

Retraction

Retracted: Personalized Education Based on Hybrid Intelligent Recommendation System

Journal of Mathematics

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] F. Zheng, "Personalized Education Based on Hybrid Intelligent Recommendation System," *Journal of Mathematics*, vol. 2022, Article ID 1313711, 9 pages, 2022.

Research Article

Personalized Education Based on Hybrid Intelligent Recommendation System

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Differentiated pedagogy is a flexible and organized adaptation of teaching and learning as it argues that students, even those of the same age, have differences in learning readiness, interests, learning style, experiences, and living circumstances. These differences are important in the determination of requirements of their learning and the way of effective learning. In addition, the foundation for effective learning is the sense of community within the classroom, the authentic learning opportunities of using educational equipment, and the connection of the lesson with the experiences and interests of the students. In essence, the support of a teacher guides the pupils to learn to work on their own during a declining guidance policy, to improve their abilities and skills. Thus, the teachers are asked to modify their teaching methods instead of applying a similar way of teaching for all students. The modified teaching style should meet the different levels of readiness of students, the different ways they learn, and their different interests. In support of this specific task for teachers, the current work presents a personalized education system based on hybrid intelligent recommendations. Specifically, a hybrid framework of artificial intelligence is proposed, which focuses on the way to provide targeted recommendations for the implementation of integrated standard lesson plans, which will be the main tool for creating flexible differentiated pedagogical programs that will perfectly meet the personal needs and particularities of each student.

1. Introduction

Differentiated pedagogy is the adaptation of teaching so that teachers respond to the different needs of students in mixed ability classes considering the differences of students in terms of their interests, their learning style, and their degree of readiness. Each student is treated as a unique entity. Opportunities are offered to demonstrate his/her skills in order to recognize his/her strengths. The choice of a teacher, regarding the form of differentiation, depends on the students that he addresses. In other words, it depends on the context he is dealing with, each time [1]. In addition, the differentiation of teaching is not a recipe to be applied but a method that treats students as biographies and meets the needs of each student. The teacher modifies his teaching method as well as the learning activities to maximize the learning opportunities in the classroom.

Differentiated pedagogy focuses on learning processes, i.e., the way children learn, but does not focus on the

results. The teacher aims to form a flexible framework where each student follows his learning path, which provides him with a margin of autonomy, while the goal is common to all [2]. Students are active in the learning process and participate in any way they can, which boosts their self-confidence. They work in groups where everyone contributes according to their levels and interests. However, the fact of permitting the mistakes without punishment provides the students an acceptable feeling which leads them to try new things. At the same time, the teacher who differentiates his teaching utilizes the experiences and interests of the students, encourages them to work independently, but all together enhances the interactions between them. He believes in the potential of all the students and the right to difference. Also, he acts as a facilitator and mediator in the classroom. Similarly, the students in such situations feel that the teacher trusts them, is permissive in their choices and mistakes, and finds motivation and interest in learning [2].

The teacher should also consider the sources of the heterogeneity of his class, i.e., the socio-economic level and cultural background of the parents and the attitude of the children toward the school. In addition, the teacher attempts to create good and strong relationships with his students. He also makes efforts to treat them as individuals and not only as students. He should also be aware that the need of students beyond the learning part is transferred to their emotional need for social interaction and the development of real relationships both with him and with each other. Finally, it is necessary to provide opportunities for meaningful dialogue and discussion. It is also important to strive to develop the feelings of belonging to a group that is governed by meritocracy and transparency [3]. Moreover, the essence is to emphasize that learning to plan as a methodology lets teachers to make decisions with more details such as the process of designing the sequences of learning and teaching activities that are pedagogically oriented and making appropriate use of the respective educational resources and available technologies. Supporting teachers in their role as learning planners is an issue of the research community that has developed around the field as it has been recognized as the key to success and improving the quality of the educational process [4]. In this way, differentiated pedagogy can be the founding stone of knowledge, maximizing motivation mechanisms for the development of individual skills and interests, the promotion of self-action and initiative, the comprehensive development of the individual, and the strengthening of cooperation and social learning. In differentiated teaching, the student tests ideas in practice, sees the correlation between the parts and the whole, and correlates the studied subject with his experiences and other subjects, while he is allowed to participate in the process to experience the joy of desire and learning [5]. Teachers, in such a process, ensure that each student, as he develops, competes with himself and not with his classmates while carrying out continuous evaluation and updating of the educational process. Also, students find the school interesting when it meets their learning ambitions. It is important to mention the fact that, in the context of differentiated pedagogy, the need to recognize the different cultures of students and the provision for its promotion and equal treatment of children from different cultural backgrounds is imperative [6].

