

Retraction

Retracted: Classification and Analysis of College Students' Skills Using Hybrid AI Models

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

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.

References

- [1] H. Tang and Y. Wei, "Classification and Analysis of College Students' Skills Using Hybrid AI Models," *Journal of Mathematics*, vol. 2022, Article ID 4428416, 10 pages, 2022.

Research Article

Classification and Analysis of College Students' Skills Using Hybrid AI Models

Huili Tang  and Yanhong Wei

Zhengzhou Preschool Education College, Zhengzhou 450000, China

Correspondence should be addressed to Huili Tang; huitang92@outlook.com

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Each individual diversifies in the population with certain characteristics. Thus, diversity is a scientifically proven and widely accepted phenomenon when the human being is a concern. One of the areas where the diversity of human beings is mostly paid attention to is called the learning process, since different forms of responses could be observed. For example, each student perceives, assimilates, and uniquely processes the information when being transmitted to him, which confirms the inherited diversity. In this regard, educational systems are required to deal effectively with students and to apply the principles of personalized learning, which is pertinent to learning processes that meet the individual needs and interests of learners. By doing so, taking into account their unique characteristics, talents, skills, inclinations, and desires are satisfied. This manuscript presents an innovative model to classify college students' skills. A hybrid artificial intelligence (AI) system that fully automates the process of personalized training is proposed based on individual skills by taking into account the priority of personalized and fully customized learning systems. The process specifically utilizes the Rasch statistical analysis model and an innovative fuzzy Bayesian network. Higher-level reasoning is generated for the automated and personalized learning process in which college students are automatically classified into a certain category based on their skills.

1. Introduction

Intensive research in both neuroscience and psychology confirms the existence of different ways to obtain [1, 2], assimilate, construct, and reuse the information and knowledge provided to students [3, 4]. However, the learning and training programs implemented by most educational systems are only suitable for one type of student, called visual students [5, 6]. This group of students has a photographic memory and recalls any information exactly as it is presented in books [7]. Otherwise, in the case of acoustic persons, that is, students who learn best by listening to information or kinesthetic formulas, or students who learn by making things themselves manually, these types of students have a lot of difficulty in learning and assimilating knowledge and therefore are very likely to fail to harmonize with the education system provided [8–10].

In this sense, individualized learning is essential for the successful completion of a framework that can cover all areas of intelligence to be beneficial for each type of student. The main features of the personalized learning model are summarized as follows [11–13]:

- (1) The adaptive structure of the educational material based on evaluation criteria and the interaction with the aim of its continuous improvement
- (2) Giving importance to different learning styles
- (3) The student-led participation in the learning process
- (4) The emphasis on participation in the learning process through collaborative environments
- (5) Accessing technology and the most up-to-date educational resources

All these suggest that the personalized learning model recognizes each student as an individual with a different

style, pace, and way of learning, as well as a different view of learning. It recognizes the value of the involvement of technology in education, providing a variety of options and opportunities so that learning programs are tailored to each learner's skills, needs, and preferences [14, 15].

The aforementioned advantages are fully realized with the holistic introduction of information and communication technologies into education and the rapid spread of the Internet, which altered conventional learning and teaching practices around the world. Especially with the pandemic crisis [16], distance learning has recently adopted advanced learning management systems as a direct and alternative way to access educational resources and services [17]. In general, e-learning can be considered as a means of overcoming the barriers of time, place, and socioeconomic status, which could reduce the access of many individuals and groups to education and knowledge and thus offers great opportunities to improve their social and professional status [8, 18, 19].

However, despite the given penetration of distance education methods (synchronous and asynchronous), the fact that the high dropout rates of the respective programs have been observed in recent years was mainly due to the lack of student satisfaction, since the same static learning was provided for all regardless of their previous knowledge, experience, preferences, and learning objectives during the interaction with the system [2, 20]. Hence, to restructure educational technologies for contemporary needs, teaching methods and the way of constructing educational material are more prominent. Innovative educational systems based on advanced artificial intelligence (AI) methodologies can offer a solution that can be compared with individualized teaching methods [21].

The emerging technologies can improve educational programs and teaching practices in many ways so the technical innovations can be a competitive advantage of the new era. That is the main reason why we need to further examine the involvement of AI, Big Data Analytics, and Machine Learning implementations in education procedures.

