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ORIGINAL

Application of artificial intelligence for the detection of educational needs and the personalization of evaluation processes

Aplicación de la inteligencia artificial para la detección de necesidades educativas y la personalización de los procesos de evaluación

Francisco Javier Santini Rodriguez[1]
Luis Carlos Rodriguez Montaño[1]
Mario Isaac Romero Lamadrid[2]

[1] Universidad de Sonora. Hermosillo, México
[2] Centro de Investigación en Alimentación y Desarrollo (CIAD). Hermosillo, México

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Corresponding Author: Francisco Javier Santini Rodriguez

ABSTRACT

Introduction: Artificial intelligence is capable of recognizing learning difficulties and adjusting assessments to the characteristics of the students. Objective: The aim of this study was to test the effects of artificial intelligence on the arrest of educational needs and the adaptation of assessment in improving the academic performance of students in Higher Basic General Education. Methodology: A quantitative, applied, explanatory-comparative and quasi-experimental study was carried out with pre-test and post-test. The population was 240 students and the sample was 148. The sample was divided into the experimental group and the control group: both groups of 74 students. The experimental group received adaptation of the assessment over the course of eight weeks while the control group continued the conventional procedure. Simulated data were used to structure the analytical model. Results: The experimental group improved 17.8 points in performance compared to the control group (6.3 points) with a large effect (d = 1.42). The presence of students with a high need for reinforcement went from 41.9% to 10.8% and satisfactory mastery increased to 63.5%. Conclusion: Personalized student assessment with Artificial Intelligence can help detect academic needs, adapt tasks and improve student performance under teacher intervention.

Keywords: artificial intelligence; educational evaluation; personalization of learning; educational needs; academic performance.

RESUMEN

Introducción: La inteligencia artificial es capaz de reconocer dificultades de aprendizaje y ajustar evaluaciones a las características del alumnado. Objetivo: El presente estudio pretendía comprobar los efectos de la inteligencia artificial frente a la detención de necesidades educativas y la adaptación de la evaluación en la mejora del rendimiento académico del alumnado de Educación General Básica Superior. Metodología: Se llevó a cabo un estudio de carácter cuantitativo, aplicado, explicativo-comparativo y cuasiexperimental con pretest y postest. La población fue de 240 estudiantes y la muestra de 148. La muestra fue dividida en el grupo experimental y el grupo control: ambos grupos de 74 estudiantes. El grupo experimental recibió la adaptación de la evaluación en el transcurso de ocho semanas mientras que el grupo control continuó el procedimiento convencional. Se utilizaron datos simulados para estructurar el modelo analítico. Resultados: El grupo experimental mejoró 17,8 puntos en el rendimiento respecto al grupo control (6,3 puntos) con un efecto grande (d = 1,42). La presencia del alumnado con alta necesidad de refuerzo pasó del 41,9% a 10,8% y el dominio satisfactorio aumentó hasta el 63,5%. Conclusión: La evaluación personalizada del alumnado con Inteligencia Artificial puede ayudar a detectar las necesidades académicas, adaptar las tareas y mejorar el rendimiento del alumnado bajo la intervención del docente.

Palabras clave: inteligencia artificial; evaluación educativa; personalización del aprendizaje; necesidades educativas; desempeño académico.

INTRODUCTION

The use of artificial intelligence (AI) in teaching systems has transformed the collection of information on learning, the interpretation of academic performance and the design of strategies for carrying out assessment. One of its most promising applications is formative assessment, since smart systems analyze responses, discover patterns of error and provide feedback on the performance of each student. These characteristics make dynamic evaluations prone, in which the information obtained is taken up again to detect difficulties and guide improvement actions immediately [1].

The ability to analyze large volumes of educational data has enabled the development of predictive models to identify students with a higher probability of academic difficulties. Machine learning algorithms analyze evaluation results, behavior on digital platforms, interaction with activities, and many other performance indicators. These models identify at-risk situations in advance, whereas traditional procedures would only detect them after low academic performance [2]. AI plays a preventive role by providing information that informs educational interventions before difficulties affect the student's trajectory.

The identification of needs becomes more useful when linked to feedback processes and teaching adaptation. Learning analytics makes it possible to transform the data generated by students into information that can be used to adjust activities, guide feedback, and facilitate individualized pedagogical decisions [3]. This represents a shift away from homogeneous assessment models, in which all students receive similar instruments and feedback mechanisms regardless of differences in prior knowledge, learning pace, or types of errors.

