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PAPER

Proposal for an Adaptive Recommender System to Support Teaching Practices

German Cuaya-Simbro[1](✉), Jose A. Gonzalez[1], Elias Ruiz[1], Helena CI Alemán[2], Alexander Barinas[2]

[1]Ingeniería en Sistemas Computacionales, Tecnológico Nacional de México/ITS del Oriente del Estado de Hidalgo, Hidalgo, México

[2]Facultad de Ingeniería y Ciencias Básicas, Fundación Universitaria Juan de Castellanos Colombia, Tunja, Colombia

gcuaya@itesa.edu.mx

ABSTRACT

The shift to online learning, which has grown by 70% in recent years, has brought unprecedented challenges to the educational landscape. This emphasizes the urgent need for innovative solutions that address the evolving needs of both educators and students. This study introduces a novel adaptive recommender system for educators, which has demonstrated significant improvements in teaching effectiveness through personalized strategy recommendations. Preliminary findings reveal a notable increase in student engagement and comprehension, underscoring the system's potential to revolutionize educational practices.

KEYWORDS

web system, educators support, smart technology, machine learning, pilot application

1 INTRODUCTION

Recommender systems are widely applied in fields such as e-commerce, entertainment, social networks, online learning platforms, and emotional support for older adults, among others [1], [2], [3], [4].

Novel technological systems, including recommender systems, have gained popularity among education stakeholders [5] and have been successfully implemented in educational contexts. The rapid expansion of online learning, particularly during and after the COVID-19 pandemic, has posed challenges such as reduced student engagement and performance [6], [7]. A systematic review published in 2024 highlights that while online learning offers flexibility, it often leads to decreased student engagement and lower academic performance due to factors such as isolation and lack of interaction [8]. Additionally, a study reported in [9] emphasizes the need for effective learning strategies within organizations to adapt to advancements such as generative artificial intelligence (AI), noting that aligning training with business strategies remains a significant challenge.

Some of the important way in which recommender systems are used in the field include: content recommenders [10], [11], where suggest relevant learning

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materials to students, including books, articles, videos, interactive activities and other educational resources that fit their interests and level of knowledge, as mentioned in where also it is mentioned the benefits of e-learning for students, teachers, and businesses, and the research provides recommendations for its implementation; suggestions for the course and study program [10], [12], [13], where the authors show that the recommender systems help students select the courses and study programs that align with their educational and career goals, by analyzing the student's academic history, interests and abilities, and conclude that such systems hold promise for supplementing traditional academic advising; personalization and feedback of learning activities, for example, in [14] it shown that recommender systems suggest learning activities adapted to the needs and preferences of the student, in addition to being able to offer personalized feedback to students, and the authors highlighting their ability to tailor learning paths to individual strengths, weaknesses, and aspirations, while acknowledging the need to address challenges such as student motivation, bias, and the human touch; adaption of teaching strategies, as in [15] is explored how the use of advanced educational technologies, such as smart learning and online teaching, can positively influence students' motivation to study science, and the authors found a significant correlation between their use and students' perceptions of increased learning advantages and positive changes in the teaching and learning process.

Generally, recommender systems in the educational field are more focused on supporting students, providing suggestions and resources adapted to their characteristics. However, there are very few recommender systems focused on giving support to teachers, and even the latter [15] does not specifically report the use of recommender systems to support teachers. Among the works where the issues of recommender systems that support teaching work are addressed, the following is found: In [16], a systematic review mapping study is presented where the authors examined the target metrics and evaluation methods used in the existing educational recommender systems (ERS) research, with a particular focus on the pedagogical effect of recommendations, and they identified that there exists a gap in ERS research concerning assessing the pedagogical effect of recommendations at scale and in informal education settings. Additionally, [17] identifies how students and instructors perceive the impact of AI systems and recommender systems on the interaction between the student and the instructor in online learning. Finally, in [18], a systematic review, it is mentioned that ERS can contribute to the pedagogical practices of the instructors through recommendations that improve their planning and help in the filtering of educational resources. For example, a recommender system could suggest relevant and personalized educational resources for a particular topic, which could save teachers time and effort in finding and selecting materials. In addition, [15] shows the importance of ERS in solving teachers' problems, and a methodology to recommend personalized educational resources is proposed finally, [19] discusses the potential impact of AI tools on instructional design (ID) workflows and organizations, which can be extrapolated for applications in the educational field. The needs that will fit the characteristics of teachers, whether experienced or young, working in urban or rural areas, and teaching elementary or university-level students. As can be seen, these works only mention the use of recommender systems as support tools for teachers as a good perspective, but none of them present the development of such a system, so our contribution is the construction of a specific recommender system for use by teachers.

Finally, most of the jobs cited refer to static recommender systems, where recommendations are generated based on predefined rules; that is, the inference engine to make the recommendation is not updated in real-time, even though the information collected is. This means that the recommendations remain constant until the system is updated or the recommendation criteria are manually changed. Therefore, it is necessary to build dynamic recommender systems, which are more robust due to their real-time adaptability, better accuracy and relevance, and improved user experience, among others. This is relevant to the contributions of our research work.

Below, there are some examples of research works that have reported the construction and use of dynamic recommender systems in education, that is, systems based on adaptive AI. [20] developed a multilayer, graph-based recommender system that leverages collective intelligence within online learning communities to recommend pedagogical resources. By utilizing emerging semantic graphs and analyzing user interactions, the system addresses the challenge of information overload in collaborative e-learning environments, demonstrating improved performance in resource recommendations.

In [21] a systematic review is presented, which shows that adaptive AI allows recommender systems to adapt and improve over time as they collect and analyze user data, learning and adjusting. The recommendations are based on individual student preferences and behaviors. Previous works highlight how adaptive AI improves the performance of recommender systems. The approach is already being used for their construction, as discussed in [22], where a dynamic educational recommender system based on recurrent neural networks is proposed, the system combines MLP, BiLSTM, and LSTM to offer more accurate recommendations by considering both current and long-term interests of the user. The approach seeks to overcome the limitations of web-based educational systems and provide more effective recommendations.