This paper presents an innovative model to classify college students' skills based on a hybrid AI system that fully automates the process of personalized learning based on individual skills. Specifically, combining the Rasch statistical analysis model and an innovative fuzzy Bayesian network leads to higher-level reasoning that is produced for the automated and personalized learning process in which the college students are automatically classified into a certain category based on their skills.

The organization of the manuscript is as follows: Section 2 discusses the researches that deal with personalized learning and its implementations based on AI technologies by giving pros and cons concurrently. The proposed method is introduced in Section 3. Section 4 conducts the implementation of the proposed method based on a data set. Section 5 presents the results of the implemented method. The conclusion and discussion are comprehensively provided in Section 6.

2. Related Literature

The literature of AI research in education, especially in recent years, has been increasing at a fast pace because of the great potential of AI in the field of the educational process and especially the personalization aspects. Most researchers conclude that AI in education and particular learning has presented a great potential from both theoretical and pedagogical points of view, but there is still a need to develop a critical stance before fully integrating it into the educational processes. Testing and evaluation of AI in educational processes are essential to avert automated processes and Machine Learning (ML). For example, Sisman-Ugur and Kurubacak [22] presented the future perspectives of AI in various contexts, such as Natural Language Processing, Machine Learning, and Deep Learning. They also utilized Social Network Analysis as a guide for the interpretation of the key concepts in AI research based on an educational perspective. Finally, their research identified three broad themes, adaptive learning, personalization, and learning styles, expert systems, and intelligent tutoring systems. Hence, AI as a future component of educational processes could emerge. However, their research is essentially a general overview of the implementation of AI in the education processes.

Also, Bozkurt et al. [23] analyzed the trend and patterns of AI implementations in education by combining descriptive statistics, t-Distributed Stochastic Neighbor Embedding (t-SNE), Social Network Analysis, and text mining. They concluded an increment of AI in the education publications during recent years.

Klašnja-Milićević and Ivanović [21] aimed to address the research by examining elements of personalized e-learning, intelligent, and interactive technologies. They ultimately have depicted the state-of-the-art online education systems empowered with AI. Their theoretical study also serves as a suggestion to institutions and organizations that want to adopt these new technologies and approaches in education.

Maghsudi et al. [14] provided a brief review of state-of-the-art research and investigated the challenges of AI/ML-based personalized education and discussed potential solutions. They concluded that "personalized education" is one of the most precious merits of AI concerning education because it significantly improves the quality of education in several dimensions by adapting to the distinct characteristics and expectations of each learner such as personality, talent, objectives, and background. Also, online education is of the utmost value under abnormal circumstances such as the COVID-19 outbreak or natural disasters. Indeed, conventional education requires significantly more resources than the online format concerning educational space, scheduling, and human resources, which makes it prone to failure with even a small shift in conditions. As such, emerging alternatives are inevitable. Despite having the potential of a revolutionary transformation from traditional education to modern concepts, personalized education is associated with several challenges.

On the other hand, Krendzelak [18] especially examined ML and its applications in e-learning environments. Also,

the authors in [24] evaluated ML methods to detect and distinguish diverse self-injurious behavior types. Iatrellis et al. [25] provided a complete tool for the optimization and calculation of the offered services by the Higher Educational Institutions in combination with the minimization of respective costs that are enhanced with Machine Learning and semantics. Finally, an improved hybrid ontology-based approach for online learning resource recommendations [1] combining collaborative filtering algorithm and sequential pattern mining techniques was proposed by Shang et al. [26].

From the aforementioned literature, we conclude that the vast majority of the research highlights the great potential of AI in educational processes but there is a lack of proposed schemes to further take advantage from a practical point of view like the current paper does.

3. The Proposed Hybrid AI System

By adopting an eclectic approach to methodological practices [21], a key goal of educational programs is to devise a combination of different methods that aim to involve the learner as actively as possible, which is always based on his particular characteristics and abilities. In this regard, the most important role in the implementation of an adaptive system of personalized learning is the appropriate choice of educational material [18].