In this scenario, the expansion of AI in education has generated a research field encompassing intelligent tutoring systems, predictive analytics, automated assessment, content generation, and personalization of educational experiences. However, the growth of these applications has also highlighted the need to study their implementation with rigorous methodological criteria, considering not only their technological capability but also their pedagogical utility, transparency, and effective contribution to learning [4]. Therefore, the analysis of educational AI requires going beyond approaches focused exclusively on automation and examining how these tools can support evidence-based teaching decisions.

From a functional perspective, AI systems can perform processes related to pattern recognition, classification, prediction, and recommendation, capabilities with multiple applications in the educational field [5]. In evaluation processes, these functions enable the identification of differences among students and the generation of responses adapted to the characteristics observed during their interaction with the instruments. Consequently, evaluation can evolve from a mechanism intended mainly to assign a grade toward a continuous process of collecting and interpreting information about individual learning needs.

Research on AI applied to education has revealed opportunities related to personalization, automation of certain tasks, performance monitoring, and the generation of decision-support systems. At the same time, challenges have been identified, including data quality, potential algorithmic biases, privacy, and the need to maintain teacher involvement in educational decisions [6]. These considerations are especially relevant when algorithms are used to classify performance or identify needs, because an inadequate interpretation of the data could lead to pedagogical decisions that do not correctly represent the student's abilities.

In contemporary education, the use of AI has spread particularly in contexts where digital platforms are capable of continuously recording information about student activity. The analysis of these records enables building learning profiles and recognizing variations in performance that can be used to design differentiated interventions [7]. In this way, technology can complement teacher observation through objective indicators derived from the activities carried out during the educational process.

Data-driven individualization constitutes a fundamental principle of these systems. Information obtained through learning analytics allows adapting resources, difficulty levels, and feedback mechanisms according to the characteristics detected during learning [8]. This approach is particularly important in heterogeneous groups, where uniform assessment can conceal relevant differences among students who achieve similar results but present different difficulties in conceptual understanding, knowledge application, or problem-solving.

The automation of difficulty detection has demonstrated its potential in the learning modality. The application of machine learning-based analysis of digital data has proven useful for characterizing students with difficulties in the early stages of the educational process [9].

These approaches show how patterns of interaction and implementation can be indicators of support needs, provided that the criteria for interpreting these patterns integrate pedagogical criteria and mechanisms for understanding the predictions they offer.

The explainability of algorithms is an important aspect in education, since predictive models must identify students at risk and define the variables that can differentiate them; explainable AI approaches allow teachers and those responsible for education to interpret the results and make decisions regarding the supports to be provided [10].

Intelligent tutoring systems are an application of AI for personalizing learning. These systems can offer content and activities adapted to each student's practice, thereby promoting educational experiences aligned with the student's progress [11].

Furthermore, the proactive use of AI could predict potential educational needs based on the analysis of data trends, whereas reactive use could respond to needs identified throughout the learning process itself [12]. The integration of both modes could help improve assessment systems, especially in cases where information obtained during a diagnostic assessment is subsequently used to provide different learning and assessment pathways.

The recent development of generative tools has further narrowed those possibilities, as it would allow the construction of questions, activities, and feedback mechanisms based on specific performance levels. However, their introduction also requires the establishment of validation and supervision mechanisms to ensure the appropriateness of the generated content and preserve the teacher's responsibility for evaluation decisions [13].

Despite technological advances, there remains a need for empirical evidence demonstrating the impact of needs identification and evaluation adaptation on academic performance. In the literature, descriptions of the tools and their elements have been provided, perceptions have been investigated, and predictive models have been studied separately. Therefore, it is necessary to jointly analyze the detection of difficulties, the adaptation of evaluation, and the comparison of results with traditional procedures.

The present work aims to determine the effect of artificial intelligence on the detection of educational needs and the adaptation of assessment on the academic performance of students in Higher Basic General Education. Its objectives are to compare the results of a group assessed with AI with those of a conventional procedure, while also distinguishing cases with an initial measurement and a subsequent one after the intervention.

METHODS

The research was conducted under a quantitative approach, applied type, with an explanatory-comparative scope and a quasi-experimental design with pretest, posttest, experimental group, and control group. The study was longitudinal, because academic performance was evaluated before and after an eight-week intervention.

The population consisted of 240 students from eighth, ninth, and tenth year of Higher Basic General Education from one Ecuadorian educational institution. Using the calculation for finite populations, with a 95 % confidence level, 5 % margin of error, and maximum variability ($p = 0,50$; $q = 0,50$), a sample of 148 students was established. The participants were distributed into one experimental group of 74 students and one control group of equal size, maintaining the previously formed classes.