From the previous literature, our research addresses a critical gap in educational technology by developing a dynamic recommender system specifically designed to support teachers. Unlike existing systems that focus on students, our system provides real-time, personalized recommendations to help teachers with lesson planning, resource curation, and adapting teaching strategies to diverse classroom contexts. This dynamic approach overcomes the limitations of static systems and fosters more effective and personalized teaching. By bridging this gap, our work has the potential to impact teaching practices and ID significantly.

2 MATERIALS AND METHODS

2.1 Recommender systems

A recommender system utilizes algorithms and techniques to provide personalized suggestions, assisting users in identifying and selecting items of interest. These systems produce useful and relevant recommendations by analyzing data, behavior patterns, and user preferences.

There are several types of recommender systems, including:

- *Content-based recommenders*: These systems use information about the items to recommend, such as characteristics or attributes, to find similarities between the items and the user's interest.
- *Collaborative recommenders*: These systems generate recommendations based on user behavior and preferences. Data from other users with similar interests

is examined to determine if there are similarities in consumption patterns or item ratings.
- *Hybrid recommenders*: These systems offer more accurate and comprehensive recommendations by combining various recommender approaches and techniques; they can combine context-based and collaborative approaches or incorporate methods such as demographic filtering or machine learning. Machine learning and demographic filtering are two techniques that allow the creation of more robust recommender systems. The first uses algorithms such as decision trees or neural networks to learn complex patterns and adjust as more information is collected from the user; the second uses demographic and socioeconomic data about users, such as age, gender, and geographic location, to provide personalized recommendations.

The recommender system developed in this study falls into the hybrid category, as it integrates machine learning with demographic filtering.

2.2 Machine learning

Machine learning is a branch of AI that focuses on creating models and algorithms that allow machines to automatically learn and improve from data without being explicitly programmed.

Some of the more common machine learning techniques used when building recommender systems are:

- *Nearest neighbors*: Identify patterns and generate recommendations. Lazy learning methods based on examples are used. When a new instance needs to be classified, it is compared with existing examples using a distance metric, and the class to the new instance is assigned using the closest examples.
- *Neural networks*: The way learning is done with a training stage of the model with a set of labeled data. At this stage, the weights and connections between neurons are iteratively adjusted to reduce the error between the actual training set labels and the predicted labels.

Other techniques have proven to be effective in certain scenarios where the characteristics of the data are relevant for classification, such as the application domain of the recommender system developed in this study. Thus, other machine learning techniques are included, which are considered to be appropriate for building the inference engine of the system:

- *Bayesian networks*: this technique finds the relevant variables of the modeled phenomenon and establishes dependency relationships between them. Using a data set of training to estimate the conditional probabilities of the variables after building the Bayesian network.
- *Support vector machines (SVM)*: These algorithms perform data classification using a supervised learning method. By using kernels to transform the data, they seek to create a hyperplane in a high-dimensional space that optimally separates samples belonging to different classes.
- *Decision trees*: These are supervised learning algorithms that perform data classification using a rule-based approach. They create a tree structure that shows a sequence of decisions based on the characteristics of the data set.

- *Bagging*: Also known as bootstrap bundling, it's a type of assembling technique that combines several classification models to improve the accuracy and stability of predictions. A specific classification, such as decision trees, SVM, or K-NN, is used to create an independent classification model for each generated bootstrap sample. Each model is trained on the appropriate bootstrap sample, and various patterns and relationships are recorded in the data.

2.3 Means of classifier evaluation

The following are the most common benchmark measures for evaluating the performance of a machine learning algorithm or technique, as well as how well it is generalizing to new data:

- *Accuracy*: This is the most common measure that shows the proportion of instances classified correctly out of the total number of instances.
- *Precision*: It indicates the proportion of instances classified as positive that are actually positive. It is also known as positive predictive value.
- *Sensitivity (Recall or True Positive Rate)*: It measures the proportion of positive instances that are correctly classified. It is also known as the true positive rate.
- *F value (F1-score)*: It is a measure that combines sensitivity and precision in a single value. It is calculated as the harmonic mean of the sensitivity and precision and provides a balanced assessment of model performance.

2.4 Development environment

Python is a general, high-level programming language that has an easy-to-understand syntax. Python's extensive standard library is one of its main advantages, as it offers a wide range of functionality and modules for a variety of tasks, such as file manipulation, database access, web development, data analysis, machine learning, and much more. Python has a large number of third-party libraries in addition to the standard library, further extending its capabilities and functionality. The ones used in this study are:

- *Flask*: This library is used to create web applications. It offers a variety of tools and features for managing HTTP requests, URL routing, template rendering, session and cookie handling, among other things. Furthermore, Flask is very customizable and easily integrates with other Python libraries and tools.
- *Flask-Bootstrap*: An extension of Flask, Bootstrap is a set of tools and predefined CSS styles that allow fast and responsive web interface design.
- *Pandas*: It is widely used for data analysis and manipulation. Its high-performance data structures, such as Data Frames and Series, allow efficient manipulation of tabular and time-series data.
- *Scikit-learn (sklearn)*: Sci-kit is a machine learning library that contains a wide range of algorithms and tools for performing tasks such as classification, regression, clustering, dimensionality reduction, feature selection, and others. It also includes features for model evaluation, hyperparameter selection, cross-validation, and other machine learning model evaluation and optimization techniques.

