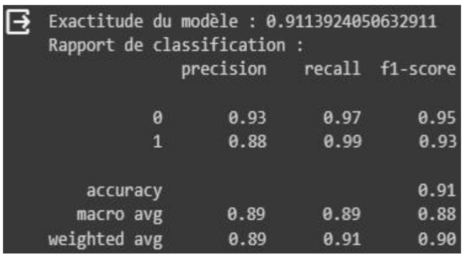


Figure 9. The influence of AI on education

3.1. Model performance metrics

3.1.1. Random forest

– Accuracy: 0.911
– Performance: the RF model displayed the highest precision, indicating its robustness in capturing intricate data patterns effectively. For example, a RF model can predict whether Moroccan students are comfortable using AI tools based on their responses to various survey questions, even if their responses are complex or include subtle patterns. This superior performance may be attributed to the model's ability to reduce overfitting by using multiple DT. Each tree is trained on a random subset of the data, and predictions are made by averaging the predictions of all trees, helping to mitigate the risk of overfitting [25], as shown in Figure 10.



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Exactitude du modèle : 0.9113924050632911
Rapport de classification :
              precision    recall  f1-score

           0       0.93      0.97      0.95
           1       0.88      0.99      0.93

    accuracy                           0.91
   macro avg       0.89      0.89      0.88
weighted avg       0.89      0.91      0.90
```

Figure 10. RF model performance

3.1.2. Decision tree
- Accuracy: 0.886
- Performance: although the DT exhibited slightly lower precision, its simplicity and interpretability make it a relevant model. For instance, a DT model can predict whether a Moroccan student is comfortable using AI tools based on factors such as age, gender, and academic background. The resulting tree structure is easy to understand and interpret, making it suitable for situations where transparency and explainability are important, as shown in Figure 11.

3.1.3. Multilayer perceptron
- Accuracy: 0.885
- Performance: the MLP's performance is very similar to that of the DT, but its complexity requires fine-tuning of hyperparameters to better identify patterns in the data. For example, in MLP models with multiple hidden layers, parameters such as learning rate, batch size, and number of neurons need careful tuning to achieve optimal performance. Without proper tuning, the model may struggle to effectively capture the nuances of the data, as shown in Figure 12.

Exactitude du modèle : 0.8860759493670886
Rapport de classification :

	precision	recall	f1-score
0	0.94	0.93	0.94
1	0.96	0.82	0.88
accuracy			0.89
macro avg	0.96	0.82	0.88
weighted avg	0.89	0.89	0.89

Figure 11. DT model performance

Exactitude du modèle : 0.885
Rapport de classification :

	precision	recall	f1-score
0	0.82	0.96	0.89
1	0.96	0.82	0.88
accuracy			0.89
macro avg	0.89	0.89	0.88
weighted avg	0.89	0.89	0.88

Figure 12. MLP model performance

3.2. Comparison of model performance
The differences in performance metrics underscore the importance of selecting the most suitable model based on the data's characteristics and specific prediction goals. When predicting AI acceptance among Moroccan students, factors such as the complexity of the data, the need for interpretability, and the trade-off between precision and complexity must be considered. The RF model's superior performance, due to its ability to capture intricate data patterns and reduce overfitting, makes it the best choice in this context. However, the simplicity and interpretability of DT, along with the potential of MLPs when properly tuned, highlight the value of these models in different scenarios.

3.3. Implications for AI acceptance in Moroccan education
The results of this study have significant implications for the integration of AI in Moroccan education. Understanding students' comfort levels with AI tools can inform strategies to enhance AI adoption and address barriers to acceptance. Policymakers, educators, and technology developers can leverage these insights to design interventions that improve students' experiences with AI, ultimately fostering a more supportive environment for AI in education.

3.4. Limitations and future work
This study has several limitations. First, the data collected may not fully capture the diversity of student experiences and attitudes towards AI across different regions and institutions in Morocco.

Additionally, the models' performance may be influenced by the quality and quantity of the data used for training. Future research should aim to collect more comprehensive data and explore other machine learning models to further enhance the accuracy and reliability of predictions. Additionally, investigating the specific factors that influence students' comfort levels with AI tools can provide deeper insights into how to effectively integrate AI into the educational landscape.

4. CONCLUSION

The overall goal of our study was to use a variety of classification models, such as RF, DT, and MLP, to predict Moroccan students' adoption of AI. Based on our findings, the RF model performed the best, achieving an accuracy of 0.911. With respective accuracies of 0.886 and 0.885, the DT and MLP models likewise demonstrated remarkable performance. It is significant to remember that a number of characteristics, including complexity, interpretability, and accuracy, affect the decision of which model is best.

For our future research, we plan to incorporate NLP models to analyze textual data provided by students. This approach will allow us to deepen our understanding and gain more comprehensive insights into Moroccan students' perceptions of AI. By expanding our methodological toolkit, we aim to address unanswered questions and contribute to the development of more effective AI tools tailored to the educational needs of Moroccan students.

In conclusion, our study provides valuable insights into the factors influencing AI acceptance among students and highlights the importance of model selection in predictive analytics. The findings have significant implications for policymakers, educators, and technology developers aiming to integrate AI into educational systems. Future research should continue to explore these dynamics to enhance the educational experience and foster a culture of innovation and acceptance of AI technologies in education.

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BIOGRAPHIES OF AUTHORS

Khoual Mohamed received a degree in networks and computer systems from Faculty of Sciences and technology Settat (FST) in 2018. He is currently a Ph.D. student in the IMS (IT Architecture and Model Driven Systems Development team) Team of ADMIR Laboratory (Advanced Digital Enterprise Modeling and Information Retrieval Research Laboratory) at ENSIAS. His research interests include Machine Learning Approach in education domain and data mining. He can be contacted at email: mohamed_khoual@um5.ac.ma.

Elkaimbillah Zineb received a degree in Computer Sciences (ENSIAS) in 2019. She is currently a Ph.D. student in the IMS (IT Architecture and Model Driven Systems Development team) Team of ADMIR Laboratory (Advanced Digital Enterprise Modeling and Information Retrieval Research Laboratory) at ENSIAS. Her research interests include semantic web, knowledge graph, ontology, information representation, and machine learning/deep learning approach in education domain. She can be contacted at email: zineb_elkaimbillah@um5.ac.ma.

Prof. Dr. Mcharfi Zineb is a computer science professor and member of the IMS Team, ADMIR Laboratory Rabat IT Center at ENSIAS, Mohammed V University in Rabat; Morocco. She has directed and continues to direct numerous doctoral theses in several themes. Her research interests include the application of artificial intelligence in education, software product line engineering, agile software development, and software traceability. She can be contacted at email: zineb_mcharfi@um5.ac.ma.

Prof. Dr. El Asri Bouchra is currently director of teaching-research at ENSIAS. She holds various positions, such as head of the software engineering department and coordinator of the Software Engineering program at ENSIAS, she has supervised and continues to supervise numerous doctoral theses in software architecture and data management in the health, industrial, and education sectors. She is a professor in the Software Engineering Department and a member of the IMS (Models and Systems Engineering) Team at ENSIAS. Her expertise and contributions extend to scientific committees, doctoral study centers, and teaching modules of the ENSIAS Software Engineering program. Her research interests include service-oriented computing, model driven engineering, cloud computing, component-based systems, and software product line engineering. She can be contacted at email: bouchra.elasri@ensias.um5.ac.ma or b.elasri@um5s.net.ma.