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Research article

Predicting open education competency level: A machine learning approach

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ABSTRACT

This article aims to study open education competency data through machine learning models to determine whether models can be built on decision rules using the features from the students' perceptions and classify them by the level of competency. Data was collected from a convenience sample of 326 students from 26 countries using the eOpen instrument. Based on a quantitative research approach, we analyzed the eOpen data using two machine learning models considering these findings: 1) derivation of decision rules from students' perceptions of knowledge, skills, and attitudes or values related to open education to predict their competence level using Decision Trees and Random Forests models, 2) analysis of the prediction errors in the machine learning models to find bias, and 3) description of decision trees from the machine learning models to understand the choices that both models made to predict the competency levels. The results confirmed our hypothesis that the students' perceptions of their knowledge, skills, and attitudes or values related to open education and its sub-competencies produced satisfactory data for building machine learning models to predict the participants' competency levels.

1. Introduction

Open Education allows people to access knowledge easily, provides means for collaboration, fosters innovation, and unites international communities of students and teachers. The exchange of knowledge, ideas, and information has always been a fundamental part of education, so free sharing is familiar in this field. Open Education seeks to expand educational opportunities by taking advantage of the possibilities offered by the Internet, allowing rapid and almost unrestricted diffusion, allowing people from all over the world to access knowledge, connect and collaborate [11]. The key concept in this idea is openness, which allows not only access to materials but also the freedom to modify and use them, the creation of communities and networks to share information and work, allowing education to be personalized to the individual needs and interests or adapt to different audiences in innovative ways [53]. Open Education is founded on sharing freely and with unrestricted access. The gratuity of the materials, the freedom of

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use, and legal tools (such as open licenses) allow educational resources to be reused and modified by anyone [45]. By promoting free and open exchange, we can increase everyone's access to education and knowledge anywhere and at any time [25]. Therefore, open education is how people construct, produce, and share knowledge, primarily through open educational resources and digital technologies.

Globally, the need for access to high-quality educational resources is a problem. In this sense, Open Education is helping to solve this problem by allowing more accessible and cheaper access to the academic community. Open Educational Resources (OER) are educational materials that are freely available and can be legally downloaded, modified and shared for the benefit of students without restriction [38]. Many educational resources have been created in digital format. What mainly differentiates OERs is that they have use licenses that grant them free and legal rights so that the public can use, modify and share them without problems. Educational resources not specified as public domain or licensed for free use cannot be considered as OER [72]. The Recommendation on Open Educational Resources from [78] is a milestone that provides guidance and strategies to all member states to advance open education worldwide and build inclusive knowledge societies.

Open education facilitates the teaching-learning process flexibly and inclusively in terms of time, space, training modality, or economic restrictions [15]. Similarly, it caters to each student's needs and interests since the student determines what to study [8]. It is closely associated with lifelong learning because it is aimed at people of any age who want to continue learning or perfecting the competencies in their areas of knowledge [50]. Another potential is autonomy in controlling their learning because students learn at their own pace [49]. It not only refers to access to information but also it's modification and free cooperation, thus connecting educational communities worldwide [41]. It allows sharing successful educational practices with other professionals and promotes innovations in various educational contexts [82].

Open education proposes that people have free and open access to knowledge and education, especially relevant for those in more disadvantaged or vulnerable contexts or traditional education systems [12]. It also allows students to broaden their training beyond what they learn in their educational institutions; even those who have accessed the labor market can improve their professional development thanks to the flexible access to continuing education activities [61]. Creating knowledge and resources by researchers has significant relevance as it allows for sharing such materials with others, thereby positively influencing students' learning experience [73]. That aligns with the current global policy agenda emphasizing the need to develop procedures to promote social justice in education. Specifically, the 2030 Agenda and Sustainable Development Goal 4 [75] call for international scientific communication and initiatives to ensure access to inclusive and equitable quality education and promote learning opportunities for all; undoubtedly, open education is a strategic measure.

Despite these potentialities, Open Education has certain limitations. Digital gap and digital transformation continue to challenge collaborative work for Open Education from innovation and research [68]. The digital gap refers to inequality in access to technology and Internet connectivity [3]. This digital gap can be a significant obstacle to full and effective participation in Open Education, as many open educational resources are online and require an Internet connection to be accessible. Therefore, Open Education also has certain drawbacks, including technical problems due to a poor Internet connection, unequal access due to lack of resources, high cost of the necessary equipment, need for greater autonomy and discipline on the part of the student, lack of continuous training for teachers in the design and development of Open Educational Resources, loss of social interaction between students, need for an active intervention of the tutor to avoid isolation and format resources that are not editable and that make it difficult to reuse [29,55].

Traditional education research methods have already accounted for the level of competence in Open Education of students [36,46]. Thanks to its enormous potential, the United Nations Educational, Scientific and Cultural Organization (UNESCO) calls for integrating artificial intelligence into educational research [76]. Machine learning is a branch of artificial intelligence that is based on algorithms capable of learning automatically and, thanks to this, can predict future behavior [67]. Digital adaptive teaching uses machine learning to create personalized study plans that fit the needs and abilities of each student, identifying areas for improvement and offering adequate educational resources for their progress. In this way, specific educational itineraries can be designed that respond to the needs of each student, using machine learning algorithms that allow content to be adapted to their individual needs [34]. Despite being an emerging technology, machine learning in education has yet to reach its full potential [21]. Machine learning can be a valuable tool to complement conventional parametric models in the analysis of Open Education. Due to its flexibility, machine learning can provide additional information about differences and similarities between different subgroups, which is helpful for researchers and educators to understand the characteristics of those students with a lower level of proficiency in Open Education [81]. Specifically, this study is based on predicting students' perceived level of Open Education proficiency using two state-of-the-art explainable machine learning models: decision trees and random forests.