2.5 Construction of the recommender system

The process of building a recommendation system generally consists of the following steps:

1. *Define the objective and scope of the recommendation system*: We recommend teaching-learning tools or strategies to higher education teachers. An example of this can be tools, such as the use of a particular simulator for experimentation with electronic devices, strategy teaching-learning, and the use of a comparison chart to show students the differences between microprocessors and microcontrollers.
2. *Collect and prepare the data*: As already mentioned, one of the contributions of the work is the database, which captures the experience of higher education teachers on the efficiency of the use of a teaching-learning tool or strategy. To define the information to be part of the database, a work meeting was held with researchers in the educational area who are experts in issues related to the foundation of education, which includes knowledge about learning theories, pedagogical approaches, educational, psychology, and sociology of education. It was agreed to collect the data shown in Table 1.

   To collect this information, two Google forms were built, one of them to collect the experiences of using the effectiveness of tools and teaching-learning strategies of teachers from a higher education institution in Colombia and another form for teachers in Mexico. A total of 92 records were obtained, 31 from teachers in Colombia and 61 from teachers in Mexico, it should be noted that the experiences recorded come from teachers from different areas of knowledge. Subsequently, a pre-processing of the data was carried out, which mainly consisted of changing the data captured as strings to an integer type, for which the process shown in Figure 1 was followed.

Table 1. The data in the database captures teachers' experiences with the efficiency of using teaching-learning tools or strategies

Data to Capture the Effectiveness of Using a Strategy	Data to Capture the Effectiveness of the Use of a Digital Tool
Academic program, subject, number of students, number of men, number of women, semester, modality	
Type of strategy most used, interactive learning strategy, collaborative learning strategy, self-learning strategy, didact strategy, competences to evaluate, evaluation strategy, general evaluation of the strategy	Competences to evaluate, digital tool used, tool license type, portfolio of functions of the tool, tool usability, tool design, tool documentation, tool updates, tool interaction, use of the tool, approval percentage (tool)

Note: The data shared by both columns is common for both recommendations, tools, or strategies.

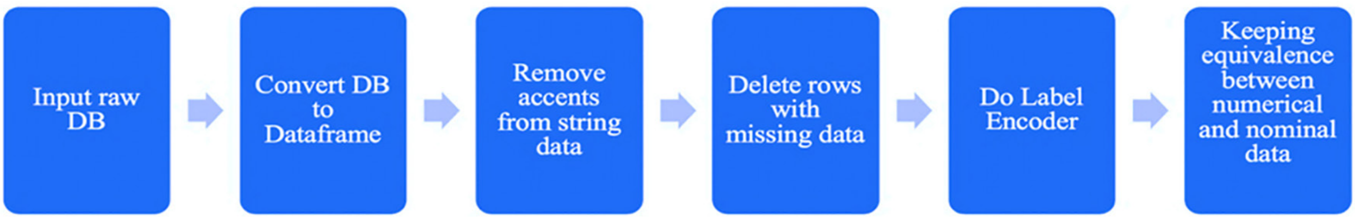

Fig. 1. Process to change the representation of the captured information

3. *Select the recommendation technique*: As already mentioned, machine learning was chosen as the recommendation technique. The algorithms implemented,

and part of the inference engine, are Naïve Bayes, bagging, KNeighbors, random forest, SVM, and multilayer perceptron.

4. *Process of building and evaluating the recommender system*: As mentioned, another contribution of this study was to apply an adaptive AI approach to the construction of the recommender system; thus, the architecture shown in Figure 2 was proposed and implemented.

   As can be seen, for the construction of the recommendation system, each time it is there, it is called, the information captured by the teachers is read, and with it six classifiers are built, which are trained and evaluated by applying the validation technique. 10-fold cross validation, taking 90% of the data for training and 10% of the data for testing, subsequently the performance evaluation measures of each classifier are obtained, and a comparison is made, and using the value of the accuracy measure the best classifier is determined and chosen, which will be, for that call, the inference engine of the recommender system, and this is an interactive task, that is, this process is repeated each time the recommender system is called, which guarantees that the model continuously adjusts the parameters of the recommendation algorithm (inference engine), so that it can at all times learn patterns and relationships in data that are continually being updated and thus generate more accurate recommendations.