The material in question may be digital (study guide, parallel texts, etc.), audiovisual (audio files, digital videos, etc.), practical (exercises and activities, case studies, digital laboratory applications, etc.), and interactive (conversations, video conferencing, etc.). This material should be formulated with a special teaching methodology and function as a preparing process. Accordingly, the variety of elements that a distance learning environment should contain lies in the fact that each of the educational resources should undertake specific objectives in the educational process to create conditions for active participation and learning [2, 21].

In conclusion, it should be suggested that the concept of learning material is related to the designed and transformed synthesis of educational resources, which can devise the right conditions and support the learning process based on each student's skills. The educational material in question concerning the context of education learning is composed of the means of teaching and practicing and like all tools of teaching. Thus, their main function is to support the learning process within the learning environment. The concept of "learning environment" is mainly related to external factors and refers to the whole range of educational and learning materials and how this environment is structured to enable the individualized learning process [14, 15, 22]. Personalization refers to the use of a learner's abilities, sensitivities, and abilities (including emotional ones) to develop his or her skills, abilities, and talents. Individualized teaching is based on carefully prepared educational materials that recognize the different forms of the students' skills and level of knowledge and their ability to learn from different learning environments and to enhance feedback and assessment of their abilities [23, 25].

To devise an intelligent framework whose main features will be easy access to the most up-to-date educational resources, diverse learning environments, personalized rearrangement in the curriculum, and the learner's ability to direct the objectives of the learning process, a hybrid AI system is proposed which aims to intelligently adapt the educational material to the unique skills of each learner.

The specific steps as well as the technical details of how the hybrid system works are presented in the next subsections.

3.1. Preliminary Questionnaire. The proposed system is based on the exploratory statistical analysis that processes questions in questionnaires of different scientific fields as well as their evaluation measure regarding the creation of a reliable measurement scale for the initial classification of the college students and the optimal adaptation of the educational material. The methodology aims at designing a questionnaire and the reliable estimation of the sum of a set of scales that are produced by successive individual measurements, for example, different questions, iterative measurements, and different measurement systems. By applying specific but simple statistical analyses, the various scales are utilized to check whether they contribute to creating a specific evaluation model. Then, the results of the process are forwarded to the next step of the proposed system called the Rasch model [27].

3.2. Rasch Model. The results obtained at the first stage are analyzed based on the Rasch model [28]. The proposed model is inspired by the Item Response Theory [29] and specifically by the peculiarities of Rasch's model, which records the probability of a person answering a question [27, 28]. The responses of the participants are aggregated in a worksheet, in which columns refer to questions and rows to individuals, which is used to generate a final score for each individual. The total score is representative of all the questions and a person with a higher overall score has a higher value position on the scale of the measured variable which is called one-dimensional because of its simplicity of calculation [28].

The application of the Rasch model recommends the creation of a scale to measure questions and the scale of the ability of individuals to respond using special methods. The scale of the questions is approached by a computational process known as item calibration. On this scale, the lower the percentage of correct answers becomes, the higher the difficulty of the questions grows, and consequently the greater the magnitude of the calibrated scale becomes. The scale of the questions is calibrated based on the scale of probabilities (in logit units) and is calibrated as the scale of measuring the responsiveness of individuals in the same way. These two scales create two frequency distributions.

In binary questions, the position of difficulty of a question on the scale corresponds to a responsive position of an individual who correctly answers this question with a defined probability of 0.5. Then, it designates the position on the difficulty of the skill scale. When a person correctly

answers a question whose corresponding position is lower than the corresponding position held by that person, the difficulty occupying a specific position on the skill scale shows a probability of the person answering this question greater than 0.5. Conversely, when the difficulty of the question occupies a position higher than the corresponding position of that person, the probability of the person answering is less than 0.5.

For a better understanding, the Rasch model uses the scale of measurement in the form of a ruler presented in Figure 1. The vertical lines on the scale are the questions that have a special place depending on their degree of difficulty [27–29].

While less difficult questions are answered on the left-hand side of the scale, more difficult ones are on the right-hand side of it. Respondents also take a special position depending on their level of responsiveness: while people with low ability (skills) are located at the left-hand side of the scale, people with a high level of ability are located at the right-hand side of it. Thus, less difficult questions can be easily answered correctly by more capable people. For example, while person B is assessed as having a very low ability after answering only four questions correctly, person D is evaluated as an average level of ability because he answers about 50% of the questions correctly. The other person called C has a high response ability because he answers almost all questions successfully. The position of the questions and the individuals along the measurement scale is calculated utilizing the model based on the percentage of the response of each individual to each question.