2. Literature review

2.1. Open education competencies

Open education aims to improve how teachers and students interact with knowledge democratically. Based on the literature review [53], authors state that open education is understood as a dynamic phenomenon that leverages open educational resources in designing, implementing, and evaluating flexible educational practices that offer more opportunities for lifelong learning. Open education includes free and open learning communities, educational networks, teaching and learning materials, open data, and open-source educational tools, among others [81]. There are various frameworks for the development of open education in different educational institutions: the Open Educators Factory Framework [42], the Opening up Education: A Support Framework for Higher Education Institutions (European Commission, 2016), the framework for selecting OER based on fitness-for-purpose [24], the OpenEd

Table 1
OER Recommendation objectives and indicators.

OER Recommendation objectives	Competency indicators according to [54]
1. Capacity building	1.1. Creation, reuse, adaptation and redistribution of OER. 1.2 Open licenses and copyright. 1.3 Digital literacy.
2. Development of supportive policies	2.1 Policies to promote open education. 2.2 Policies for privacy and data protection.
3. Effective, inclusive and equitable access to quality OER	3.1 Open access sharing programmes or technology platforms. 3.2 Development of inclusive OER. 3.3 ICT and broadband infrastructure.
4. Promoting the development of sustainability models	4.1 Sustainability models. 4.2 Funding sources and sustainability. 4.3 Linguistic translation of open licenses.
5. Promotion and facilitation of international cooperation.	5.1 Projects with international cooperation. 5.2 International funding mechanisms. 5.3 Peer networks (local, regional and global).

Quality Framework [66] and the 6E Evaluation Framework [14]. Also, tools have been created for their assessment, including the Open and Distance Education Accreditation Standards Scale [7], the Perspectives and Opinions on OER and Other Online Educational Resources Scale [51], and the Digital Competency and Use of Open Educational Resources (CD-REA) Scale [62].

In educational sciences and technology, there is a demand to transfer frameworks and scientific knowledge to a set of actions that improve the training of professionals and solve real problems within contextual educational practices [13]. Some works, such as [79] and [2], authors consider the development of knowledge transfer indicators as under-researched. In [10], authors indicate that much of the academic sector's research needs to discover synergies that lead to knowledge transfer and educational innovation. Based on this need and aiming to follow the Recommendation on Open Educational Resources (OER) from UNESCO [77], Table 1 shows competency indicators proposed in [54] for open education.

There are several studies that have evaluated the perception of students about the open education competence according to the established indicators:

- **Capacity building.** Students participating in open education programs have been found to have higher digital skills than traditional students [60]. The findings suggest that training students in content production and management skills are essential to promote a culture of OER production [44].
- **Development of supportive policies.** Open education is a tool that can be used to improve the education and training of people around the world, and the development of appropriate policies is critical to its success. Student participation has been shown to ensure that open education policies are effective and relevant to students [52]. Students should be actively involved in decision-making processes. Promoting appropriate student participation can improve the quality of open education and ensure that policies are more effective and relevant to all students [37].
- **Effective, inclusive and equitable access to quality OER.** Open education has a positive impact on inclusive education. Students perceive how open education provides flexible, personalized, and affordable learning opportunities for those who would otherwise not have access to traditional education [23]. Open education helps address educational exclusion and improves the inclusion of marginalized groups, such as students with disabilities, who perceive how OERs exist that address accessibility barriers to ensure all students can benefit [74].
- **Promoting the development of sustainability models.** It is considered that to increase the sustainability of OERs, and it is necessary to improve the visibility of the resources available in the different locations and platforms currently only visible to a limited number of students [48]. In this sense, students demand learning ecosystems with connected resources [59].
- **Promotion and facilitation of international cooperation.** The findings suggest that students can create high-quality open educational resources and that collaboration among students can be especially effective for this purpose [43]. Open education requires students to have solid international communication and cooperation skills, especially in virtual environments. It has been shown how students who participate in open education programs are more likely to use virtual communication tools and collaborate with other students online [26].

On the other hand, the level of competency in open education has been evaluated. In [71], authors have evidenced the need to foster changes in the beliefs and perceptions of students and teachers about open education to favor the acquisition of competencies that allow developing practices. The literature has also pointed out some variables that influence open education practices, specifically sociodemographic characteristics such as gender. In [31], authors analyzed the texts of open education resources from a gender perspective and determined the need to offer a more robust vision of equality and promote the inclusive language. Taking this variable into account, authors from [28] examined the level of participation in open education programs, the reasons for their participation, the time they allocate to training and the use of the computer and internet, and they found that women preferred this typology of programs. Similarly, significant differences were found in the choice of massive and open courses: women tend to participate in practical ICT and test anxiety courses and less in entrepreneurship courses [40]. However, the study [16] focused on the perception of self-directed learning and performance in open education processes and found no significant differences in gender. The academic year is another variable considered in the studies. Open educational resources have been proven to improve student's learning and performance throughout undergraduate courses compared to those who received a teaching that did not employ them [19,18]. Therefore, this variable allows extracting relevant information that impacts teacher education processes focused on open education competency.

2.2. Machine learning

Machine Learning (ML) models are powerful and flexible tools that develop computer programs that learn and improve from experience without being explicitly programmed to perform specific tasks like prediction [5]. These computer programs encompass computer-intensive methods that utilize data to discover patterns to make predictions based on the given examples using non-parametric methods for modeling and variable selection. Therefore, most ML computer programs do not require distributional data assumptions or explicit model specifications to analyze survey data like traditional methods [6]. ML models are more tools to analyze surveys to look for aspects such as data processing in perception studies in different research areas. In education research, machine learning models have improved processes such as grading students, increasing student retention, predicting student performance, and testing students. In [35], authors explained that machine learning allows problem-solving in reasoning, knowledge representation, prediction, learning, and perception. Also, authors such as [27] identified trends in machine learning in educational technologies where they identified areas of opportunities to use Big Data and learning analytics in education. Therefore, machine learning brings promising techniques for developing new educational models using students' and teachers' perceptions. For example, authors from [69] analyzed students' perceptions of the online learning process to determine variables that influence the students' satisfaction with online learning. In [33], authors applied machine learning to study the association between the word-count length of a test item written in Chinese, item difficulty, and students' perceptions about items in science term examinations. In [57], authors analyzed the teachers' perceptions about the school's organization activities in Massive Open Online Courses (MOOCs) and Information and Communication Technologies (ICT) using machine learning models. In [20], authors employed machine learning to predict MOOC learner satisfaction and estimate their relative effects from specific learner-level and course-level factors. Education research has leveraged new developments in machine learning to perform complex analyses and make accurate predictions by explaining such models.