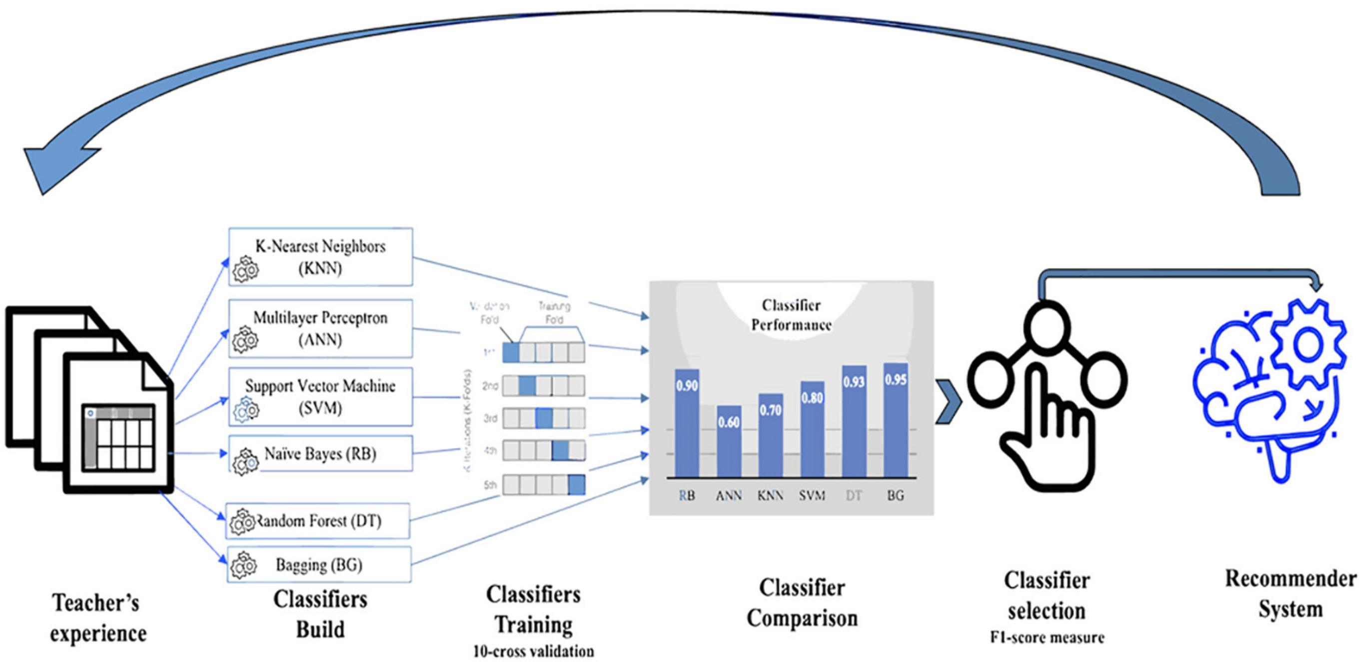

Fig. 2. Architecture of the construction of the inference engine based on adaptive artificial intelligence

3 RESULTS

3.1 Evaluate system performance

Using the 92 collected data points, six classifiers were developed, and the most effective one was selected as the inference engine for the recommendation system. This system operates across three modes: tool recommendations, strategy recommendations, and a general combined mode. The results obtained are presented in Table 2.

Table 2. Accuracy values of the classifiers

Classifier	Tool Recommendation System	Strategy Recommendation System	Tool and Strategy Recommendation System (general)
NaïveBayes	0.81	0.51	0.64
Bagging	0.94	0.84	0.86
KNeighbors	0.78	0.54	0.67
RandomForest	1.00	0.84	0.86
SVM	0.81	0.57	0.53
Multilayer Perceptron	1.00	0.73	0.78

As it can be seen, according to the type of recommendation to be obtained, the best classifiers are identified, and when making a comparison of different classification methods, it is ensured to select the one that best fits the data. It should be noted that, in the case of obtaining a tie in the accuracy measure, preference is given to the initial classifier constructed, in this case, random forest, to recommend a tool and bagging for the case of general and recommendation of a strategy. It is important to note that the results of system performance validation, i.e., evaluation of the system with new data, are not reported since it is necessary to start data capture, which is estimated to take at least 6 months, to have a new dataset and then deploy the recommender system so that teachers can use it before the beginning of a new semester, and finally, at the end of the semester, teachers report the effectiveness of the recommendations they received from the system.

The random forest classifier achieved the highest accuracy in recommending tools, demonstrating its ability to handle complex educational scenarios. This reliable performance can significantly benefit educators by providing timely and relevant recommendations and enhancing student engagement and outcomes. The strong performance of the bagging classifier highlights the effectiveness of ensemble methods in improving prediction accuracy. This encourages further exploration of ensemble techniques to refine future recommendations. Overall, these results indicate that the recommendation system can provide valuable support to educators. By fostering trust and providing personalized recommendations, the system can improve teaching practices and enhance student learning experiences. Additionally, the system's adaptability allows for continuous improvement as more data is collected and analyzed.

Since 10-fold cross-validation is a widely used technique to assess a model's performance without relying on additional statistical significance tests. This approach effectively reduces bias and variance, making it a robust and statistically sound method for evaluating model performance.

3.2 Implement and deploy the system

For the implementation of the recommendation and deployment system, Python and the following libraries were used: Flask, Flask Bootstrap, Pandas, and Learn. The recommender system is hosted on a computer with the following characteristics: Intel Core i9-12900K processor, 16GB DDR5 RAM, and 1TB solid-state drive.

The principal interfaces of the system are shown in Figure 3, and we can summarize the principal recommendations of the system as follows:

1. *Evaluation of the effectiveness of a digital tool, a teaching/learning strategy, or a combination of both (mode 1)*: If a teacher wants to know if a tool or strategy is recommended for teaching a subject, the system will give him a recommended or not recommended rating. For example, if a teacher wants to know if a teaching strategy, such as asking students to prepare a presentation on a topic, is adequate for the student to achieve the desired competence, the system will respond with a positive or negative evaluation, according to what has been learned from the experiences reported by other teachers.
2. *Give recommendations on which tools, strategies, or a combination of both can be used to teach (mode 2)*: In this case, if a teacher wants to obtain recommendations on which tools or strategies have been successful in teaching a topic, the system will provide a list of those that have been reported as successful by other teachers. For example, if a teacher does not know what kind of digital tools, such as the use of software to create concept maps, can be used so that the student can build a concept map of a large and complicated topic in an agile and simple way, the system will provide the teacher with a list of tools that other teachers have reported as useful for the generation of concept maps.