In general, Rasch's model allows the algebraic separation between the parameters of the question and the parameters of the individual. Therefore, the estimations of the statistical parameters are conducted. The procedure is performed using the dependent maximum probability in which the response dimension is divided into segments concerning the individual's overall score. While the latter provides important information about the individuals concerning the content of the question, the former, which is the overall score of the questions, provides detailed information about the latent characteristics of the individuals [27–29].

The full utilization of the above process and in particular the results of the Rasch model is forwarded to the next step of the framework called the Personalized Classification.

3.3. Personalized Classification. The Personalized Classification process is a methodology used to extract knowledge from the data gathered employing the Rasch model. Each element is assigned to a predefined set of categories to classify the college students into the respective classes that represent their skills and abilities. The process is based on an innovative fuzzy Bayesian network.

Bayesian networks [30] are initially used to generate a probabilistic representation of the data structure derived from the Rasch model and their hypothetical independence through a Directed Acyclic Graph (DAG) in which complete and combined probability distributions are substantiated. The aim is to categorize a sample into one of the predefined

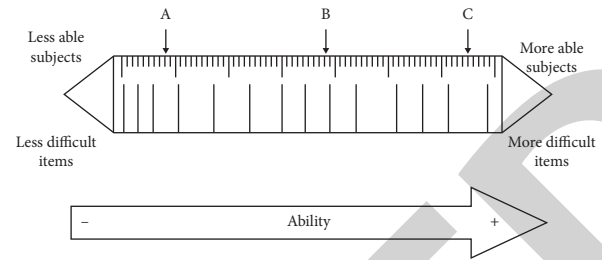


FIGURE 1: Rasch model rule.

categories represented by C_1, C_2, \dots, C_n using a probability model defined by the Bayes theory. In essence, this is an initial categorization process by simply evaluating probabilities and not taking into account forecasts. Its more usefulness and efficiency and quick feature extraction are observed experimentally. Besides, the forecasts have been represented by a degree. The purpose is to minimize the expected costs in the sequel. Each category is characterized by a previous probability. Assume that the given sample belongs to a category C_i . Utilizing the definitions and Bayes theory helps determine the probability [31]. Essentially, the step of the process is related to understanding the dependence between the results of the questionnaire and assigning probabilities to them. Thus, ensuring how the appearance of one event likely occurs is changed when the other is presented. By doing so, the proposed system integrates the previous knowledge gained from the Rasch model into the learning process model through a probabilistic representation of the data structure that emerges from each learner.

Besides, uncertainty has existed in the parameters of the model generated by some sources such as noise, random, or misleading answers. The method uses a gradual assessment that is described with the aid of a membership function in the interval $[0, 1]$. The proposed model introduces the four types of fuzzy set operations between sets, which are the following:

- (1) Fuzzy Disjunction:

$$\mu_{A \cup B}^{\sim}(x) = \mu_A^{\sim}(x) \vee \mu_B^{\sim}(x) = \max[\mu_A^{\sim}(x), \mu_B^{\sim}(x)] \forall x \in X. \quad (1)$$

- (2) Fuzzy Conjunction:

$$\mu_{A \cap B}^{\sim}(x) = \mu_A^{\sim}(x) \wedge \mu_B^{\sim}(x) = \min[\mu_A^{\sim}(x), \mu_B^{\sim}(x)] \forall x \in X. \quad (2)$$

- (3) Fuzzy Product:

$$\mu_{A \cdot B}^{\sim}(x) = \mu_A^{\sim}(x) \cdot \mu_B^{\sim}(x) \forall x \in X. \quad (3)$$

- (4) Fuzzy Complement:

$$\mu_A^{\sim} = 1 - \mu_A. \quad (4)$$

3.4. Evaluation. To have an objective evaluation process of the model, both self-evaluation and comparison with corresponding alternative models are needed. The procedure is

validated by content testing based on the original questionnaire that was originally constructed. This process is more suitable in adapting the model to changing problem areas related to the ability to self-adaptive learning, which provides the ability to redefine learning and improve its behavior over time in any iteration process.