Applying machine learning in acquiring educational skills offers numerous benefits, including personalized learning, enhanced knowledge retention, prediction of academic outcomes, and early detection of learning difficulties. In [83], the authors explore how machine learning can be utilized to assess student performance in STEM courses. The findings suggest that this approach can yield a more precise and objective evaluation of students' acquisition of educational competencies. Furthermore, research has demonstrated how integrating machine learning into teaching subjects like statistics can enhance comprehension of concepts and foster problem-solving skills among students [58]. Evidence from [1] supports how machine learning improves feedback and facilitates the acquisition of student competencies. Additionally, researchers have successfully employed machine learning to identify students who may require additional support to improve their academic performance [22]. Thus, the integration of machine learning in educational settings has demonstrated its potential to revolutionize the assessment of student performance, enhance the acquisition of competencies, and provide personalized learning experiences.

Machine Learning offers the ability to comprehensively and accurately evaluate educational competencies, enabling effective feedback and intervention in students' learning. It has been used in assessing educational competencies encompasses various approaches, including: (1) analyzing educational data and extracting patterns to identify competencies that need improvement in university entrance exams [39]; (2) conducting initial diagnostic assessments to determine student's starting level in specific educational competencies of a training program [9]; (3) grouping students into competency levels to receive more personalized learning [70]; and (4) analyzing competency levels as indicators that assess the quality of academic programs in universities [65]. Assessment of educational competencies through machine learning models provides a more comprehensive and precise evaluation, enabling targeted feedback and intervention to enhance students' learning experiences.

3. Methodology

In this work, we propose that students' perceptions of their knowledge, skills, and attitudes or values related to open education could be the basis for models predicting each participant's perceived open education competencies. This study adopts a quantitative paradigm and utilizes machine learning techniques, a branch of artificial intelligence with great potential for predicting phenomena. However, it is important to note that the purpose of our research was not to compare groups or test hypotheses, and therefore, a statistical analysis was not conducted. Specifically, we use eOpen data to predict students' perceived open education competencies using two state-of-the-art explainable machine learning models: Decision Trees (DT) and Random Forest (RF).

Decision Trees (DT) is a non-parametric supervised learning method that consists of a root node, branches, and leaf nodes. Each root node represents a test on an item response, and the output from the root node is a branch. Each class label is represented in each leaf [63]. On the other hand, Random Forest (RF) is an ensemble learning method that constructs many decision trees during training time to perform classification and regression tasks [4].

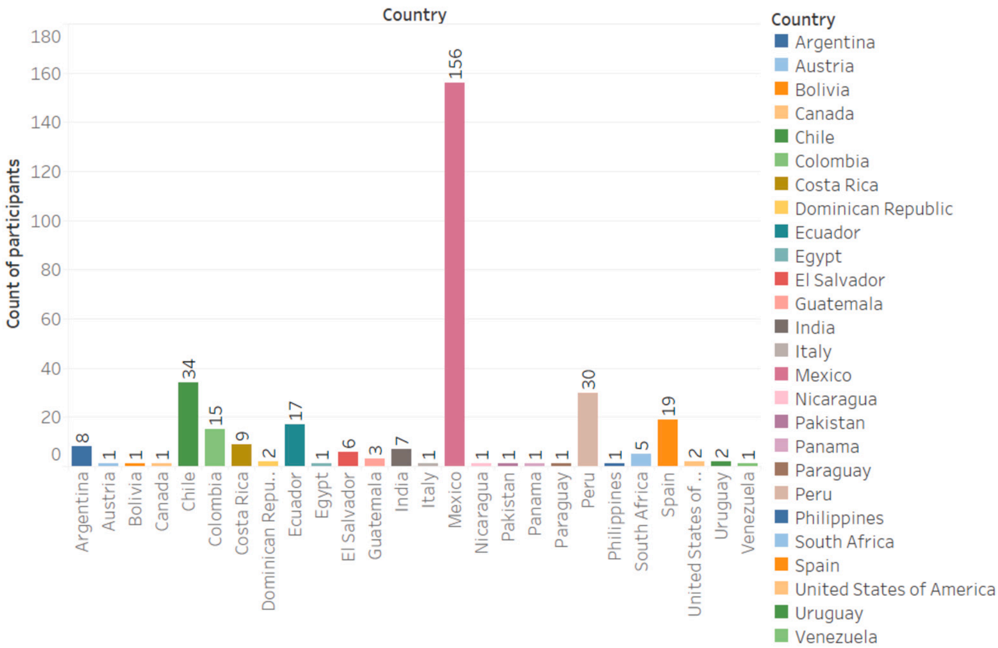


Fig. 1. Count of participants for each country. Color shows details about the country.

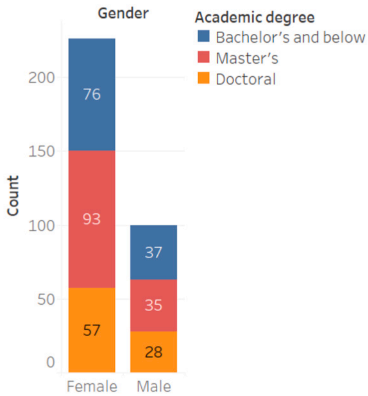


Fig. 2. Count of participants for each gender. Color shows details about academic degrees.

We evaluate the models' performance using accuracy and confusion matrices. The use of accuracy and confusion matrices as metrics in this study provides a reliable method for assessing the effectiveness of the models [17]. Accuracy measures the proportion of correct predictions over the total number of forecasts, providing a quantitative measure of the model's overall performance [47]. The confusion matrix offers a more detailed analysis of the model's performance by showing the number of true positives, true negatives, false positives, and false negatives [32]. That allows a nuanced evaluation of the model's strengths and weaknesses, including identifying misclassification patterns. Together, these metrics provide a robust evaluation framework that enables us to assess the accuracy and reliability of the models and make informed decisions about their suitability for the intended application.