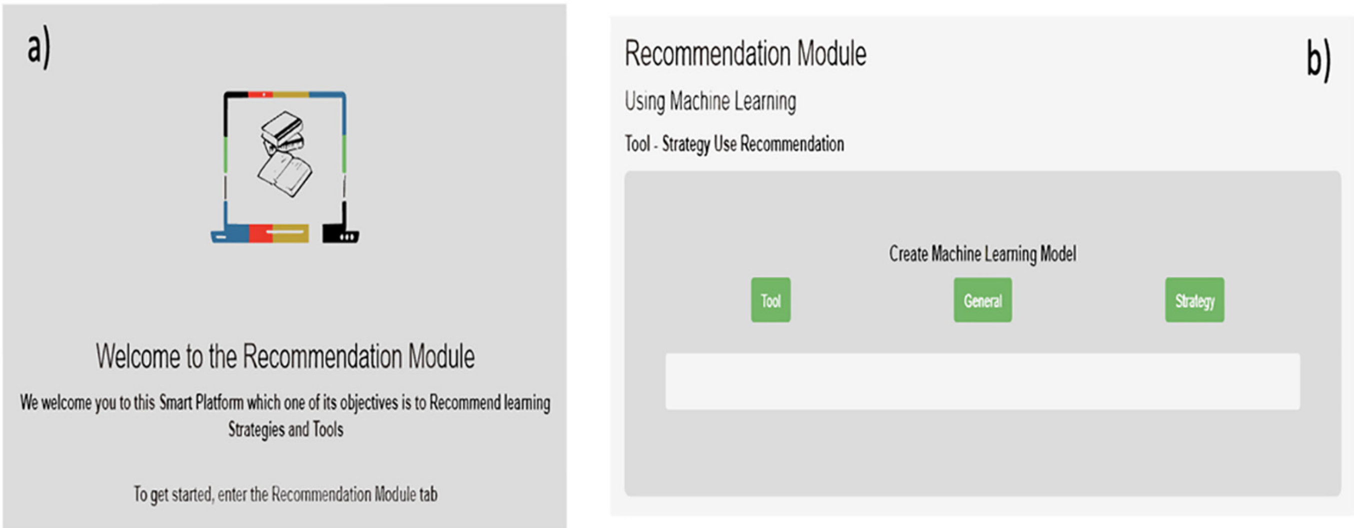

Fig. 3. a) Welcome screen, b) Selection screen of kind of recommender

Notes: Tool: A system of recommending tools suitable for teaching a specific topic is built, examples of tools: zoom, simulators, videos, etc., Strategy: A system of recommending teaching-learning strategies suitable for teaching a specific topic is built, example of strategies: use of concept maps written exams, exhibitions, etc., General: A recommendation system is built that provides both the strategy and the suggested tool to teach a specific topic, for example, strategy: written exam, tools: Socrative.

Next, a graphical example of the use of the general recommender system is presented and discussed to evaluate the effectiveness of a digital tool in conjunction with a teaching or learning strategy (see Figure 4) and to give recommendations on which tool and strategy to use to teach a topic (see Figure 5).

In the first example, we can see how the recommendation system works in mode 1. A teacher wants to know if a particular strategy and tool are suitable for teaching a specific topic. To do so, he/she enters detailed information about the situation, such as the semester, the class modality, the number of students (male and female), and the subject's characteristics. The system, based on an inference engine fed by the experiences reported by other teachers, automatically analyzes the teacher's proposal. In this way, it determines whether the combination of strategy and tool is effective for teaching the topic in question. In the example, a social work teacher asks whether it is appropriate to use a project-based strategy in conjunction with Google Forms to assess a project-related procedural competency. The system, in this case, indicates that this proposal is feasible.

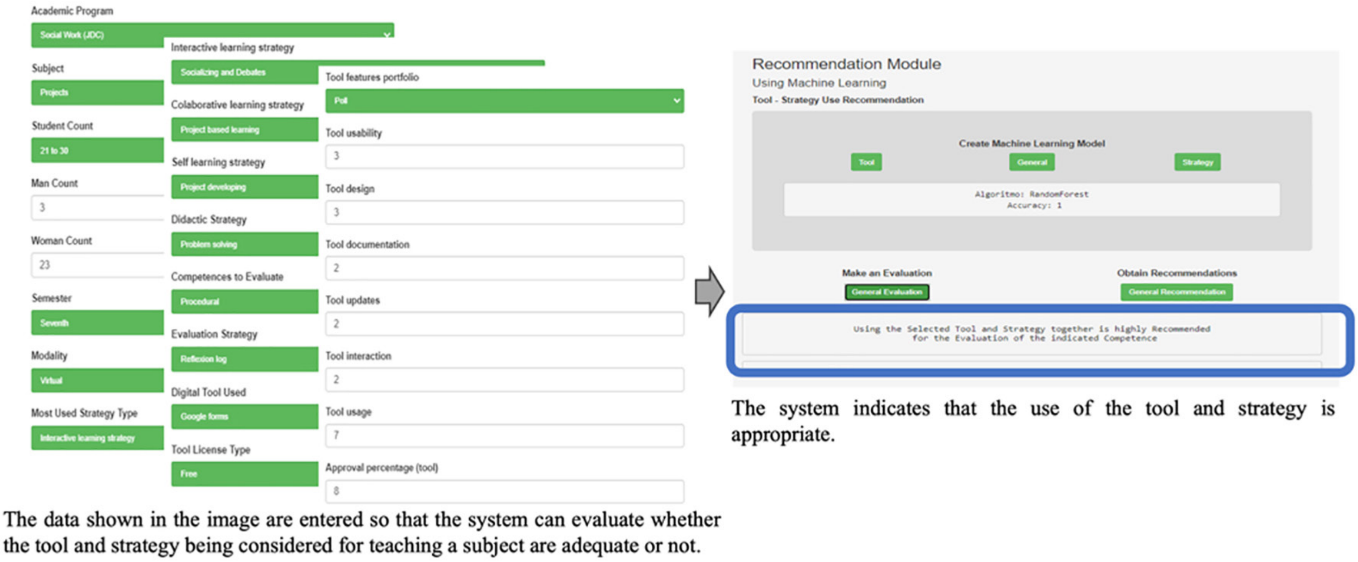

Fig. 4. Example of evaluation of the effectiveness of a digital tool in conjunction with a teaching/learning strategy to teach a topic

As can be seen, the system, based on the data captured, can give an evaluation of whether the use of a tool and strategy is recommended.