Verification is in the form of referring to the personalized learning process. If a measure threshold is activated to allow the accurate calculation of the output vector, it is optimal in the sense of the minimum approach error. In particular, verification refers to the process of achieving the desired behavior through an iterative process of updating the proposed system. It should be emphasized that each algorithm used in the process offers a different way of adapting to the desired result as well as different adaptation techniques which are completely dependent on the problem to be solved. The goal is to systematically and quickly find the appropriate parameters of the system to minimize the error between the actual and the desired outputs.

3.5. Educational Material. When the verification process is completed, it is considered that the educational content has been classified based on the needs and skills of each trainee. The intelligent production process of the educational material proposed is the result of the production of reasoning, that is, knowledge that does not come from an instructor, but is a scientific-technological breakthrough in an environment of uncertainty. For this purpose, the structure and mathematical representation of the educational content which are distributed and disposed of are taken as a fuzzy fact. Defining fuzzy sets is proposed as to how events are combined to produce logical propositions, relationships, and conclusions [32–34].

3.6. Self-Adaptive Fuzzification. Finally, it is possible to perform some additional segmentations and distributions based on the self-adaptive fuzzification process among the ambiguous sets resulting from the previous process [35, 36]. The procedure in question concerns operations between ambiguous sets borrowed from probability theory and concerns the possibility of joining and intersecting two contingencies. A clear distinction between the fuzzy sets and the probability space is then conducted which results in the use of more general expressions for the union and intersection of the sets in question. Specifically, the model produces inference rules that are represented in a logical form or guide consisting of hypotheses that are represented as follows:

- (1) Modus Ponens: $\{(\bar{A} \rightarrow \bar{B}) \wedge \bar{A}\} \rightarrow \bar{B}$
- (2) Modus Tollens: $\{(\bar{A} \rightarrow \bar{B}) \wedge \bar{B}\} \rightarrow \bar{A}$
- (3) Hypothetical Syllogism: $\{(\bar{A} \rightarrow \bar{B}) \wedge (\bar{B} \rightarrow \bar{C})\} \rightarrow (\bar{A} \rightarrow \bar{C})$

With the completion of this step, the educational content has been created and segmented with full evaluation criteria based on the particularities of each trainee. The redefinition process is achieved through the continuous evaluation of the

trainees as the process approaches the target as close as possible.

4. Experiments

The scenario developed concerns a preliminary test for the classification of students in respective level departments having similar difficulty and respective courses. A preliminary questionnaire was distributed to a total of 350 college students. The questions are related to their skills and aspirations from the curriculum. Learners were asked to answer the questions using the Likert scale in which the five grades were listed from 1 to 5 whose expressions are as follows: totally disagree, disagree, neither disagree nor agree, agree, and totally agree, respectively.

The processing of the results to assess the reliability of the questionnaire resulted in a total Cronbach index of 0.776, which is a value higher than the generally accepted value of 0.7. This principally suggests that at least some questions are capable of measuring the same composition of anxiety in the pretest process. Cronbach's alpha [37, 38] is not a statistical test, called a coefficient of reliability (or consistency). It measures internal consistency, that is, how a set of items are closely related as a group. It is considered to be a measure of scale reliability. It can be written as a function of the number of test items and the average intercorrelation among the items. Cronbach's alpha is defined in the following equation:

$$a = \frac{N\bar{c}}{\bar{u} + (N-1)\bar{c}}, \quad (5)$$

where N is the number of items, \bar{c} is the average interitem covariance among the items, and \bar{u} is the average variance. As the average interitem correlation increases, Cronbach's alpha increases as well (when the number of items is kept constant).

Note that the process of defining the difficulty and ability parameters is calculated based on the probability of a successful outcome (odds) (quotient of probability p to probability $q = 1 - p$). Its logarithmic version determining the ability of the individual is defined by

$$P(\theta) = \ln \ln \left(\frac{p}{1-p} \right). \quad (6)$$

When the right-hand part of the equation is calculated, $P(\theta) = \theta - \beta$, which expresses that the probability of validation of a question that is equal to the difference between an individual's ability and the difficulty of the question can be calculated. The closer the difference equals 1, the greater the chance of a correct response becomes. Conversely, the smaller the difference grows and the closer it gets to 0, the greater the chance of a wrong answer is. When the capacity scale is measured in units of normal distribution, the response has a 0.50 probability of being correct when the capacity value is $\theta = 1.0$.