In recent decades, differentiated pedagogy has been repeatedly promoted in the relevant research literature. Besides this, it also guides teaching approaches and practices published in the framework of international or national organizations and institutions. In contrast, technology-based approaches that incorporate new methods in the context of diversified pedagogy implementations are minimal in the international literature.

The next section reviews the related literature. In Section 3, the proposed systems are comprehensively explained in stepwise manner. The experimental evaluation is carried out in Section 4. Section 5 presents the discussion, and Section 6 concludes the study.

2. Related Literature

A typical example of the implementation of pedagogical strategies that are adapted to the real individual skills of students is the adaptive educational systems (AES) that adapt their teaching content to the educational needs and skills of students. Demertzi et al. [7] proposed a new adaptive educational e-learning system (AEELS) that can collect and analyze data from learning repositories and adapt it to the curriculum according to students' skills and experience. It is a new hybrid machine learning system that combines a semi-supervised classification method for matching educational ontologies and a recommendation mechanism that uses a hybrid method of content-based filtering techniques to provide a personalized learning environment for each student. Urdaneta-Ponte et al. [3] in 2021 conducted a systematic review of academic research on recommendation systems that support educational practices to learn more about the types of education and areas addressed, the developmental approach used, and the elements recommended, as well as identifying any gaps in the field for future research. The review included 98 articles, of which it was determined that the majority are geared toward recommending educational resources for users of formal education, with the collaborative approach, content-based approach, and hybrid approach the most common approaches used in recommendation systems, emphasizing the utilization of machine learning in the last two years. Bourkoku et al. [8] proposed a tailored E-learning system based on Felder and Solomon's psychological model and appropriate collaborative filtering algorithms. They wanted to create an adaptive curriculum that used appropriate learning scenarios to meet each learner's unique needs. They used the idea of making predictions about a learner's preferences or tastes based on the preferences of a group of similar learners.

The system suggests the initial learning technique after determining the learning style using a questionnaire. This occurs when there is a dearth of information about the learners and their preferences, making it unable to offer appropriate recommendations. Gulzar et al. [9] demonstrated a recommendation system that proposes and leads a learner in choosing the appropriate courses for their needs. The goal of this research is to build and construct a hybrid recommender system that can be incorporated to improve the effectiveness of any E-learning system, make the material more accessible, and give learners more personalized experiences.

To obtain important information and produce correct suggestions, the hybrid technique was combined with ontology. Learners may benefit from such an approach if they want to improve their performance and happiness. The outcomes of this study's experiments suggest that using RS to select courses works well. Bourkoku and Bachari [10] described LearnFitII, an adaptive learning system that can automatically adjust to learners' changing preferences. The goal of this project is to propose a personalized framework that uses a hybrid-based recommendation strategy to provide suitable recommendations and to cope with the cold-

start problem, which occurs when there is a lack of knowledge about a new learner. Through testing the psychological model of learners and mining their server logs, the system recognizes different patterns of learning style and habits. Using the Felder and Silverman model, the device first provided a personalized learning scenario to address the cold-start problem, and then it mined information about learners' activities and interactions to assess the habits and preferences of the learners.

Finally, using a hybrid recommender system based on k-nearest neighbors and association rule mining methods, the learning scenario is examined and revised. The system's findings in real-world settings show that considering the learner's preferences improves learning quality and satisfies the learner. Bhaskaran et al. [11] developed a split and conquer strategy-based clustering to create an intelligent recommender that can adjust to the learners' needs, interests, and levels of expertise automatically. The recommender automatically examines and learns the styles and characteristics of learners. The split and conquer strategy-based clustering is used to process the various learning styles. To extract the learners' functional patterns, the proposed cluster-based linear pattern mining approach is used. The system then makes intelligent recommendations based on the ratings of frequently occurring sequences.

