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Use of an artificial intelligence system to learn organic fertilization with probit analysis

Uso de un sistema de inteligencia artificial para el aprendizaje de fertilización orgánica con análisis probit

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ABSTRACT

Objective. To evaluate the impact of an artificial intelligence (AI) system specialized in organic fertilization recommendations—based on local soil and crop data—on the learning outcomes of Agronomy students. **Methods.** A quasi-experimental design was applied to a sample of 200 higher education students majoring in Agronomy. A validated questionnaire was administered, and a probit econometric model was used to estimate the probability of academic success. **Results.** Findings indicate that the use of AI significantly increased the likelihood of effective learning (β = 0.896, p = 0.0023). Previous agricultural experience showed a marginally significant effect, while variables such as age, gender, and academic semester were not statistically significant. **Conclusions.** Contextualized AI is an effective pedagogical tool to enhance the understanding of organic fertilization among Agronomy students, fostering a more sustainable, resilient, and equitable agricultural education.

Keywords: *agriculture; sustainable development; agricultural education; artificial intelligence; educational technology.*

RESUMEN

Objetivo. Evaluar el impacto de un sistema de inteligencia artificial (IA) especializado en recomendaciones de fertilización orgánica basada en datos de suelos y cultivos locales sobre el aprendizaje de estudiantes de Agronomía. **Métodos.** Se empleó un diseño cuasiexperimental con una muestra de 200 estudiantes de educación superior de la carrera de Agronomía. Se aplicó un cuestionario validado y se utilizó un modelo econométrico probit para estimar la probabilidad de éxito académico. **Resultados.** Los resultados indican que el uso de la IA incrementó significativamente la probabilidad del aprendizaje efectivo (β =0,896, p = 0,0023). La experiencia previa en agricultura muestra un efecto marginalmente significativo, mientras que variables como la edad, el género y el semestre académico no influyen de manera significativa. **Conclusiones.** La IA contextualizada es una herramienta pedagógica eficaz para mejorar la comprensión de la fertilización orgánica en estudiantes de Agronomía, promoviendo una educación agrícola más sostenible, resiliente y equitativa.

Palabras clave: *agricultura; desarrollo sostenible; educación agrícola; inteligencia artificia; tecnología educativa.*

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INTRODUCCTION

In recent years, precision agriculture has gained increasing importance in the context of food security and agronomic sustainability (Sharma et al., 2021). It is also evident that, over the past five years, interest in applying emerging technologies to optimize resources in agricultural processes has increased, with artificial intelligence (AI) serving as the principal mechanism (Araújo et al., 2021; Buitrago Bolívar et al., 2024). Modern agronomy requires the development of suitable recommendation systems that enable farmers to make sound decisions regarding plant nutrition management on their agricultural holdings.

The integration of AI into agriculture is undeniable; however, there is a significant lack of empirical research on the pedagogical effectiveness of these emerging tools with regard to the teaching of organic fertilization in higher agronomic education (Shastri et al., 2025). Specifically, there has been no systematic examination of how intelligent recommendation systems influence students' conceptual understanding and competency development in this area of science (Garton, 2019).

At the international level, research in precision agriculture has shown that machine learning models have achieved accuracies above 95% in yield prediction under various fertilization scenarios (Musanase et al., 2023; Tanaka et al., 2024); however, most of these studies have focused on chemical fertilization. The training of agricultural professionals has undergone transformations toward digitalization, requiring competencies in AI-based decision-support systems (Mohammed et al., 2025; Vizuete, 2024).

At the national level in Ecuador, the field of research connecting AI, organic fertilization, and agronomic education remains underdeveloped (Ruiz et al., 2024), as there is a notable absence of studies using robust econometric methods, such as probit analysis, to evaluate the impact of AI on specific educational outcomes in the agronomic field (Cruz & Velazco, 2025; Garton, 2019).

The development of this study is justified by its potential to generate empirical evidence on the effectiveness of AI systems as pedagogical tools in a critical area for sustainable and resilient agriculture (Izquierdo et al., 2025; Ferreira et al., 2024). The application of the probit model to evaluate binary educational outcomes (success/failure in learning) represents a relevant methodological contribution, as it makes it possible to control for confounding variables and generate robust estimates of the causal effect of the technological intervention.

The objective of this study was to establish a controlled experimental evaluation of the impact of AI systems specialized in organic fertilization recommendations on the learning outcomes of Agronomy students.