3.1. Participants

The data used in this study was collected from a convenience sample of $m = 326$ students from 26 different countries, with 226 females and 100 males. The students belonged to three academic degree levels: Doctoral, Master's, and Bachelor's and below. Fig. 1 displays the distribution of students across countries, while Fig. 2 provides a breakdown of the participants by gender and academic degree. The data collected from [54] was acquired with the approval of the ethics committees at the participating institutions, and informed consent was obtained from all individual participants during the data collection. The data were collected through a Google Forms self-assessment questionnaire answered voluntarily.

Table 2
Original scores and preprocessed values.

Original data							
	Gender	Academic degree	Capacity of building	Development	Promotion	Creation	Intl. Cooperation
mean	0.6932	0.9141	2.9444	2.9294	2.9401	2.6365	2.7990
std	0.4618	0.7757	0.5420	0.5191	0.5202	0.6654	0.5843
Preprocessed data							
	Gender	Academic degree	Capacity of building	Development	Promotion	Creation	Intl. Cooperation
mean	1.19e-16	-6.91e-17	1.49e-16	-2.05e-15	3.89e-16	2.58e-17	-2.6e-16
std	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

3.2. Instrument

The eOpen instrument is intended to be of value to academic, scientific, and social communities interested in open education, educational innovation, research evaluation, and complex environments (see questionnaire in Table 5). The instrument designed in [54] measures students' perceptions of knowledge, skills, and attitudes or values related to open education and its sub-competencies using a 30-item questionnaire:

1. Capacity building (items 1, 2, 3, 4, 5, 6, 7, 8);
2. Development of support policies (items 9, 10, 11, 12, 13, 14, 15);
3. Promotion of effective, inclusive and equitable access (items 16, 17, 18, 19, 20, 21);
4. Creation of sustainability models (items 22, 23, 24, 25);
5. Promotion of international cooperation (items 26, 27, 28, 29, 30);

The eOpen instrument uses a four-point Likert scale (1: Strongly disagree, 2: Disagree, 3: Agree, 4: Strongly agree) to level the self-assessment questionnaire.

3.3. Data pre-processing

In this experiment, we initially computed the mean value for each sub-competency score before categorizing the perceived open education competency into low-perceived and high-perceived. This categorization was based on a cut-off determined by the mean of the average students' perception of their sub-competencies. Additionally, we incorporated socio-demographic variables into our analysis, including gender (represented as 0 = male and 1 = female) and academic degree (represented as 0 = bachelor's degree and below, 1 = master's degree, and 2 = doctoral degree). To reduce bias gained by machine learning models in the learning process from categories and questions with high numerical contribution, we utilized data pre-processing methods such as data normalization and balance techniques [30,64]. We followed the standardized procedure of two steps: 1) normalization, which was applied to the standard procedure over the sub-competencies scores from eOpen data, and 2) oversampling the class with lower occurrences to level its size to the class with major occurrences using duplicate instances. In Table 2, we show the original sub-competencies scores and the pre-processed values in which the means are practically zero and the standard deviation is one in all cases, which means that all values are in the same range to avoid bias. After that, to evaluate the performance of the models, we split the data into training and testing phases. By doing so, we could assess how well the models could generalize to new data.

4. Results

Table 3 displays the dataset resulting from several pre-processing steps, including setting the competency level, normalizing the data, oversampling, and dividing the data into training and testing subsets. Initially, we computed the average perception for each participant across all sub-competencies. Then we calculated the mean of these averages ($mean = 2.858289$) to establish a threshold for low- and high-perceived competency levels. Fig. 3 illustrates the distribution of participants by open education competency level and gender. The data were subsequently normalized using standard normalization techniques. Since the competency levels were well-balanced, we determined that oversampling was unnecessary. The resulting dataset consisted of 236 samples in each class, as indicated in Table 3. Finally, we divided the dataset into training and testing subsets for use in the classification algorithms. The *training* and *testing* subsets correspond to approximately 90% and 10% of the total data, respectively. The respective columns in Table 3 display the class compositions of these subsets.

We utilized scikit-learn v0.21.2 to construct the Decision Tree (DT) and Random Forest (RF) machine learning models. The hyperparameters for each model were selected empirically, and we provide an outline of our process below:

- **DT**: We used the default setting with the Gini impurity criterion for the Shannon information gain.
- **RF**: The number of trees in the forest was set to *10*, and the maximum depth of the tree was set to *30*.

Table 3
Dataset configuration.

Level of perception	Original	Balanced data	Training	Testing
Low	163	163	146	17
High	163	163	147	16

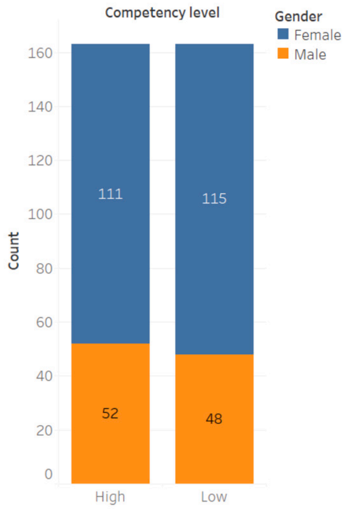


Fig. 3. Count of participants for each open education competency level. Color shows details about gender.

Table 4
Results from computing the rate of correct predictions (*accuracy*) of the two machine learning models in the training and testing stages.