Experiments were carried out on various groups of learners and datasets, and the proposed model recommended essential learning activities to learners based on their learning style, interest classification, and talent characteristics. When compared to learners in the no-recommender cluster category, it was discovered that the suggested cluster-based recommender enhances recommendation performance by resulting in more lessons completed. Based on the gap identified in the ways of implementing integrated standard lesson plans, this article proposes an advanced hybrid artificial intelligence system that optimizes the learning development processes for the implementation of differentiated pedagogical programs. It is a hybrid mechanism of artificial intelligence that focuses on how to provide targeted recommendations for the implementation of integrated standard lesson plans, which will be the main tool for creating flexible diversified pedagogical programs that will best meet the personal needs and particularities of each student.

3. Proposed System

The proposed system recommends to the teacher integrated lesson plans in the form of templates, in the sense that he/she can use a template to intervene in it to create his lesson plan, which will fully meet his abilities, considering the individual needs and learning abilities of each student [3]. The operation of the proposed system, which is based on interaction, is initialized by the completion by the teacher of an indicative preferences questionnaire, which includes relevant data based on thematic, pedagogical method, subject area, level, evaluation model, mode of distribution, and duration. The specific criteria, as it has been proven in the literature, are identified as the most important features that document

the learning systems and judge the appropriateness of their reuse framework. The proposed architecture optimally combines multiple technologies in an innovative hybrid system, which is presented step by step below:

Step 1. To determine whether the topic area of a lesson plan is relevant to the topic set by the teacher, lexical analysis is performed based on the keywords related to the topic area in question. For this reason, intelligent natural language processing techniques are used [7]. A key feature of complexity in the process of converting words into concepts is related to the required rearrangements of the words in the original sentence to create the conceptual expression. The process to determine the keywords_matching parameter first involves extracting the entries to create a list (L_{FOL}).

The sentence is analyzed, and considering only words that have an entry are included in the first list, a second list (L_{NL}) is created, which contains the words in the order that they appear in the sentence.

Also, duplicates of a predicate are removed, and only its first occurrence is considered. The predicates from the L_{FOL} list, which were not found in the sentence, are deleted, ensuring that there is the same number of discrete elements in both lists. For each word in the L_{FOL} , its difference from the order in which it appears in the L_{NL} list is calculated. If a word is in position n_1 in the L_{FOL} list and position n_2 in the L_{NL} , then the position difference is defined as $|n_1 - n_2|$. Keywords_matching is the sum of the absolute values of the position differences of all words [12, 13]:

$$\text{Keywords_Matching} = \sum_{i=1}^n |\text{pos}_1(x_i) - \text{pos}_2(x_i)|, \quad (1)$$

where n is the number of words in the lists and $\text{pos}_1(x_i)$ and $\text{pos}_2(x_i)$ are the functions that return positions n_1 and n_2 of element x in the L_{FOL} and L_{NL} lists, respectively.

Step 2. The evaluation model and the way of distribution for each lesson plan is automatically inferred from the proposed system, which, considering the differentiated pedagogy requested, identifies all the lesson plans that implement the specific pedagogy based on an evaluation measure. The indirect feedback model that uses Jeffrey's adaptation rule is used to find the likelihood that a lesson plan is relevant from the data gathered from the teacher's interactions [14]. This method takes into account the uncertainty of the indirect indications of interest and uses various measures to describe the value or value of the elements of a representation. Jeffrey's model presupposes the existence of a relativity path in a set of mutually exclusive terms in the information space. This relativity path is considered as a new source of information for updating a new possibility.