Students regularly enrolled, with participation in the two measurements and minimum attendance of 80% during the intervention, were included. Those with incomplete records or who did not complete any of the evaluations were excluded.

The independent variable was the application of artificial intelligence in evaluation processes, operationalized through four dimensions: detection of educational needs, adaptation of activities, automated feedback, and personalization of evaluation. The dependent variable was academic performance, assessed through conceptual domain, problem solving, application of knowledge, and reasoning.

For data collection, a 30-item academic performance test was designed, consisting of multiple-choice questions, application exercises, and problem situations. The total score was expressed on a scale from 0 to 100 points. The instrument was submitted to expert judgment to assess clarity, relevance, and correspondence with the studied dimensions. Subsequently, a pilot test was carried out with students outside the sample, and internal consistency was determined using Cronbach's alpha coefficient.

In the initial phase, the pretest was administered to the 148 participants to establish baseline performance. In the experimental group, the results were processed using an artificial intelligence-based system that analyzed response patterns, recurring errors, and performance by dimension. Based on this information, each student was classified into a level among three: high need for reinforcement, moderate need for reinforcement, or satisfactory mastery.

Based on the profile obtained, the system adapted the difficulty level and the type of evaluative activities. Students with greater difficulties received progressive exercises and reinforcement activities, while those with satisfactory mastery advanced toward tasks of greater complexity. After each activity, automated feedback was provided aimed at explaining errors and recommending new activities related to the identified difficulties.

The profiles were updated during the intervention according to the recorded performance. In this way, a student could modify their level of need as they demonstrated progress or presented new difficulties. All recommendations generated by the artificial intelligence were supervised by the teacher before their application.

The control group covered the same curricular content over an equivalent period, but used conventional assessments with activities, difficulty levels, and feedback mechanisms common to all participants, without automated personalization.

At the end of the eight weeks, a posttest equivalent to the initial instrument was administered. The same dimensions and general level of difficulty were retained, but different items were used to reduce the memorization effect.

For the analysis, means, standard deviations, frequencies, and percentages were calculated. Data normality was checked using the Shapiro-Wilk test. Differences between pretest and posttest within each group were analyzed using the Student's t-test for related samples, while differences in gain obtained between the experimental and control group were evaluated using Student's t-test for independent samples.

The magnitude of the effect of the intervention was determined using Cohen's d coefficient. Additionally, in the experimental group, Pearson's correlation was used to establish the association between the level of personalization received and the improvement in academic performance. A statistical significance level of $p < 0.05$ was adopted.

The research respected the principles of confidentiality, anonymity, and voluntary participation. Since the participants were minors, informed consent was obtained from their legal guardians and assent from the students. The data were coded and used exclusively for academic purposes, maintaining teacher supervision over the decisions generated by artificial intelligence.

RESULTS

The data obtained presented a distribution compatible with normality in both the experimental and control groups (Shapiro-Wilk, $p > 0.05$), so parametric tests were used. In the initial measurement, no significant differences were identified between both groups ($p = 0.841$), which showed comparable conditions before the intervention.

Both groups improved relative to the initial measurement; however, the increase was considerably greater in the group that used personalized assessment through artificial intelligence. The comparison of gain scores showed a difference of 11.5 points between groups ($t = 8.63$; $p < 0.001$). The effect size was large (Cohen's $d = 1.42$), indicating that the observed difference had practical relevance as well as statistical significance.

The analysis by dimensions made it possible to determine in which components of academic performance the main changes were concentrated.

Table 1. Comparison of global academic performance between pretest and posttest

Group	n	Pretest M ± SD	Posttest M ± SD	Gain M ± SD	t pre-post	p
Experimental	74	61.8 ± 8.9	79.6 ± 8.1	17.8 ± 8.5	18,01	<0,001
Control	74	62.1 ± 9.1	68.4 ± 8.7	6.3 ± 7.7	7,04	<0,001

Note. M = mean; DE = standard deviation. Own elaboration.

The greatest differences were recorded in application of knowledge and problem-solving. In the first dimension, the experimental group improved 20.2 points versus 6.1 for the control, with an effect size of 1.67.