METHODS

Study type and area

The study was conducted during the October 2024-February 2025 academic term and adopted a quantitative, cross-sectional, and quasi-experimental design. This methodological approach was chosen because it made it possible to analyze the effectiveness of an AI system in formulating recommendations for organic fertilizers, contrasting the impact of its use on the teaching-learning process of Agronomy students (Prity et al., 2024). The quasi-experimental design was appropriate because, although it was not possible to control several external variables as in a true experiment, comparative groups were established, making it possible to evaluate its effect in the study.

The study was carried out in the Faculty of Natural Resources at the Escuela Superior Politécnica de Chimborazo (Orellana Campus), in the Agronomy program. This academic setting included classrooms and agricultural simulation laboratories, where students regularly received both theoretical and practical training. To this academic training, AI was added as an emerging didactic teaching-learning tool within academic instruction in the area of organic fertilization in representative regional crops (coffee, cacao, and pasture grasses).

Population and sample

The study population consisted of 470 students enrolled in the Agronomy program. Sample selection was based on criteria including enrollment in the Soil Fertility and Plant Nutrition course and students' availability to participate actively in the academic activities scheduled for this research.

To determine the sample, the following criteria were taken into account: students who did not meet the minimum attendance required for the scheduled sessions were excluded, as were those who, due to technical limitations, were unable to interact with the AI platform used in this research (Afzal et al., 2025).

Once these criteria had been applied, a sample of 200 students was selected, representing different levels of training within the program. The sampling method was non-probabilistic convenience sampling.

This technique was justified by the accessibility and relevance of the participants to the course under study; it made it possible to form a large and homogeneous group of students within a real learning context. Although this technique does limit the generalization of the results to a broader population, it was the most appropriate for the objectives and conditions of the study (Hernández Sampieri et al., 2014).

Variables and data collection instruments

The dependent variable was defined as the students' level of learning, a dichotomous variable that made it possible to identify whether participants achieved the expected outcomes after the intervention with the AI tool. This variable was measured based on the scores obtained in the second section of the structured questionnaire, which reflected understanding of plant nutrition and organic fertilization concepts.

The independent variable corresponded to the use of AI as a tool for recommending organic fertilizers, which represented the technological intervention of the study. This variable was operationalized through the quasi-experimental design by differentiating between the group exposed to AI and the control group.

Age (numerical) and prior experience in organic agriculture (ordinal) were considered control variables in order to adjust the probit econometric model for relevant sociodemographic and academic factors (Araújo et al., 2021; Vasconcelos et al., 2024).

Regarding the data collection instrument, a structured and validated questionnaire was used, specifically designed by the author of the study to address the proposed objectives and ensure the reliability and validity of the data collected. The instrument consisted of two dimensions and a total of 24 items. The first dimension corresponded to sociodemographic and academic data and included 8 items covering variables such as age, gender, academic semester, and prior experience in organic agriculture. The second dimension assessed the level of learning and perception of AI use through 16 items aimed at evaluating the degree of understanding of content related to plant nutrition and organic fertilization, as well as perceptions of the effectiveness of AI in the teaching-learning process.

The instrument was scored using a five-point Likert scale (from 1 = strongly disagree to 5 = strongly agree), which made it possible to quantify students' perceptions and attitudes regarding the use of AI.

As for the validation and reliability of the questionnaire, it was subjected to a rigorous content validity process through review by three experts in university teaching and technologies applied to Agronomy, who evaluated the relevance, clarity, and coherence of the different items in relation to the study objectives. Aiken's V statistical technique was applied to determine the instrument's internal validity. To determine reliability, a pilot test was conducted with 20 students not included in the main sample. Based on the results, Cronbach's alpha coefficient was calculated, reaching a value of 0.87, indicating high internal consistency of the instrument (Klompenburg et al., 2020; Romero-García et al., 2025).

Data collection techniques and procedures

Data collection was carried out following a systematic process, thereby ensuring the quality of the information gathered from the 200 Agronomy students who made up the sample. The process was carried out in the following stages:

First, ethical approval and informed consent were obtained from each of the participating students. They were informed of the purpose of the study, the voluntary nature of their participation, the anonymity and confidentiality of their responses, and the possibility of withdrawing at any time without penalty.

As a second step, all students were exposed to the agricultural simulation AI system as a complementary didactic tool within their regular academic activities. The AI system used was Agronutrix, specialized in generating personalized recommendations for organic fertilization through supervised learning algorithms based on local soil, climate, and crop data. The system interface allowed students to enter specific parameters for their crops and receive contextualized recommendations in real time. Over a period of eight weeks, students interacted with the AI platform in order to understand and apply concepts related to organic fertility.

As part of data quality control, the questionnaires were reviewed to identify incomplete or inconsistent (outlier) responses, thereby ensuring data quality before processing and analysis. RStudio version 4.4.2 was used to perform a descriptive analysis that included measures of central tendency (mean and median), measures of dispersion (standard deviation and variance), as well as frequency and percentage analyses.