The following function is used to update the odds based on this new data [14–16]:

$$P'(t) = \left[P(t=1|p_t) \frac{P(t=1)}{P(t=1)} + P(t=0|p_t) \frac{P'(t=0)}{P(t=0)} \right] \cdot P(t). \quad (2)$$

The probability of relativity of a lesson plan along the entire length N of the path is denoted P_N and is given by the function [17, 18]:

$$P_N(t) = \sum_{i=1}^{N-1} c_i \cdot I_i \cdot \left[(P_i(t=1)p_i) \frac{P_{i+1}(t=1)}{P_i(t=1)} + P_i(t=0|p_i) \frac{P_{i+1}(t=0)}{P_i(t=0)} \right] \cdot P_i(t), \quad (3)$$

where a representation in step i on path p is denoted as p_i . Trust in the value of the representation is denoted by c_i , and I_i is the informative value of the representation. Once the odds are updated, they remain constant until the next revision (i.e., the next route of interest).

Step 3. Next, the proposed system identifies groups of similar lesson plans in the sense of similarity in the sequence of activities they include. Specifically, the nearest neighbor algorithm is used to calculate the similarity and produces an estimate considering the weighted average of all ratings [11, 12]. The most numerous groups created in this way reveal the tendency of teachers to implement the specific pedagogy with the specific sequences of learning activities. In each of the more populous groups, the proposed system attempts to identify the lesson plan that satisfies most of the preferences stated by the teacher in the original preferences

form and at the same time the one that has gathered the highest preference from the educational community.

Step 4. The lesson plans that are identified are recommended to the teacher. Each proposal is accompanied by comments explaining the rationale behind why it is proposed as relevant studies demonstrate that providing explanations of the recommendations provided can improve the user experience with these systems. The teacher can evaluate the recommendations made to him using a simple voting system [19]. The evaluations made by the teacher influence future recommendations. More specifically, lesson plans that have been rated with fewer votes, as well as the like, are excluded from future lists of recommendations. This recommendation approach takes into account the teacher's interaction process to recommend a range of interactions.

The procedure in question is defined as follows [9, 19, 20]:

$$is(n, N_{S'}) = \sum_{n_i \in N_{S'}} \left(\begin{array}{c} (lr'(n_i) \cdot \xi^{l-1} \cdot w) \\ \exists p = n_i \rightarrow n_j \rightarrow n \\ w \in \{n_j, n, w\}, l \end{array} \right) = l_{\text{length}}(p), \quad l < L_{\text{MAX}}, \quad (4)$$

where p is the path between each node n_i and node n , considering the directionality of their connection. N is the path length, having a distance that is less than a maximum length L_{MAX} . Finally, ξ is a length reduction factor, the value of which is determined experimentally. A diagrammatic overview of the above process under flow chart type is presented in Figure 1.

4. Experiments and Evaluation

To investigate the proposed method, an electronic invitation was sent for voluntary participation with the questionnaire methodology, with the final participation of 487 teachers. The Likert 5-point grading method [21] was used ((i) I do not agree at all, (ii) I agree slightly, (iii) I agree moderately, (iv) I strongly agree, and (v) I strongly agree).

As already mentioned, the questionnaire included 10 questions with relevant data based on the topics, the pedagogical method, the topic area, the level, the

evaluation model, the method of distribution, and the duration. An indicative statistical analysis of the responses that made up the data set used is presented in Table 1.

The recommendation mechanism implemented for the establishment of lesson plans considering the collection of indirect feedback from the relevant questionnaire was implemented with weights that compose the teacher's answers so that everyone's profile is updated by taking new features thus making the profiles dynamic for reflecting changes in behavior and preference that may be required. Specifically, the information provided by the teacher about his personal preferences is implemented by assigning fixed weighted gradient values so that $W_0 > 0$, $W_A > 0$ for all connections, respectively. Let a_{p_i} also be the level of preference given by the teacher to the term P_i (e.g., it could be 0 or 1, or it could take values from a finite set). Then, the initialization of the weight values is performed in the links [21, 22]:

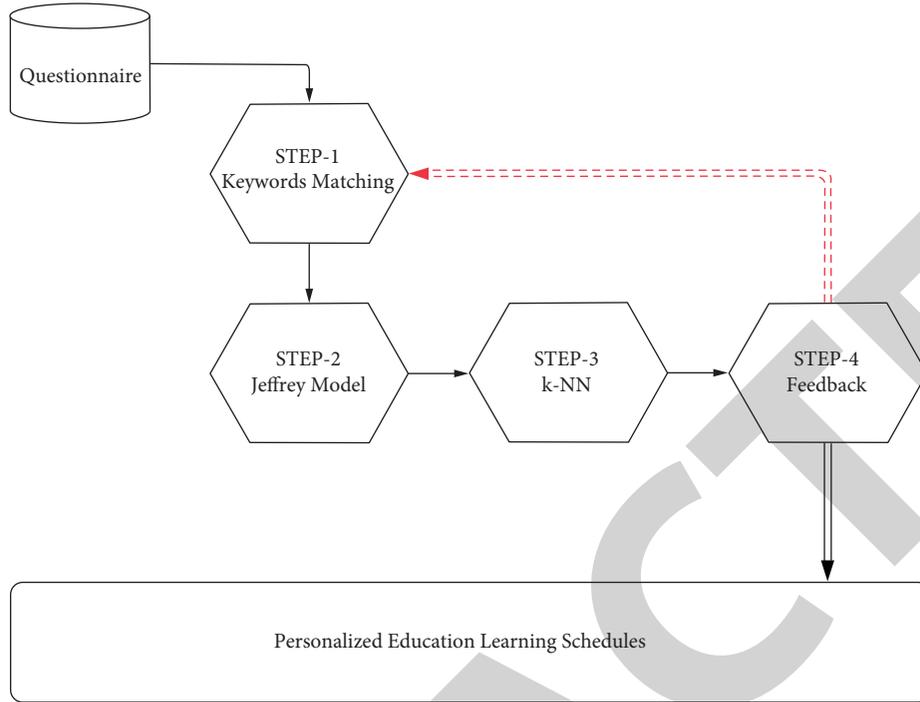


FIGURE 1: The proposed system.

TABLE 1: Statistical analysis of the data set used.

| | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Avg | 49,98 | 40,73 | 24,69 | 35,32 | 40,30 | 55,55 | 36,87 | 40,96 | 35,86 | 45,98 |
| Std | 1,06 | 0,73 | 0,38 | 0,90 | 1,03 | 1,21 | 0,92 | 1,05 | 0,89 | 0,88 |
| Med | 48 | 40 | 25 | 36 | 40 | 56 | 38 | 40 | 37 | 47 |
| PrevPr | 37 | 22 | 35 | 68 | 35 | 79 | 57 | 64 | 64 | 32 |
| MSD | 23,49 | 16,01 | 8,45 | 19,92 | 22,69 | 26,66 | 20,20 | 23,11 | 19,70 | 19,37 |
| Kurt | -1,11 | -1,23 | -1,21 | -1,19 | -1,18 | -1,30 | -1,29 | -1,23 | -1,13 | -1,11 |
| Asym | 0,11 | 0,10 | -0,06 | -0,01 | 0,00 | -0,07 | -0,06 | -0,06 | -0,07 | -0,07 |
| Range | 83 | 54 | 29 | 48 | 101 | 89 | 51 | 78 | 62 | 73 |
| Min | 10 | 15 | 10 | 8 | 11 | 10 | 15 | 6 | 18 | 11 |
| Max | 93 | 69 | 39 | 69 | 79 | 99 | 69 | 79 | 69 | 79 |

Avg = average; Std = standard error; Med = median; PrevPr = prevailing price; MSD = mean square deviation; Kurt = kurtosis; Asym = asymmetry; Min = minimum; Max = maximum.

$$W_{P_i} = a_{P_i} W_0, \quad \forall P_i,$$

$$W_P^{\max} = \max_i \{W_{P_i}\},$$

$$W_{P_i} \leftarrow \frac{w_{P_i}}{W_P^{\max}},$$

$$A_{P_i P_j} = a_{P_i} a_{P_j} W_A, \quad \forall P_i, P_j,$$

$$A_P^{\max} = \max_{i,j} \{A_{P_i P_j}\},$$

$$A_{P_i P_j} \leftarrow \frac{A_{P_i P_j}}{A_P^{\max}}.$$

(5)