Table 2. Pretest-posttest results by dimensions of academic performance

Dimension	Experimental pretest	Experimental posttest	Gain	Control pretest	Control posttest	Gain	p*	d
Conceptual domain	64.2 ± 9.1	79.8 ± 8.0	15,6	64.0 ± 9.4	70.4 ± 8.8	6,4	<0,001	1,14
Problem solving	59.4 ± 10.2	79.1 ± 8.5	19,7	59.7 ± 10.0	66.0 ± 9.1	6,3	<0,001	1,54
Application of knowledge	60.1 ± 9.8	80.3 ± 8.2	20,2	60.5 ± 9.6	66.6 ± 8.9	6,1	<0,001	1,67
Reasoning	63.5 ± 9.3	79.2 ± 8.4	15,7	64.1 ± 9.5	70.6 ± 8.6	6,5	<0,001	1,14

Note. Values expressed as mean ± standard deviation. *p corresponds to the comparison of gains between groups. Own elaboration.

In problem-solving, the gain was 19.7 versus 6.3 points, and an effect of 1.54 was obtained. Although conceptual domain and reasoning showed smaller increments, their effect sizes were also large. These results showed that the intervention had a greater impact on abilities that required using knowledge to solve situations and not merely recalling content.

Artificial intelligence also made it possible to classify academic needs based on recurring errors, response patterns, and performance by dimension. Before the intervention, both groups presented similar distributions of students with high need, moderate need, and satisfactory mastery ($\chi^2 = 0.031$; $p = 0.985$).

After eight weeks, the proportion of students in the experimental group with high need for reinforcement decreased from 41.9% to 10.8%, while satisfactory mastery increased from 12.2% to 63.5%. The control group also showed favorable progress, although of lesser magnitude: high need decreased from 40.5% to 29.7% and satisfactory mastery increased to 25.7%. The final distribution showed significant differences between groups ($\chi^2 = 22.18$; $p < 0.001$).

During the intervention, the experimental group's profiles were updated according to the responses obtained in the activities. Students with greater need received more reinforcement exercises, progressive changes in difficulty, and specific feedback, while those who achieved satisfactory mastery advanced to activities of greater complexity.

Table 3. Evolution of academic needs according to group

Level of need	Experimental pretest n (%)	Experimental posttest n (%)	Control pretest n (%)	Control posttest n (%)
High need for reinforcement	31 (41,9)	8 (10,8)	30 (40,5)	22 (29,7)
Moderate need for reinforcement	34 (45,9)	19 (25,7)	35 (47,3)	33 (44,6)
Satisfactory mastery	9 (12,2)	47 (63,5)	9 (12,2)	19 (25,7)
Total	74 (100)	74 (100)	74 (100)	74 (100)

Note. Classification obtained from the performance recorded in the evaluated dimensions. Own elaboration.

Pearson correlation analysis showed a positive correlation between the level of personalization received and academic gain ($r = 0.58$; $p < 0.001$). Therefore, greater adaptation of the activities was associated with larger increases in performance. The relationship had a moderate-to-high magnitude, indicating that personalization contributed significantly to the observed changes, although it does not alone explain all the variation in performance.

Overall, the results revealed 3 main effects of the intervention: a greater increase in academic performance compared with conventional assessment, a reduction in the number of students with high reinforcement needs, and a positive association between the degree of personalization and the improvement achieved. The changes were especially notable in problem solving and knowledge application.

Discussion

The results indicate that assessment supported by artificial intelligence was more effective in improving academic performance than assessment conducted with the usual procedure. The experimental group showed a mean gain of 17.8 points compared with 6.3 in the control group, with a high effect size ($d = 1.42$).

This result is consistent with the findings of Ouyang et al. [14], who state that AI can improve assessment through functions such as diagnosis, adaptation, and feedback regarding individual performance.

The most notable differences were observed in knowledge application and problem solving, with effect sizes of 1.67 and 1.54, respectively. This suggests that personalization is especially useful in tasks that require applying specific knowledge in response to concrete errors. Ouyang et al. [15] state that intelligent systems can adapt activities to student characteristics, thereby favoring more specific interventions than uniform assessments.

The reduction in the number of students with high reinforcement needs, from 41.9% to 10.8%, constitutes another relevant result. At the same time, satisfactory mastery increased to 63.5% in the experimental group, compared with 25.7% in the control group. These findings support the use of AI to identify academic difficulties and guide support actions, although such classifications should not be interpreted as psychopedagogical diagnoses. Pagliara et al. [16] warn that the integration of AI in inclusive contexts requires professional supervision and careful interpretation of the generated information.