The relationship between the successful outcome (correct choice) and the measured latency characteristic (individual capacity) is described in the form of a sigmoid

characteristic curve of the Item Response Function (IRF) [27, 29]. Figure 2 depicts it.

Rasch's model is applied to estimate some characteristics of the sample of students such as individual ability and behavior, which are presented in the form of a latent variable. It is used in the preparation of special questionnaires for the evaluation of the mentioned variables by processing the responses of the participants [27, 28]. The model estimates the probability of responding to the two-parameter function: the "person" and the "question." In particular, it measures the probability of occurrence of the correct answer resulting from the difference between the parameter of the respondent and the question.

Regarding the progress of exams in education, the parameter of the questions is related to the degree of difficulty of each question and the parameter of the student is pertinent to his ability to answer successfully. Thus, the greater a person's ability to respond to a relatively difficult question grows, the more likely he or she is expected to have answered the question correctly. If the magnitude of the difficulty of a question is equivalent to the magnitude of the responsiveness of the individual, then the probability of giving the correct answer is set at 0.5 (50%). Specifically, the outcome of a successful answer to a question is determined by the probability assessment defined by

$$P_r(X_i = 1 | \theta_j, \beta_i) = \frac{e^{\theta_j - \beta_i}}{1 + e^{\theta_j - \beta_i}}, \quad (7)$$

where $X_i = 1$ is the correct answer to question X_i , the condition on the dichotomous variable is denoted by θ_j based on the ability of the trainee j , and β_i is the difficulty of question i .

By applying the logarithm of the student's probability ratio (logit) to the correct answer for a given question, the ratio is equal to $\theta_j - \beta_i$. In addition, this ratio also applies to a correct answer for a second question. It is equal to the difference between the positions of the two questions expressed by

$$\log - odds(X_i = 1 | r_j = 1) = \beta_2 - \beta_1, \quad (8)$$

where r_j is the student's overall score regarding the answer to the two questions. It is easy to see that the presentation of the responses using the logarithm ratio in the correct answer provides the estimate of $\beta_2 - \beta_1$ which does not contain the term θ_j . Thus, the dependent maximum probability technique directly serves to calculate the difficulty of the questions.

Thus, Rasch's model takes the model of question response theory where the total score along the questions characterizes exclusively the individual and therefore is calculated based on a single parameter related to the individual (ability) and the other parameter (difficulty) that corresponds to each category of the question and called a threshold [27, 28]. Thus, there exist four thresholds for the five-part questions of the questionnaire under consideration.

By taking into account all the questions of the questionnaire and all the students participating in the exam, we evaluate the answer function of the questions and plot the

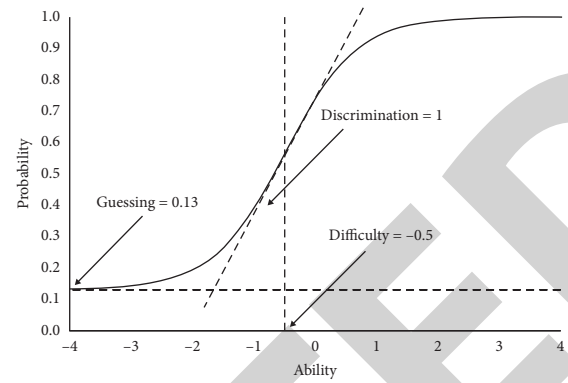


FIGURE 2: Item Response Function.

curve of the IRF questions showing the probability of a correct answer as a result of the students' ability [29]. The IRF graph of the 10 questions in the questionnaire is shown in Figure 3.

Each estimated capacity value is associated with a standard measurement error quantifying the degree of uncertainty of the estimate. The same is true for the estimated values of the questions with a noticeable difference. Thus, the standard errors of the difficult questions are much smaller than those of the individual ability assessment values as the answers to the questions usually outweigh the responses of the individuals. The standard error of individual estimates is narrower in the region where the IRF slope is steeper, that is, in the interval of progress points, since Rasch's model is based on the application of the Poisson distribution [39]. It was experimentally shown and demonstrated that the number of response errors made by an individual is the quotient of the difficulty of the question to the ability to answer by the person. The response estimation measure is based on this assumption.