Then the weight value K_u which expresses the sum of all the relativity feedback is calculated as follows [21-23]:

$$K_u = \frac{R_a^X W_{2a} + R_b^X W_{2b} + R_c^X W_{2c} + R_d^X W_{2d} + R_e^X \text{lev}}{R_a^X + R_b^X + R_c^X + R_d^X + R_e^X}, \quad (6)$$

where R_a^X is with the significance/weight attached to the indirect feedback mode. Similarly, R_b^X represents the meaning given to the type of pedagogical method, R_c^X is the meaning of feedback, R_d^X is the meaning of enrichment and, finally, the term R_e^X indicates the meaning of explicit feedback. Finally, the similarity is calculated as follows [21, 23]:

$$\text{simil}(x, y) = \frac{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)(r_{y,i} - \bar{r}_y)}{\sqrt{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r}_x)^2 \sum_{i \in I_{xy}} (r_{y,i} - \bar{r}_y)^2}} \quad (7)$$

where I_{xy} is the set of items scored and $r_{x,i}$ is the x user's rating for item i . The items are finally graded according to the above similarity in descending order. Because r ranges from zero to one, collaborative content-based filtering (recommendation) is performed.

To evaluate the above procedure given that there is the feedback that can be provided in stages, the error is calculated in each iteration. The goal is to minimize the cumulative error for all iterations, and by using the square loss function (SLF), the goal is to minimize the empirical error calculated by the function [24, 25]:

$$I_n[w] = \sum_{j=1}^n V(\langle w, x_j \rangle, y_j) = \sum_{j=1}^n (x_j^T w - y_j)^2, \quad (8)$$

where $x_j \in R^d$, $w \in R^d$, and $y_j \in R$ and X $i \times d$ is a data table and Y $i \times 1$ is a table of target values after the arrival of the first i data points are assumptions. Assuming that the correlation table $\Sigma_i = X^T X$ is invertible, the optimal solution $f^*(x) = \langle w^*, x \rangle$ for the linear least squares problem is given by the function [17, 18, 24, 25]:

$$w^* = (X^T X)^{-1} X^T Y = \sum_i^{-1} \sum_{j=1}^i x_j y_j. \quad (9)$$

Also, the root mean squared error (RMSE) was used which calculates the average error of the recommendation values relative to the actual preferences, with the following formula [17, 25]:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^n (P_{(ij)} - T_j)^2}, \quad (10)$$

where $P_{(ij)}$ is the recommendation value i for a simple hypothesis j and T_j is the target value for the simple hypothesis j . The success of a recommendation model requires extremely small values, while the best case, which implies an absolute correlation between proposals and preferences and therefore the absolute success of the model, is achieved when $P_{(ij)} - T_j = 0$.

The root relative squared error (RRSE) was used accordingly, which is calculated as follows [17, 26]:

$$\text{RRSE} = \frac{\sum_{j=1}^n (P_{(ij)} - T_j)^2}{\sum_{j=1}^n (T_j - \bar{T})^2}, \quad (11)$$

where $P_{(ij)}$ the predicted value i for a simple hypothesis j , T_j is the target value for the simple hypothesis j , and \bar{T} is calculated from the following relation [18]:

$$\bar{T} = \frac{1}{n} \sum_{j=1}^n T_j. \quad (12)$$

The perfect correlation between recommendations and actual preferences is achieved when this is equal to 0. Table 2 presents the results of the process as a 3-class problem where there is a full correlation (class A), partial correlation (class B), and absolute disagreement (class C). Exact errors are presented as performance metrics in the same Table 2.

Respectively, the diagrammatic representations are shown in Figures 2–6. Figures 2–6 show the performance of the model, giving visualized indications of the quality of the model.

Based on the results obtained and presented in detail above, it is obvious that the utilization of the proposed algorithm can find a reliable solution to the extremely difficult problem of creating and sharing lesson plans for the implementation of individualized curricula. The methodology proved that through the widespread use of intelligent methods, important educational tools can emerge so that the teacher can easily manage the student potential of his class and know the specific characteristics of each group, thus offering high-quality education through differentiated approaches considering the special educational needs of each trainee. Undoubtedly, this is a reliable model that can model the problem of differentiated pedagogy with high accuracy.