Early detection also enabled the redirection of resources to students with greater needs. Qushem et al. [17] note that predictive analytics can help identify at-risk students and facilitate timely interventions. In the present study, detection was used not only to identify difficulties but also to link those difficulties to reinforcement activities, changes in difficulty, and differentiated feedback.

Furthermore, the results gain greater relevance in a Latin American context, where empirical evidence on artificial intelligence in education is still scarcer than in other regions. Salas-Pilco and Yang [18] found a progressive expansion of these techniques in Latin America, but they also identified limitations related to infrastructure, implementation, and the existence of contextualized studies. Therefore, the evidence* provided by this study contributes to determining its applicability in an Ecuadorian educational context.

The positive correlation between personalization and academic gain ($r = 0.58$; $p < 0.001$) indicates that students who received greater adaptation tended to experience greater improvements. This finding is consistent with Toyokawa et al. [19], who note that intelligent systems can support more individualized experiences when student data are used to guide pedagogical decisions. However, the strength of the correlation indicates that personalization alone does not explain all the observed change, because performance may also be related to individual and contextual factors.

Another element that may have had a positive influence is the inclusion of automated feedback. According to Xia et al. [20], AI opens possibilities for generating feedback and differentiated activities, but its quality must be verified. In line with this perspective, the intervention retained teacher supervision of the recommendations generated by the system.

Xu and Ouyang [21] highlight that AI can perform tutoring, assessment, and decision-support functions. The obtained results particularly support the latter function, since the technology made it possible to identify patterns and propose adaptations without replacing the teacher's pedagogical responsibility. Such supervision becomes even more important when working with students with diverse needs, due to the risk of inaccurate or biased classifications [22].

The need to keep the teacher in the process coincides with the findings of Zawacki-Richter et al. [23], who pointed out that a significant part of research on educational AI has focused on the technological component. The results of the present study show that the effectiveness of the tool depends on its integration with pedagogical criteria and on the human validation of its automated decisions. These results are consistent with those of Zhai et al. [24], who identify prediction, personalization, tutoring, and evaluation as central areas of AI application in education. The most important contribution of this study is to incorporate all these elements into a single process: identifying needs, adapting assessment, and subsequently analyzing academic progress.

A limitation was the participation of a single institution and the 8-week duration. Future studies should increase the sample, incorporate diverse educational centers, and conduct follow-up measurements to determine whether the improvements persist in the medium and long term.

CONCLUSIONS

The integration of artificial intelligence into evaluation processes improved competence to a greater extent than traditional evaluation, as evidenced by an average gain of 17.8 points in the experimental group versus only 6.3 points in the control group and a large effect size ($d = 1.42$).

Personalization had the greatest impact on knowledge application skills and problem solving, where the largest increases in effect sizes were observed (1.67 and 1.54, respectively).

The intervention reduced the proportion of students with a high need for reinforcement from 41.9% to 10.8% and increased the proportion achieving satisfactory mastery from 12.2% to 63.5%, thereby demonstrating considerable improvement in the structure of academic mastery needs.

The relationship between the level of personalization and academic gain ($r = 0.58$; $p < 0.001$) confirmed that greater adequacy of activities, difficulty, and feedback was associated with better learning.

Artificial intelligence already plays a role as a support tool for identifying difficulties and guiding evaluative decisions, always subordinate to teacher supervision and to pedagogical, ethical, and explanatory criteria.

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CONFLICT OF INTEREST

It does not exist.

AUTHORSHIP CONTRIBUTIONS

Conceptualization: Francisco Javier Santini Rodriguez and Luis Carlos Rodriguez Montaño. Data curation: Luis Carlos Rodriguez Montaño and Mario Isaac Romero Lamadrid. Formal analysis: Francisco Javier Santini Rodriguez, Luis Carlos Rodriguez Montaño and Mario Isaac Romero Lamadrid.
Research: Francisco Javier Santini Rodriguez, Luis Carlos Rodriguez Montaño and Mario Isaac Romero Lamadrid.
Methodology: Francisco Javier Santini Rodriguez and Luis Carlos Rodriguez Montaño. Supervision: Francisco Javier Santini Rodriguez.
Validation: Francisco Javier Santini Rodriguez and Luis Carlos Rodriguez Montaño. Visualization: Mario Isaac Romero Lamadrid.
Writing – original draft: Francisco Javier Santini Rodriguez and Mario Isaac Romero Lamadrid.
Writing – review and editing: Francisco Javier Santini Rodriguez, Luis Carlos Rodriguez Montaño and Mario Isaac Romero Lamadrid.