Algorithm	Training accuracy	Testing accuracy
DT	100%	84.85%
RF	100%	93.94%

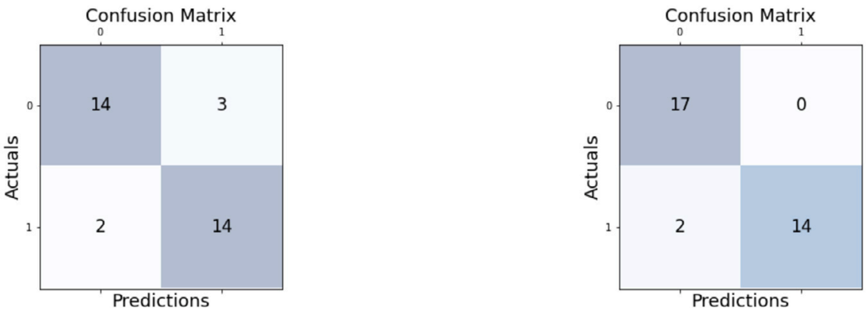
The performance of the Decision Trees (DT) and Random Forest (RF) models was evaluated using the accuracy metric. Table 4 shows the accuracy of each model during the training and testing phases. The accuracy of each model is presented in a separate column.

During the training phase, both DT and RF achieved a perfect accuracy score of 100%. That suggests that both models could learn the relationships between the input features and the output labels effectively. The behavior of the two models during the training phase was similar, which indicates that they could capture the underlying patterns in the data equally well. However, the performance of the models differed during the testing phase. RF achieved a higher accuracy rate of 93.94%, while DT's accuracy rate was lower, at 84.85%. This difference in performance may be because RF is an ensemble model that combines multiple decision trees, while DT is a single decision tree. RF is designed to reduce overfitting and improve the model's generalizability, which may explain its superior performance on the testing data.

It is worth noting that both models performed well on the testing data, with accuracy rates above 80%. That indicates that both models are suitable for predicting open education competencies based on students' perceptions of their knowledge, skills, and attitudes related to open education. However, the higher accuracy rate of RF suggests that it may be a better choice for this task, mainly when generalization to new data is essential.

The confusion matrices in Fig. 4 provide a more detailed analysis of the models' performance beyond accuracy. In particular, they allow us to examine the models' specific types of errors. The diagonal of the matrix shows the correct predictions for the open education competency level, while the off-diagonal elements indicate the prediction errors. Each intersection between the column (prediction) and the row (actual value) represents the model's prediction compared to the original open education competency level. In Fig. 4, low and high open education competencies are represented with the numbers 0 and 1, respectively.

The performance of DT is presented in Fig. 4a, where the number of students incorrectly classified by the model in predicting their open education competency level is illustrated. Three students were classified as high competency level when they actually had a low competency level, and two students were predicted to have a low competency level when they actually had a high competency level. Fig. 4b displays the performance of RF and only shows two prediction errors. Specifically, two students were predicted to have a low competency level when they actually had a high competency level. To compare the performances of the two models, one can



(a) DT (b) RF

Fig. 4. Confusion matrices used for visualizing the performance of both model. Left image (a) shows DT performance meanwhile right image (b) shows the RF performance.

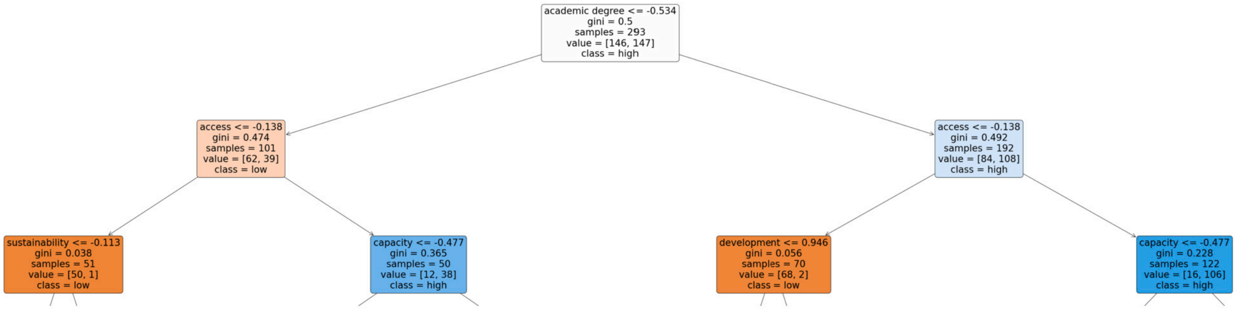


Fig. 5. Top features from tree model generated from Decision Tree model.

observe that the RF model had a higher true positive rate than the DT model, indicating that it was more effective in predicting the high competency level. However, the RF model still made two misclassifications where it predicted a low competency level for students who actually had a high competency level. Interestingly, the DT model also made the same two misclassification errors, which suggests that these instances were particularly challenging for both models.

The DT model's top features we acquired during our experiment are illustrated in Fig. 5, while the complete tree can be found in the Appendix section (Fig. A.1). The tree diagram represents the model's decision-making process based on the collected data features. The trees generated by DT and RF models have an advantage over other models since they are easily interpretable. The top features that contribute the most to the prediction of open education competency level are displayed at the top of the tree. The most critical features in the model's decision rule were the academic degree and the sub-competency of promoting effective, inclusive, and equitable access. Additionally, the sub-competencies of capacity building, development of support policies, and creation of sustainability models also played a significant role in the model's prediction.

The decision rules learned by RF using the eOpen data are presented in Fig. 6, and the complete model can be found in the Appendix section (Fig. A.2). In contrast to DT, the decision rules formulated by RF gave more importance to three sub-competencies: the development of support policies, capacity building, and promotion of effective, inclusive, and equitable access. These sub-competencies were the most crucial features used for building a tree from RF. Moreover, at the subsequent level of the tree, gender was also considered, along with the sub-competencies of development and access. The visual representation of the decision rules obtained from RF offers a better understanding of the factors contributing to the prediction of open education competency level, making it a valuable tool for policymakers and educators.

One of the main advantages of using DT and RF in machine learning is that these models produce decision rules that are easily interpretable and explainable. That means we can easily understand how the model arrived at its predictions, which is particularly useful when understanding the factors contributing to a particular outcome or identifying areas for improvement. Furthermore, both DT and RF demonstrated exemplary performance in predicting the open education competency level of the testing instances, achieving at least 84.85% accuracy. Although RF performed better than DT, both models effectively predicted the competency level. Despite these differences, DT and RF offer complementary strengths, and choosing the appropriate model for a particular task will depend on the specific characteristics of the problem and the available data. Overall, the results obtained in this study demonstrate the effectiveness of both DT and RF in predicting open education competency levels and highlight the importance of selecting appropriate machine learning models for specific tasks.