5. Discussion

As indicated above, in the context of several factors that influence the guidance of an educational policy, the transformation of teaching practices according to the principles of differentiated pedagogy is in many cases closely linked to the expectation of a fair response to student heterogeneity. The specific pedagogical practices, developed in the light of differentiated pedagogy, are often declared to be capable of promoting the principles of pedagogical integration. In the context of the discussion on the development of teaching practices that fall within the logic of inclusive education, it is important to consider, on the one hand, the risk that, in some cases, different interpretations of differentiation are associated with different trends and values of educational policy and, on the other hand, which is a confused and contradictory context, such interpretations can often be combined, thus leading in the opposite direction, i.e., in perpetuating discrimination and exclusion in education. With the conjuncture of the pandemic which changed the ways of education and in parallel with the modern social, economic, and political reality which favors the application of innovations in the educational policy at an international level, the global educational landscape is constantly introducing reformed efforts that focus on the transformation of educational systems according to the rules of the market and competition between students and

TABLE 2: Performance metrics.

| Accuracy | AUC | Recall | Prec. | F-score | RMSE | RRSE |
|----------|--------|--------|--------|---------|--------|--------|
| 0.8908 | 0.9772 | 0.8694 | 0.8920 | 0.8898 | 0.8260 | 0.8273 |

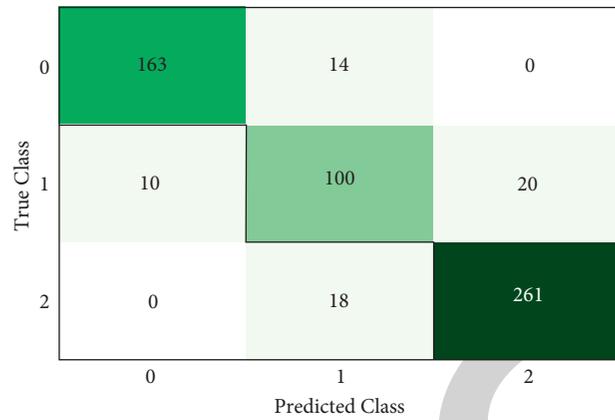


FIGURE 2: Confusion matrix.

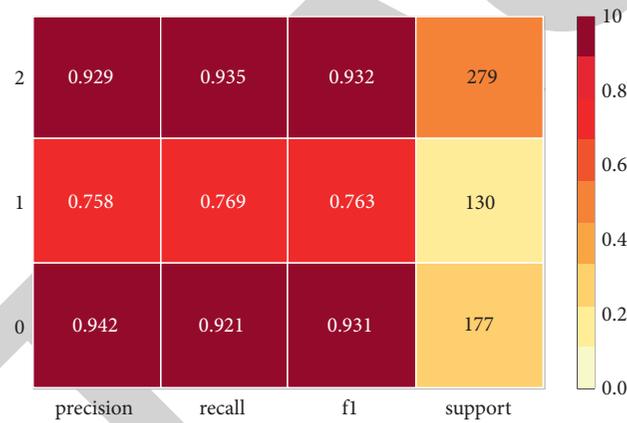


FIGURE 3: Precision-recall-F-score.

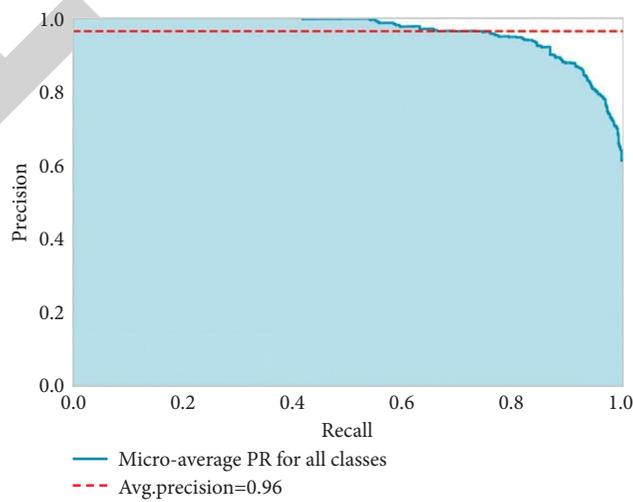


FIGURE 4: Precision vs. recall.