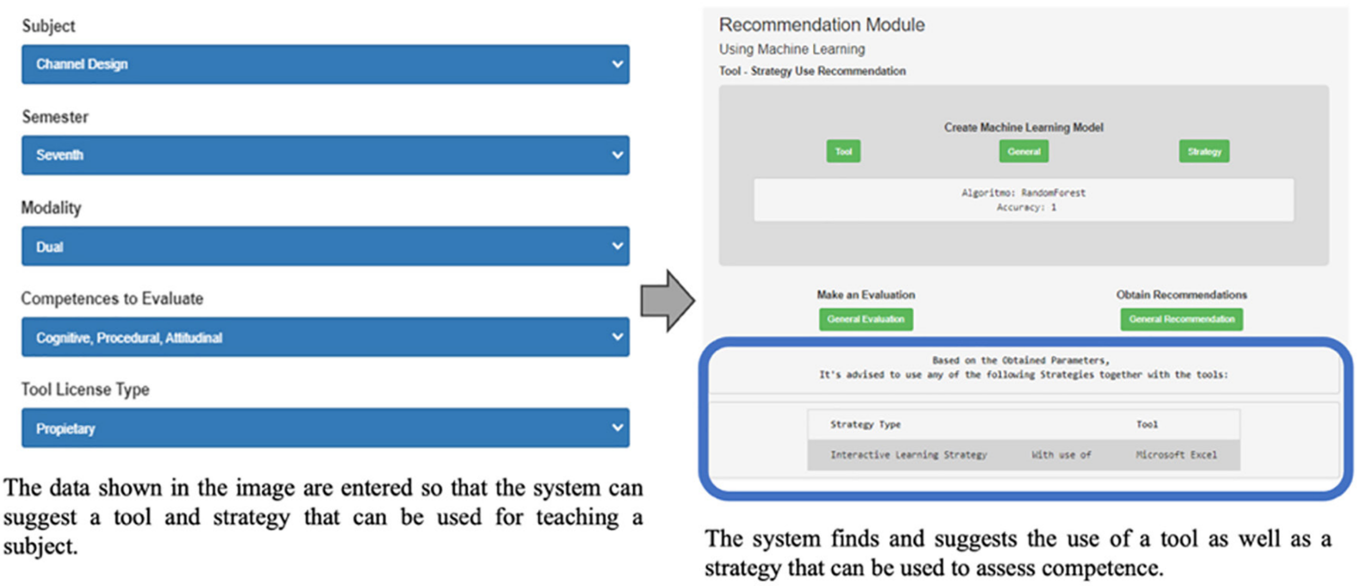

Fig. 5. Example of recommendation on which tools and strategies to be used to teach a topic

The second example illustrates how the system works in mode 2. Whereas in the previous example, the teacher sought to validate a specific proposal, in this case, the teacher is not clear on which strategy or tool to use. Instead of evaluating a proposal, the system suggests a combination of strategy and tools based on the information provided by the teacher. In the example, a teacher indicates that he/she wants to develop procedural competencies in his/her students in a channel design course (dual mode), and the system suggests the use of an interactive learning strategy in conjunction with a spreadsheet.

It is worth mentioning that the system is not able to always provide a suggestion on the use of any tool, strategy, or both, which is due to the fact that it does not have a robust database, which limits the performance of the engine. The gathering is so necessary to expand this database.

3.3 Preliminary assessment of the system

From September to November 2023, a pilot test of the system was conducted, obtaining the evaluation of the teachers on the effectiveness of the recommendation of the system for the use of a teaching-learning strategy to teach a topic of a subject of a computer system engineering course. 60 responses were obtained, and most of the teachers reported a high effectiveness of the strategies that were suggested and applied in their groups, as shown in Figure 5.

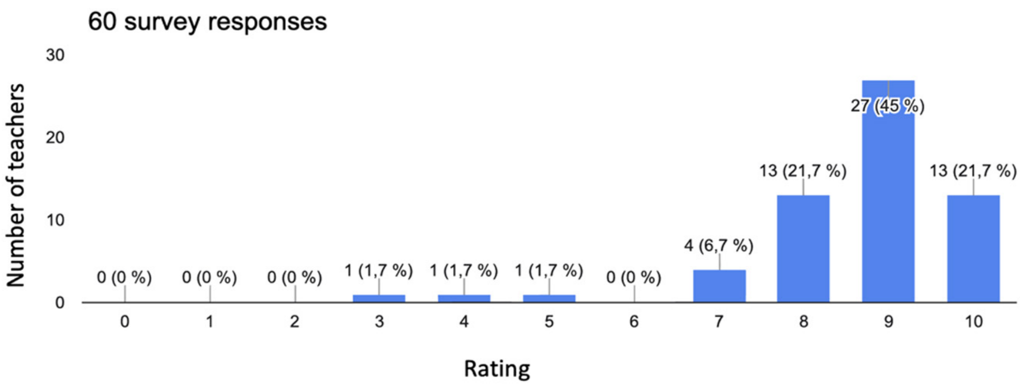

Fig. 6. Overall assessment of the strategy suggested by the system

The above data are corroborated when reviewing the percentage of approval of the group where the strategy suggested by the recommendation system was applied. As shown in Figure 6, more than 95% of the groups had more than 70% accreditation. This gives evidence of how the system can be used as a tool to support the teaching work automatically by suggesting strategies that are effective for the teaching of specific topics of some subjects which allows for improving the teaching work.

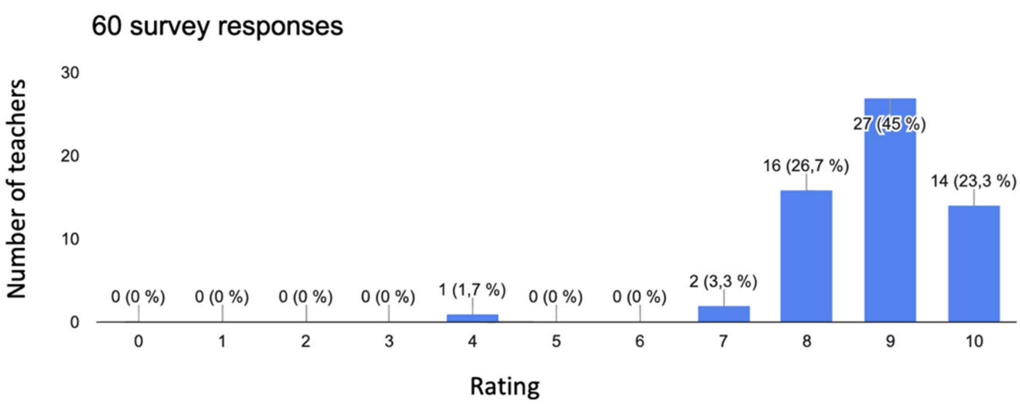

Fig. 7. Percentage of approval of the group where the teacher applied the teaching and learning strategy

Note: 0 = 0% and 10 = 100% of group approval.