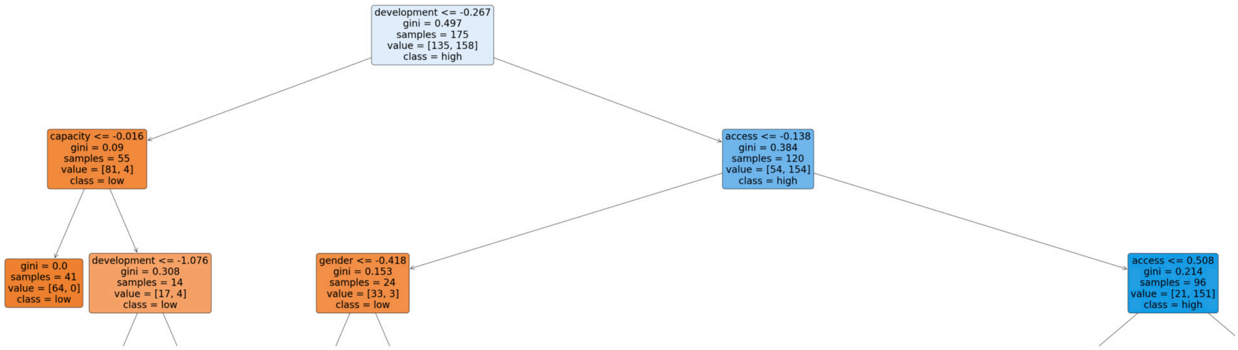


Fig. 6. Top features from a tree model generated from Random Forest model.

5. Discussion

Machine learning has become a popular approach to analyzing large datasets and has shown promising results in many fields. In education, machine learning models can be used to analyze data related to students' perceptions and identify patterns that may not be apparent using traditional statistical analysis techniques. The ability of DT and RF models to predict open education levels from self-assessment surveys, as shown in Table 4, is an example of how machine learning models can be used to provide valuable insights into students' perceptions. This finding is consistent with the results obtained in [56], who also employed machine learning techniques to analyze perception data. In [39], authors employed machine learning techniques to gather insights into students' performance in educational competencies for identifying potential areas for improvement within the teaching and learning process. In [70], a personalized learning approach was designed based on the distribution of students into competency levels. Similarly, in [9], in which an initial assessment was performed to identify training needs and develop a more contextualized educational competency program. By providing a better understanding of students' perceptions, machine learning models can help educators develop targeted interventions that can improve student learning outcomes.

Machine learning models' forecasting errors can be revealed through confusion matrices, offering valuable insights. As shown in Fig. 4, both DT and RF models misclassified as high-competency levels of the same two students. Nonetheless, it's typical for high-dimensional datasets such as eOpen to present difficulties when constructing precise decision boundaries for accurately classifying all instances. Similar challenges have been reported in other studies, such as [30] and [64], where confusion matrices were used to analyze bias in prediction models related to student's academic achievement and dropout rates. Given the importance of confusion matrices in identifying model bias and detecting challenging instances, they can play a crucial role in model selection. Analyzing confusion matrices can help develop strategies to reduce bias and challenging instances to establish the limits of such models. By leveraging the insights provided by confusion matrices, we can enhance the performance of machine learning models and better understand their limitations. Overall, these matrices are a valuable tool in interpreting and evaluating machine learning models.

Decision trees (DT) and Random Forest (RF) models generate decision rules by selecting the most important data features to predict the open education competency level. Similarly, DT and RF models have been employed in other studies, such as in [65], which focused on analyzing students' competency levels as indicators for assessing the quality of academic programs in universities. The top features used in both models can be seen in Figs. 5 and 6. According to [80], machine learning models can identify self-reported predictors from perception data, indicating the potential of using these models to enhance our understanding of human behavior and perception. Thus, DT and RF are advanced machine learning models that can identify the data features critical for predicting open education competency levels. Understanding these critical features can provide significant insights into students' perceptions, which can help create better educational policies and strategies. Furthermore, both models can predict the competency level with high accuracy, making them reliable tools for analyzing large datasets in the field of education.

6. Conclusions

In recent years, the field of education has seen an increase in interest in open education to democratize access to education and provide more equitable opportunities for learners. However, despite its potential benefits, there are still challenges in measuring and assessing open education competencies. This study aimed to address this issue by exploring the use of machine learning models to predict open education competency levels based on student perceptions. The study results suggest that machine learning models can effectively predict competency levels using features extracted from student perceptions. This finding is significant because it demonstrates the potential of machine learning to provide valuable insights into learners' competencies and inform educational practices. The goal is to create a more inclusive and accessible education system to support learners of all backgrounds and abilities better.

This research used two machine learning models to analyze the eOpen dataset. Our approach involved several steps: 1) extracting decision rules from students' perceptions of knowledge, skills, and attitudes or values that are associated with open education to predict their competency level using Decision Trees and Random Forests models, 2) examining the forecasting errors of the machine learning models to detect any potential bias and challenging instances, and 3) interpreting the decision rules generated by the models to gain insight into the features that were used to predict the competency level. With the help of these techniques, we were able to easily classify students' competency levels based on the eOpen data. These methods offer a more flexible and effective means of analyzing students' perceptions data, which has traditionally been challenging to analyze using traditional methods due to their reliance on explicit model specifications and distributional assumptions prior to prediction.

While this study demonstrates the potential of machine learning models in analyzing perception data and predicting competency levels, the study's limitations must be acknowledged. One limitation is that decision trees only reveal the features chosen by the model to build decision rules, and it requires the researchers to interpret and explain the model's decisions. Moreover, while this study utilized a sample size of 326 student answers, it is essential to note that further research is necessary to ascertain the generalizability of the findings to larger populations. Finally, while machine learning models offer new opportunities for data analysis, they require significant expertise and resources to be implemented effectively, which may limit their applicability in some settings.