The results of the aforementioned statistical analysis of the questions and the probabilistic values resulting from the Rasch model process [28] are a basic criterion to map the answers of each student into a pair of variables entering the Bayesian network [31] whose form is denoted by $B = \langle G, \Theta \rangle$, where G is the DAG whose nodes X_1, X_2, \dots, X_n represent the variables and their probability values resulted from each question in the questionnaire and their edges. Thus, the direct dependencies are represented between these variables (the answers to each question). Graph G encodes independence assumptions. Each variable X_i is independent of the inheritance assumed by G . Θ denotes the set of network parameters. Specifically, this set contains the parameter $\theta_{x_i|\pi_i} = P_B(x_i|\pi_i)$ for each x_i implementation of X_i in the condition π_i , for the set of X_i parents in G . Therefore, B defines a unique probability distribution over the variables; namely,

$$P_B = (X_1, X_2, \dots, X_n) = \prod_{i=1}^n P_B(\pi_i) = \prod_{i=1}^n \theta_{X_i|\pi_i}. \quad (9)$$

The result of the process is to generate a probability value for each variable (answer) that essentially reveals the interdependence of the variable with a class, indicating the

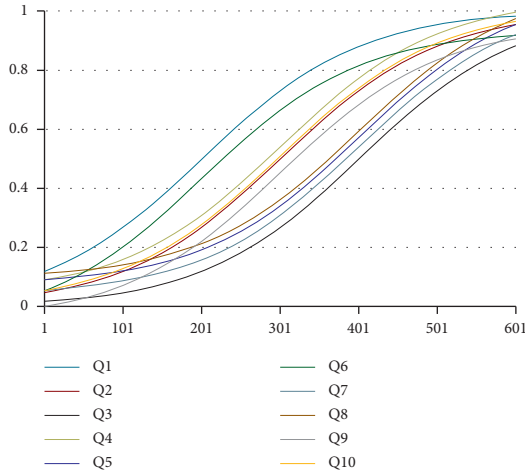


FIGURE 3: Item characteristic curves.

direction of the influence resulting from each question. An initial categorization of the answers into clear classes can determine the choices and abilities of each student in this way. With this example utilizing the questionnaire, the implemented algorithm of the Bayesian network generates three classes, which are called Theoretical Direction, Positive Direction, and Technological Direction, based on their answers.

5. Results and Discussion

The following criteria were used to evaluate the performance of the hybrid AI system [40–43]:

- (1) Overall Accuracy (OA): this measure denotes the number of correctly classified samples divided by the number of test samples.
- (2) Average Accuracy (AA): this indicator shows the average of the categorizations of all categories.
- (3) Kappa Rate: this is a statistical measurement providing information with the amount of agreement between the truth map and the final classification map, which is calculated by

$$k = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e}, \quad (10)$$

where p_o is the relatively observed agreement among raters and p_e is the hypothetical probability of a chance agreement.

- (4) McNemar Test: to assess the importance of classification accuracy resulting from different approaches, a McNemar Test was conducted, which is defined by

$$z_{12} = \frac{f_{12} - f_{21}}{\sqrt{f_{12} + f_{21}}}, \quad (11)$$

where f_{ij} represents the number of samples classified correctly in classification i and incorrectly in classification j .

- (5) Coefficient of Determination (R^2): it is used to express the correlation of two variables represented by a percentage. The Coefficient of Determination gives the percentage of variability of Y calculated by X and vice versa and it is defined by

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}, \quad (12)$$

where Y_i represents the observed values of the dependent variable, \hat{Y}_i represents the estimated values of the dependent variable, \bar{Y} is the arithmetic mean of the observed values, and n is the number of observations.

- (6) Root Relative Squared Error (RRSE): this function calculates the absolute correlation between actual and predicted values and therefore the absolute success of the model, which is achieved when this is equal to zero, is defined by

$$\text{RRSE} = \frac{\sum_{j=1}^n (P_{(ij)} - T_j)^2}{\sum_{j=1}^n (T_j - \bar{T})^2}, \quad (13)$$

where $P_{(ij)}$ is the value predicted by the program for a simple hypothesis j , T_j is the target value for the simple hypothesis j , and \bar{T} is calculated by

$$\bar{T} = \frac{1}{n} \sum_{j=1}^n T_j. \quad (14)$$

Table 1 depicts the results of the process.