It should be noted that these are preliminary results, and as future work is planned to continue collecting more data and then use and assess the system during the next school cycles, not only in the effectiveness of a teaching and learning strategy but also in the effectiveness of the use of a digital tool.

4 DISCUSSION

4.1 Limitations

A notable limitation of this study is the small sample size of 92 teacher experiences, which may be insufficient to generate adequate evaluations (mode 1) or provide suggestions for teaching strategies (mode 2)., i.e., this affects the reliability and generalizability of the results obtained; that is why we recognize the need to extend the sample size, incorporating information from other teachers from different institutions and countries, and subsequently corroborate the effectiveness of the system.

On the other hand, currently, we are developing a web page to capture new information to speed up the process of getting and storing new teachers' experiences; in this way, when a teacher makes use of the recommendation system automatically during the process of construction and identification of the best inference engine for the recommendation system, described in section 2.5, all the data (experiences) captured and stored in the system's database are used.

Another current limit is that to verify the effectiveness of our system using new data, it is necessary to invite new teachers to get their experiences using Google Forms, which takes approximately 6 months, and then to conduct a study with a new group of teachers who are using the system and reporting the results of the system's recommendations, which takes approximately one semester more.

However, we consider that the results obtained in this study constitute a starting point for the development of a more effective recommendation system focused on teachers' needs for the following reasons: i) this exploratory study has allowed us to identify initial trends and generate promising hypotheses about the effectiveness of the recommended strategies; ii) the detailed qualitative analysis of the responses has provided an in-depth understanding of teachers' experiences and challenges in implementing these strategies.

4.2 Practical implications

The results of the preliminary assessment of the recommender system have relevant implications for teaching practices and teaching strategies in institutions. In principle, the recommender system offers educators a personalized approach to selecting teaching strategies and tools that fit a specific subject matter and group characteristics. This customization can lead to more effective teaching outcomes, as seen in Figure 7, a percentage of approval after using the recommendation of the system since educators can leverage strategies that have been empirically validated by their peers. For example, if a teacher is having difficulty capturing students' attention on a complex topic, the system can recommend interactive tools or teaching methods that have been reported by other teachers to be effective in improving student comprehension in similar contexts. This not only saves educators time in the search for effective practices but also allows them to make informed decisions that can improve student engagement and learning outcomes.

Moreover, incorporating the use of such a system into educational institutions can foster a culture of collaboration and shared learning among educators. By enabling the capture of information on successful pedagogical strategies and tools, the system creates a repository of best practices that can be accessed by all educators in an institution. This collective knowledge base encourages teachers to share their experiences and insights, fostering professional development and continuous improvement of teaching methodologies, and educational institutions can organize workshops or training sessions based on the system's recommendations, increasing educators' skills and confidence in using innovative pedagogical strategies. The system's ability to adapt and update recommendations based on educators' experiences makes it a dynamic tool that can evolve along with educational practices. Institutions can take advantage of this adaptability to stay abreast of new teaching trends and technologies, ensuring that their educators have the most effective resources at their disposal.

Finally, the system's versatility could allow various educational applications, among which we can mention that it can tailor teaching strategies to diverse cultural backgrounds in multicultural classrooms, provide cost-effective STEM resources for rural schools, and offer differentiated instruction for students with special needs. Additionally, it can support professional development initiatives by recommending evidence-based practices. These features collectively demonstrate the system's potential to enhance educational equity and improve learning outcomes for a diversity of students.

4.3 Scope and generalizability

The recommendation system, initially designed for higher education in Latin American institutions, can be adapted to other educational levels and contexts. To achieve this, we propose to create customized data collection instruments for each level and context, capturing information similar to the current one (teaching experience) but adjusted to the particularities of each environment. This involves collaborating with subject matter experts to obtain relevant information on teaching methodologies that align with each discipline's curriculum and learning objectives, whether STEM, humanities, or vocational education. In addition, it is crucial to consider international competencies (such as ABET) to ensure the overall relevance of the recommendations and facilitate the inclusion of diverse pedagogical strategies.

On the other hand, it would be necessary to have a different way to collect teachers' experience; our proposal is to use a web page, and the recommender system must be redesigned to be modular and thus allow segmenting of the recommendations according to the specific needs of each level and context. In addition, taking advantage of the system's adaptive approach, the students' developmental stages can be taken into account, ensuring that the recommendations are age-appropriate and pedagogically correct for primary, secondary, or higher education contexts.

It should be noted that when adapting the system to different educational environments and contexts, it is also essential to consider cultural factors that influence learning, such as educational values, teaching practices, communication styles, and socioeconomic contexts. In this way, and with continuous evaluation mechanisms, the recommendation system can become a versatile tool that responds to the needs of educators in different contexts and educational levels, promoting more effective and equitable pedagogical practices globally.

4.4 Ethical considerations

The use of AI-based systems, such as our proposal system, to influence teaching strategies can present several ethical issues; for such reasons, one must be careful in the use of the same, and we vehemently encourage improving the culture and education on the use of these types of tools, among the possible problems we can mention: (i) These systems can perpetuate biases present in their training data, (ii) Transparency and accountability are crucial, as educators need to understand how recommendations are generated, (iii) Privacy and data security must be prioritized to protect sensitive information, which could deter educators from fully engaging with the technology (iv) Informed consent is essential to ensure that stakeholders understand the implications of AI use, (v) Over-reliance on AI may reduce the role of educators, limiting their agency and potentially restricting the agency of students, and (vi) Careful consideration must be given to the long-term consequences, including the impact on educational practices and student-teacher relationships.