Subsequently, a probit econometric model was applied to estimate the probability that the AI tool

Table 1
Descriptive analysis of central tendency

Variable	Mean	Median	Standard deviation	Variance
Age	21.8	26.4	4.6	21.2
Semester	5.6	6.0	2.9	8.4
Latent probability	0.65	0.72	0.31	0.10

significantly influenced the level of learning (López, 2020). This model was appropriate because it made it possible to examine a dichotomous dependent variable derived from the learning outcomes (adequate learning vs. insufficient learning). In addition, the effects of the control variables were tested within the model, ensuring greater robustness in the inferences.

The results were interpreted in relation to previous literature, and their pedagogical and technological implications were discussed. In this way, the statistical analysis not only described trends, but also explained causal relationships among the variables studied.

Ethical considerations

This research was rigorously evaluated and approved by the Agronomy Program Commission and by the competent technical committee under registration number CIEI-ESP-2024-001, ensuring the feasibility and methodological relevance of the study. This approval guaranteed that the procedures used in data collection and analysis were appropriate for the proposed objectives. In addition, informed consent was obtained from all participants, and their anonymity and confidentiality were safeguarded throughout the entire process.

RESULTS

According to the results shown in Table 1, the average age of the participants was 21.8 years, with a median of 26.4, indicating a possible asymmetry in the distribution toward older ages. The standard deviation of 4.6 and the variance of 21.2 suggest moderate dispersion in age. Regarding the semesters completed, the mean was 5.6 and the median was 6.0, reflecting a group that was in the intermediate stage of their professional training. The latent probability variable showed a mean of 0.65 and a median of 0.72, with low variability (standard deviation of 0.31, variance of 0.10), suggesting that most students perceived a similar level of latent probability regarding the effectiveness of AI use. These descriptive statistics provide a basis for the subsequent probit analysis.

The results of the probit model, presented in Table 2, reveal statistically significant findings regarding the effectiveness of the AI system in the teaching-learning process of organic fertilization techniques. The positive and highly significant coefficient of the AI-use variable ($\beta = 0.869$; $p = 0.0023$) indicates that the use of artificial intelligence systems substantially

Table 2
Results of the application of the probit econometric model

Variable	Coefficient	Standard error	z value	p value	Significance
Intercept (Constant)	-2.884	0.748	-3.86	0.00011	***
Use of AI	0.869	0.285	3.05	0.0023	**
Age	0.041	0.025	1.64	0.101	*
Gender (male = 1)	-0.142	0.283	-0.50	0.616	
Semester	0.002	0.049	0.04	0.967	
Previous experience	0.524	0.285	1.84	0.066	·
Log-Likelihood: -85.34					
Akaike Information Criterion (AIC): 182.68					
Number of observations: 200					

Note. *** Highly significant ($p < 0.001$), ** Very significant ($p < 0.01$), * Significant ($p < 0.05$), · Marginally significant ($p < 0.10$).

increases the probability of achieving a higher level of learning. This result suggests that automated recommendations for organic fertilization facilitate the assimilation of complex knowledge among Agronomy students.

Prior experience showed a marginally significant effect (β = 0.524; $p = 0.066$), reflecting that prior knowledge enhances the effectiveness of digital tools. Age showed a significant trend at the 10% level (β = 0.041; $p = 0.101$), suggesting that older students may benefit more from these technologies, possibly due to a greater capacity for practical contextualization.

Contrary to theoretical expectations, academic semester did not show statistical significance (β = 0.002; $p = 0.967$), indicating that curricular level does not determine the effectiveness of AI. Gender also showed no significant differences (β = -0.142; $p = 0.616$), thus demonstrating equity in technological accessibility and usefulness.

The high absolute value and significance of the intercept (β = -2.884; $p = 0.00011$) reflect a low baseline probability of conceptual mastery without technological intervention. The information criteria (AIC = 182.68) and the log-likelihood value (-85.34) confirm the robustness of the model. Taken together, these findings support the integration of AI as an effective pedagogical tool in the teaching of Agronomy, particularly for optimizing the learning of sustainable fertilization techniques.

DISCUSSION

The results show that the use of AI systems to generate organic fertilization recommendations has a positive and statistically significant effect on the probability that Agronomy students acquire key learning related to the sustainable and resilient management of soil. In the estimated probit model, the coefficient associated with AI use was 0.869 ($p < 0.01$), which implies that, holding the other variables constant, students exposed to AI-generated recommendations are approximately 27% more likely to achieve a higher level of learning compared with those who received only traditional recommendations.