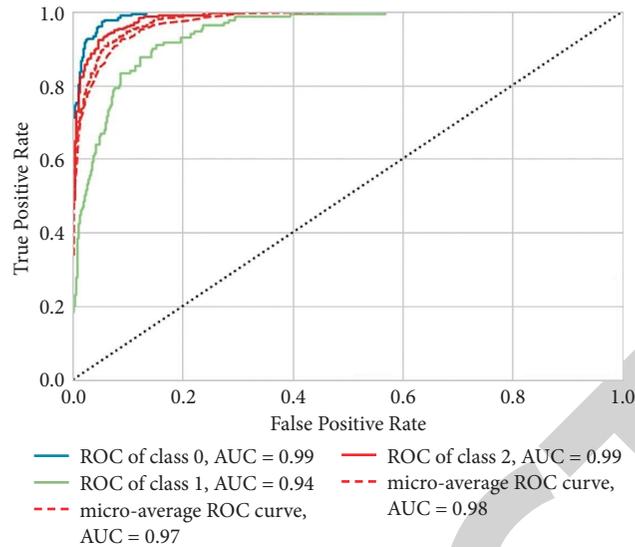


FIGURE 5: ROC curves.

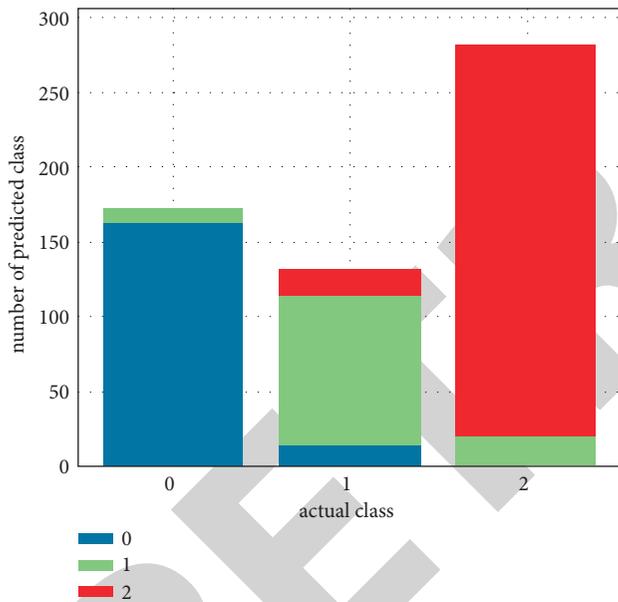


FIGURE 6: Error by class.

schools. In addition, the promotion of discrimination and unequal access of students to knowledge is taking place. Furthermore, it is often emphasized that if there is a place for differentiated pedagogy in the current socio-political context, it can be ensured through the “political clarity” of all those involved in approaching and analyzing issues of student diversity. Speaking of the advantages of the proposed method, the most important benefit is the diverse application to overcome substantial difficulties arising from institutionalized standards and procedures. Another supporting presumption is that there is no limit to the data that can be accepted as quantitative data, nor to

the evaluable factors arising from the multifaceted and holistic evaluation of the curriculum.

6. Conclusion

The proposed algorithmic approach gave realism and went beyond the physical limitations that might arise at the functional levels. From a technical point of view, this study proposed an algorithm for the first time in the literature that showed a higher degree of convergence, which is evidenced by the higher results of recommendations that were achieved and experimentally confirmed. The proposals for the additional research concerns includes the complete automation of the modeling system of the recommendation system, with greater accuracy and efficiency. Moreover, it also embraces the evolution of the system with automatic optimization of the questionnaires with intelligent methods of classification in fields of interest. Finally, an important step for further development is the expansion of the methods to fuzzy logic technologies.

Data Availability

Data sharing does not apply to this article as no data set were generated or analyzed during the current study.

Conflicts of Interest

The author declares no conflicts of interests regarding the publication of the research article.

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