This study implies for practice and research that machine learning models can be used to predict open education competency levels based on students' perceptions of their knowledge, skills, and attitudes or values related to open education. That can assist educators in identifying areas where students may need additional support or resources. The results also highlight the importance of using perception data to gain insight into students' competencies, as this data can be more quickly and accurately analyzed using machine learning techniques. Also, this study contributes to the growing body of literature on machine learning and its applications in education. The findings suggest that machine learning models can effectively analyze perception data to predict competency levels, which could lead to further research on using machine learning in education. Additionally, the study highlights the importance of understanding the decision-making process of machine learning models and the potential biases that may be present. Further research could explore how to mitigate biases and challenging instances and improve the accuracy of the predictions. Overall, this study provides a foundation for future research on using machine learning in education and highlights its potential for improving our understanding of students' competencies.

Ethical approval

Writing Lab and Research for Complexity Research Group, Institute for the Future of Education, Tecnologico de Monterrey. Approval Code: wl-2022-12-08-646. Approval Date: 2022-12-08.

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CRediT authorship contribution statement

Gerardo Ibarra-Vazquez: Conceptualization, Data curation, Formal analysis, Writing – original draft. **María Soledad Ramírez-Montoya:** Conceptualization, Data curation, Investigation, Writing – original draft. **Mariana Buenestado-Fernández:** Conceptualization, Data curation, Formal analysis, Writing – original draft. **Gustavo Olague:** Conceptualization, Formal analysis, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

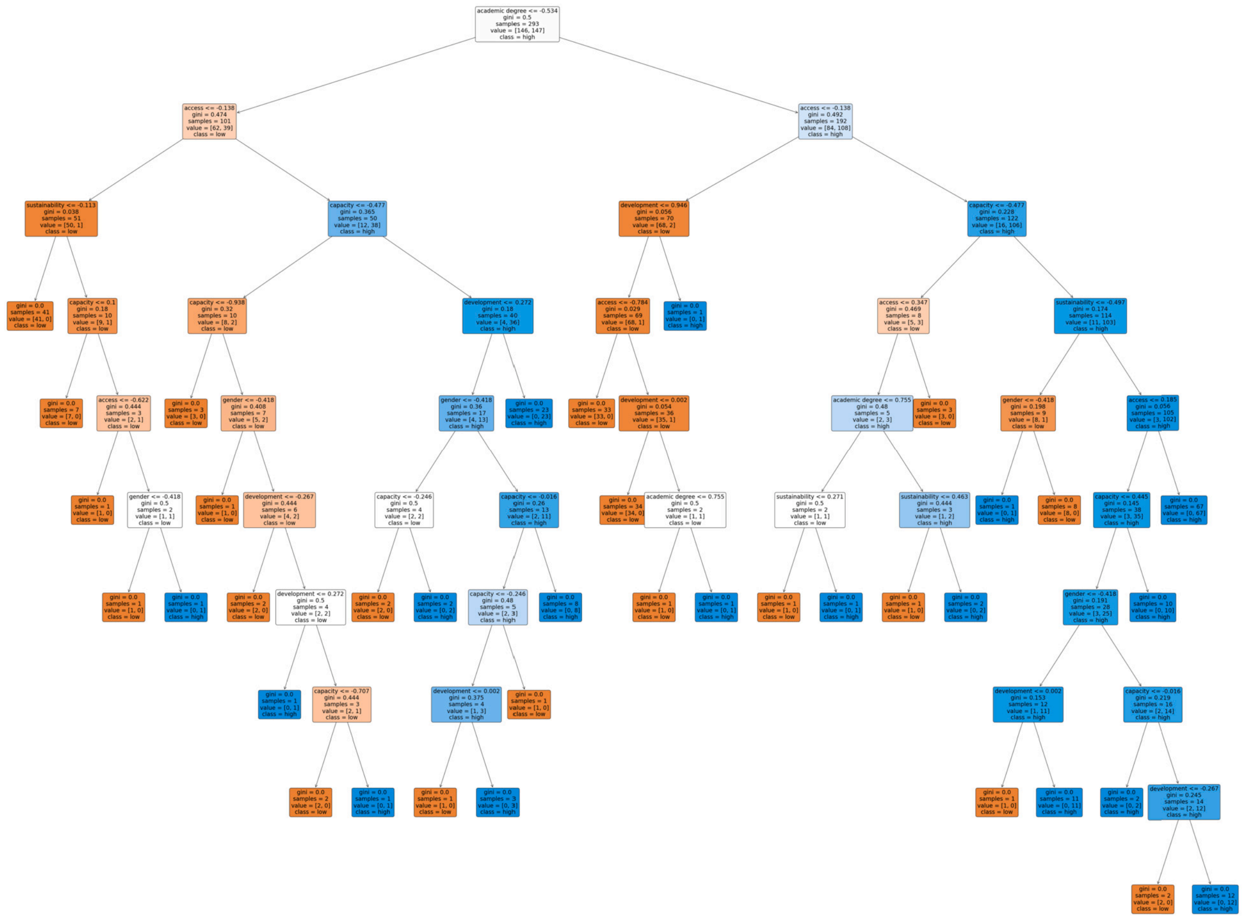

Fig. A.1. DT tree model generated from eOpen data.