Table 1 presents accurate results of the proposed method that takes into account the complexity of the implemented scenario. Besides, the proposed method produces a stable environment without recurring issues of unspecified cause. The reliability ($k \geq 0.70$) is found to be high due to the Rasch method allowing the maintenance of the most relevant data for the forthcoming forecasts.

The McNemar test is also presented to show the importance of the difference in the accuracy of the classification of the educational material selected for each student, which is statistically significant when compared to the rest. The result of the simulated process is the devising of completely personalized content for each of the 50 students.

In conclusion, it should be suggested that there were very few cases of students (4 students) with significant content overlap (<85%), while in the number of cases (37 students) the content was different by >30%.

Also, the high reliability and the precision of the model are depicted by the high values of R^2 and the minimum values of the RRSE. On the other hand, various options of the above parameters can lead to various inherent operating standards, so that the firing threshold represents the personalized requirements of each learner. In addition, the integration of the self-adaptive fuzzification mechanism makes it possible to manage multiple intermediate representations. The hybrid approach is based on the individual

TABLE 1: The outcomes of the assessments.

Class	OA (%)	AA (%)	Kappa	McNemar	R ²	RRSE
1	99.44	98.67	0.8992	30.172	0.989	0.0459
2	98.37	97.52	0.8885	29.674	0.981	0.0518
3	99.12	98.33	0.8973	30.029	0.987	0.0479

needs of each learner, the adaptive structure of the educational material based on evaluation criteria, and the interaction with the aim of its continuous improvement. This leads to high performance even for problems that require student-led participation in the learning process, with emphasis on collaborative environments and access to technology's up-to-date educational resources.

6. Discussion and Conclusions

This paper presented an innovative hybrid AI system that fully automates the process of personalized training based on individual skills. The Rasch statistical analysis model and an innovative fuzzy Bayesian network are used concurrently. Higher-level reasoning is produced for the automated and personalized learning process. By doing so, college students are automatically classified in a certain category based on their skills.

This is an innovative effort to effectively rearrange the educational content of educational systems based on evaluation criteria. Technologically, the proposed system combines a hybrid AI model with statistical methods, Machine Learning algorithms, and fuzzy logic concurrently for the first time. Thus, ensuring the optimal adaptation of the system is conducted for new situations. It offers a high level of generalization, realistically addressing the expectations of those involved, while the application of adaptation and rearrangement rules is done in a completely understandable and clear way.

The process measuring the difficulty and ability parameters of the questions responded to by the students provides probability assessments. Thus, the dependent maximum probability technique directly serves to calculate the difficulty of the questions, which is to generate a probability value for each variable (answer) that essentially reveals the interdependence of the variable with a class, indicating the direction of the influence resulting from each question. An initial categorization of the answers into clear classes can determine the choices and abilities of each student in this way. Then, those values are updated by a fuzzy Bayesian network which results in three classes of Theoretical Direction, Positive Direction, and Technological Direction, based on their answers.

The main future research would be the expansion of the method to use high-level intelligence by sophisticated Machine Learning techniques to model uncertainty aiming at reaching a result of greater accuracy and efficiency.

Abbreviations

α :	Cronbach's alpha in [0, 1]
N :	The number of items

\bar{c} :	The average interitem covariance among the items
\bar{u} :	The average variance
p :	Successful outcome
$P(\theta) = \theta - \beta$:	The difference between an individual's ability and the difficulty of the question
$P_r(X_i = 1 \theta_j, \beta_i)$:	The outcome of a successful answer to a question
θ_j :	The ability of trainee j
β_i :	The difficulty of question i
$P_B = (X_1, X_2, \dots, X_n)$:	The joint probability density function of the questions
k :	Kappa Rate
\tilde{A} :	Fuzzy set
μ_A :	Membership function of fuzzy set \tilde{A}
R^2 :	Coefficient of Determination
RRSE:	Root Relative Squared Error
Y_i :	i th observed value
\hat{Y}_i :	Estimated i th observation.
\underline{Y}, \bar{Y} :	Average value.

Data Availability

The data used to support and prove the findings of this study are available from corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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