From the above, we consider that in the educational environment, the ethical considerations where the greatest care should be taken are:

- Biases inherent in training data can lead to skewed recommendations, potentially favoring specific demographics or contexts. For example, a system trained primarily on urban school data may overlook effective strategies for rural or under-resourced settings. To mitigate this, diverse and representative data collection is essential, as we mentioned. Actively seeking input from educators across various regions and disciplines can create a more inclusive dataset.
- Transparency regarding the system's algorithms and data sources is crucial. By understanding the rationale behind recommendations, educators can critically evaluate and adapt them to their specific needs, fostering trust and informed decision-making.

4.5 Challenge to adoption

In order to achieve the adoption of this type of system by educators, several potential challenges must be addressed that could hinder its effectiveness and integration into educational practices, among which we can mention: i) Resistance to change by educators, who are accustomed to traditional teaching methods and skeptical about relying on technology to support teaching. This resistance may be due to concerns about the accuracy and reliability of the recommendations provided by the system, as well as fear of losing free professorship. ii) Implementation of the system requires adequate training and professional development for educators to effectively use the system and interpret its recommendations. Without adequate support, teachers may find it difficult to integrate the system into their current workflows, leading to frustration within them. iii) Ensuring that the system remains relevant in diverse educational contexts and adaptable to various teaching strategies is an ongoing challenge, as it requires continuous updates and improvements based on user feedback and evolving educational standards.

4.6 System comparison with related works

As we mentioned, significant advances have been made in the development of recommender systems focused primarily on student support, and this study is distinguished by specifically addressing the needs of educators, an area relatively underexplored in the existing literature.

Studies, such as [11] and [22], focus primarily on recommender systems that help students select courses or learning materials. Research was conducted in countries such as the United States and the United Kingdom and has demonstrated the effectiveness of content recommenders in improving student engagement and learning outcomes. However, our work departs from that trend by proposing a system tailored to educators, thus filling a gap in the literature. The emphasis on teacher support is especially relevant in contexts where educators face increasing demands to adapt their teaching strategies to the diverse needs of learners.

On the other hand, the methodology employed in this study, which involves the collection of educator data (experiences) to feed into machine learning algorithms, aligns with similar approaches adopted in other research. For example, other studies have used teacher feedback to refine educational technologies. However, this study goes a step further by developing a dual-mode system that recommends strategies and evaluates their effectiveness, providing a comprehensive tool for educators. This is why we believe that our approach could serve as a model for future research and development in other educational contexts. By focusing on the specific needs of educators and addressing the challenges they face, this study offers a valuable perspective that can inform future developments in this field and ultimately improve teaching and learning in diverse educational systems [2].

Finally, other systems may employ similar algorithms, such as random forest or bagging, and emphasize aligning recommendations with international competencies. This approach not only improves the relevance of the recommendations but also facilitates the inclusion of diverse teaching strategies, making it a pioneering effort in the field of educational technology [20].

Our study fills a crucial gap in the literature by focusing on the specific needs of educators rather than solely on student support. Unlike previous studies, our dual-mode system not only recommends teaching strategies but also assesses their effectiveness, providing actionable insights for improved teaching practices. By utilizing machine learning algorithms, our system offers dynamic, data-driven support, addressing a significant void in teacher-focused educational technologies.

5 CONCLUSION

This study contributes to the educational field by identifying the critical need for tailored support systems for educators and developing a novel framework that leverages machine learning algorithms to provide personalized recommendations for teaching strategies and tools.

This study highlights the importance of equipping teachers with adaptable resources that improve their pedagogical practices and educational outcomes. The results show that the proposed system allows educators to evaluate the effectiveness of various teaching strategies while receiving personalized suggestions that are tailored to their specific needs and contexts.

In addition, the study underscores the importance of using educators' experiences in developing the recommender system, ensuring that recommendations are based on practical, real-world applications. This approach improves the relevance of recommendations and fosters a sense of ownership and trust among educators, which is crucial for system adoption.

We believe this study lays the groundwork for future advances in teacher-centered recommender systems, paving the way for more effective integration of technology into educational practices. By addressing the multiple challenges faced by educators and providing a viable and adaptable solution, this study contributes to the continued evolution of educational technology, with the goal of improving the quality of teaching and learning in diverse educational settings.

In future work, we aim to enhance the recommender system's usability and functionality by addressing current limitations and expanding its scope to better support educators. This includes collaborating with diverse educational institutions in urban, rural, and international settings to enrich the dataset with a broader range of teaching experiences and disciplines, integrating international competencies into the data collection instrument, and improving data gathering through a web interface. Additionally, we plan to incorporate user feedback mechanisms to refine the system iteratively and improve the accuracy of recommendations. By exploring advanced machine learning techniques, such as deep learning, we aim to analyze complex patterns in educator data and adapt to evolving educational practices. These efforts will contribute to the development of a robust, adaptable, and user-centered recommender system that effectively enhances teaching methodologies across diverse educational contexts.

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8 AUTHORS

German Cuaya-Simbro is with the Ingeniería en Sistemas Computacionales, Tecnológico Nacional de México/ITS del Oriente del Estado de Hidalgo, Hidalgo, México (E-mail: gcuaya@itesa.edu.mx).

Jose A. Gonzalez is with the Ingeniería en Sistemas Computacionales, Tecnológico Nacional de México/ITS del Oriente del Estado de Hidalgo, Hidalgo, México.

Elias Ruiz is with the Ingeniería en Sistemas Computacionales, Tecnológico Nacional de México/ITS del Oriente del Estado de Hidalgo, Hidalgo, México.

Helena CI Alemán is with the Facultad de Ingeniería y Ciencias Básicas, Fundación Universitaria Juan de Castellanos Colombia, Tunja, Colombia.

Alexander Barinas is with the Facultad de Ingeniería y Ciencias Básicas, Fundación Universitaria Juan de Castellanos Colombia, Tunja, Colombia.