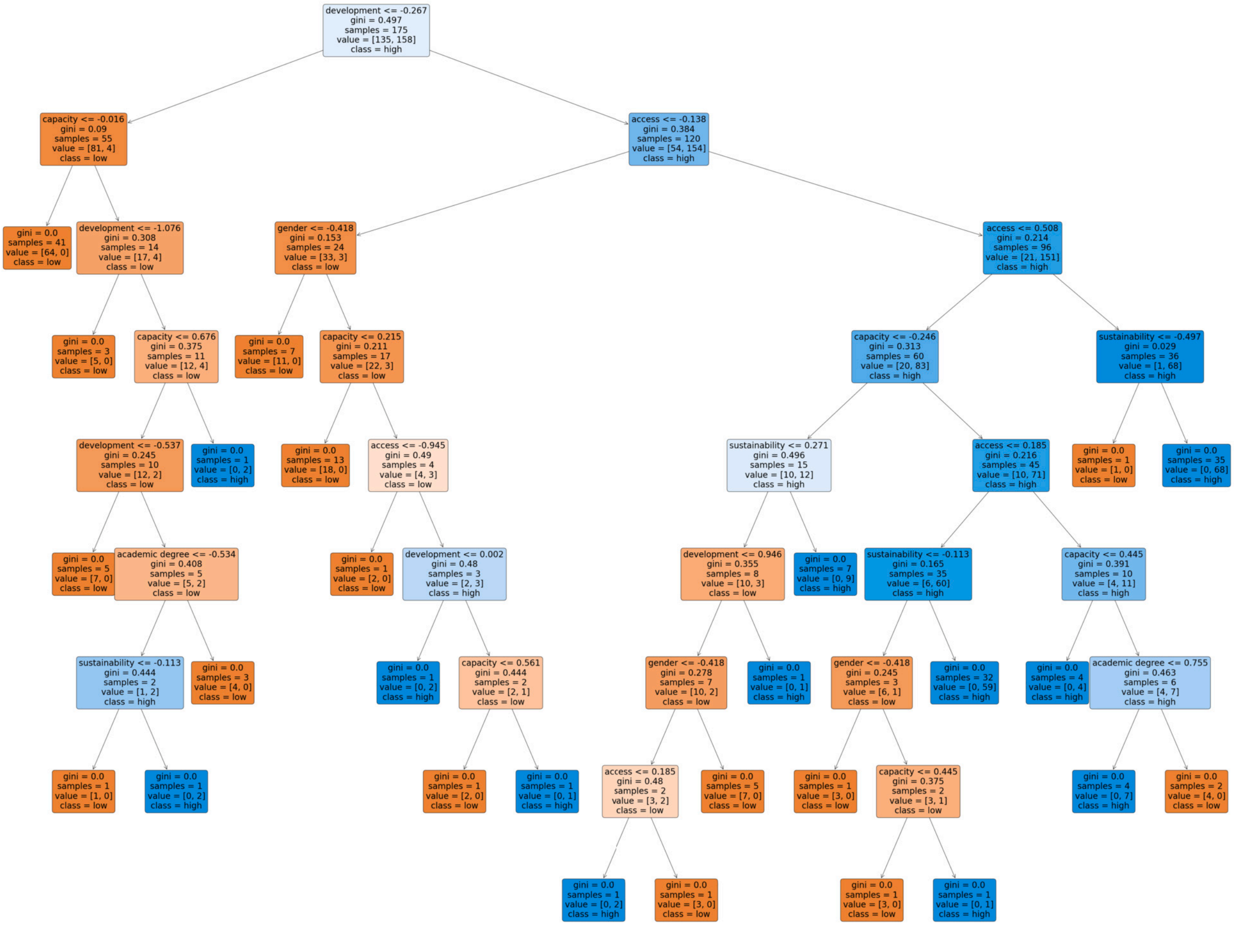

Fig. A.2. RF tree model generated from eOpen data.

Table 5
eOpen instrument.

Capacity building	Creation, reuse, adaptation and redistribution of OER	1. I integrate open educational resources (OER) in my academic and/or professional activities.
		2. I know virtual platforms where open educational resources can be found, for example: MERLOT, OER Commons, Procomún, among others.
		3. I build open educational resources from other existing educational resources.
	Open licensing and copyright	4. I apply open licenses such as Creative Commons for resources or General Public License for software, which I develop.
		5. I implement information in multiple formats (video, image, digital presentations, text, among others) in my open education practices.
		6. I build open education resources in different digital formats (video, image, digital presentations, text, among others).
	Digital literacy	7. I know and respect the copyrights of the resources I use in my open education practices.
		8. I value open education as an incentive to develop my technological and collaborative skills.
Development of support policies	Policies to promote open education	**9.** I identify standards or norms for the protection of personal data in my open education activities.
		10. I distinguish between intimate data protection and personal data protection policies.
		11. I verify that privacy policies are in place when I share or use open education resources.
	Privacy and data protection policies	**12.** I design regulatory frameworks or policies that encourage open licensing of educational resources or research.
		13. I adopt policies that promote open education.
		14. I value the role of libraries as promoters of open access to information policies.
	Policies or regulatory frameworks to promote open licenses	**15.** I identify support programs that bring Internet services to people who belong to vulnerable sectors.

Table 5 (*continued*)

Promotion of effective, inclusive and equitable access	Programs or technology platforms that share in open access	**16.** I identify the conditions for an open education that democratizes knowledge to make it accessible to everyone. **17.** I share resources on open access Internet sites or platforms.
	Development of inclusive OER	**18.** I develop open resources that contemplate the principles of universal design (needs for: alternative texts, enlarged font, contrast, among others). **19.** I make effective use of Internet applications and/or services for my open education practices.
	ICT and broadband infrastructure	**20.** I prioritize the publication or dissemination of my work in journals and/or universal open access sites. **21.** I value participating in education projects that consider diverse needs (e.g. disability, vulnerable communities).
Creation of sustainability models	Sustainability models	**22.** I identify models of economic sustainability for the viability of open education. **23.** I implement projects with funding (public or private) for the sustainability of open education.
	Sources of financing and sustainability	**24.** I prioritize the use of sustainability approaches (training programs, accreditation systems, quality certificate guarantees, among others) that promote inclusion. **25.** I choose to look for ways to make sustainable projects that promote education for all.
Promotion of international cooperation	Projects with international cooperation	**26.** I identify funding opportunities (national or international) for open education projects. **27.** I use culturally diverse educational materials (from different gender perspectives, in multiple languages and formats).
	Peer-to-peer networks (local, regional and global)	**28.** I operate international cooperation projects related to open education. **29.** I support inclusion actions in the international peer networking projects in which I participate. **30.** I value participating in networking activities to promote open education.

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