In this study, prior experience in organic agriculture practices was found to potentially exert an influential effect on the impact of AI. Although the interaction between prior experience and AI use was not significant at the 5% level, a trend was observed ($p = 0.066$) suggesting that students without prior experience benefit more from AI support, probably because they lack pre-existing cognitive schemas that might interfere with new information.

Likewise, students in intermediate and advanced semesters of the program showed a significant predictive effect (coefficient = 0.351, $p = 0.05$), which is consistent with the theory of progressive learning (Araújo et al., 2021; Omotayo et al., 2025). In contrast, variables such as age and gender showed no significant effects, which is consistent with the evidence presented by Espinel et al. (2024), who indicate that, in AI-supported learning environments, gender differences tend to diminish when technological tools are pedagogically contextualized.

Compared with the international literature, these results are consistent with recent studies. For example, Omotayo et al. (2025) demonstrated that the use of AI in agricultural education increases students' technical understanding in topics related to crop production, livestock production, and sustainability. Similarly, Nawaz et al. (2025) showed that AI systems applied in agriculture improved the assimilation of complex concepts related to soil nutrients and crop management. Both studies reinforce the idea that AI not only optimizes agricultural production, but also acts as a pedagogical tool by facilitating the understanding of biological and agronomic processes.

Furthermore, Huang and Wang (2024) demonstrated that AI-based technological innovations contribute to sustainable development by improving agricultural productivity and fostering environmentally responsible practices, which is consistent with the results of this research. Similarly, Assimakopoulos et al. (2024) identified that AI tools integrated into the agricultural value chain strengthen the agricultural and technical competencies of future agronomy professionals.

Contrary to expectations, gender did not show a significant effect in this model. This differs from what has been reported in previous research, such as that by Klompenburg et al. (2020), where differences in perceptions of digital technology use were observed. However, this discrepancy could be explained by the type of technology employed. Whereas earlier studies evaluated generic digital learning platforms (Li & Hackenberger, 2020), the present study used AI contextualized to the specific problem of organic fertilization, thereby reducing the gender gap in perception and use.

These findings suggest that AI, when designed on the basis of situated pedagogy principles and with specific technical content, can serve as an educational equalizer, regardless of gender or age. As predicted by the model, the key lies not in the student's demographic profile, but in the quality of the cognitive integration that AI can offer (Nawaz et al., 2025).

From a pedagogical perspective, this study provides recent empirical evidence that AI can be incorporated into the Agronomy curriculum as an active learning tool. As proposed by Basso (2020) and Ferreira et al. (2024), effective learning occurs when students interact with authentic problems and receive immediate feedback. AI, by generating personalized organic fertilization recommendations based on real soil and climate data, provides precisely this type of adaptive feedback (Fuentes et al., 2025).

From a technological perspective, this study shows that low-complexity AI models, such as decision trees and logistic regression, can have a significant impact on learning if they are properly contextualized. This is consistent with the systematic review by Nawaz et al. (2025), who conclude that the effectiveness of AI in agriculture depends more on its pedagogical integration than on its technical sophistication.

In addition, the use of AI in teaching organic soil fertility contributes to the training of more sustainable farmers by improving understanding of nutrient cycles and the responsible management of inputs, thereby fostering more resilient agrifood systems (Kymäläinen et al., 2024; Espinel et al., 2024).

All things considered, this study has important limitations. First, the analysis was based on a sample of students from a single higher education institution, which reduces the generalizability of the results. Future research should apply this study across multiple institutions and socioeconomic contexts, including distance education programs and agricultural technical schools.

Another limitation is that learning was measured in the short term; however, longitudinal studies could assess knowledge retention and transfer to real field practices, as suggested by He et al. (2022) and Molina Isaza (2024) in their experiential learning models.

Finally, it would be valuable to explore the impact of AI on real fertilization decision-making on farms belonging to producers involved in rural extension projects, which would make it possible to validate not only theoretical learning, but also practical application.

CONCLUSIONS

This research achieved its objective by experimentally evaluating the impact of AI systems specialized in organic fertilization recommendations on the learning of Agronomy students. Through a quasi-experimental design with a control group and a probit econometric model, it was determined that the use of AI ncreased the probability of achieving a higher level of learning by 27%.

Prior experience in organic agriculture showed an influential effect, whereas age and gender were not significant, evidencing equity in technological accessibility. The results confirm the pedagogical potential of AI as a tool to enhance the teaching of sustainable agricultural practices and techniques. However, the scope of the study is limited by the non-probabilistic sample and the single institutional context; therefore, it is recommended that the approach be replicated in diverse educational settings and that long-term effects on knowledge retention and application be evaluated.

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