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ORIGINAL

Impact of generative artificial intelligence on the decision-making of university students in the health sciences: A transversal study

Impacto de la inteligencia artificial generativa en la toma de decisiones de estudiantes universitarios en el área de las ciencias de la salud: Un estudio transversal

Darwin Marcelo Varela Lascano[1], Tania Lisbeth Chicaiza Zambrano[1], Eduardo Xavier Macías Collahuazo[1], Yordan Ernesto Calero Ocaña[1]

[1]Escuela Superior Politécnica de Chimborazo. Riobamba, Ecuador.

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Corresponding author: Darwin Marcelo Varela Lascano

ABSTRACT

Advanced AI systems, such as those in their generative phase, cause uncertainty among higher education students about their functionality and the academic level they may have when interacting with IAGs such as ChatGPT. The study aimed to examine how interaction with AI tools, such as generative language models, influences students' ability to select learning strategies, manage academic resources, and make informed decisions during their professional training. A quantitative, descriptive, non-experimental approach was used. The initial population was 500 students from the Faculty of Medicine of two recognized higher education institutions in Ecuador, after applying certain inclusion criteria through random convenience sampling. The results showed that generative artificial intelligence significantly influences the academic decision-making of medical students, with scalability and efficiency standing out as key factors. In contrast, user satisfaction showed an inverse relationship, and institutional integration was not a determining factor. It is concluded that the impact of these tools depends on their strategic functionality rather than their superficial perception.

Keywords: Higher Education; Artificial Intelligence; Decision-Making; Students; Health Sciences.

RESUMEN

Los sistemas avanzados de la IA como su fase generativa causan incierto entre los estudiantes de educación superior sobre su funcionalidad y el nivel académico que pueda tener al momento de interactuar con IAG como ChatGPT. El estudio tuvo como objetivo examinar cómo la interacción con herramientas de IA, como los modelos de lenguaje generativo, influye en la capacidad de los estudiantes para seleccionar estrategias de aprendizaje, gestionar recursos académicos y tomar decisiones informadas durante su formación profesional. Se utilizó un enfoque cuantitativo de tipo descriptivo y no experimental, la población inicial fue de 500 estudiantes de la Facultad de Medicina de dos IES reconocidas en el Ecuador, posteriormente después de aplicar ciertos criterios de inclusión mediante un muestreo aleatorio por conveniencia. Los resultados evidenciaron que la inteligencia artificial generativa incide significativamente en la toma de decisiones académicas de estudiantes de medicina, destacándose la escalabilidad y eficiencia como factores clave. En contraste, la satisfacción del usuario mostró una relación inversa y la integración institucional no resultó determinante. Se concluye que el impacto de estas herramientas depende de su funcionalidad estratégica más que de su percepción superficial.

Palabras clave: Educación Superior; Inteligencia Artificial; Toma de Decisiones; Estudiante; Ciencias de la Salud.

INTRODUCTION

Artificial intelligence has revolutionized various sectors of human knowledge, emerging with particular force in the field of education. Among its many strands, generative artificial intelligence, represented by large-scale language models such as GPT, has attracted increasing attention for its ability to generate content, provide automated feedback and assist in academic decision-making.[1] This technology, for Bellas[2] based on deep learning architectures, allows the contextualized production of coherent texts, as well as adaptive interaction with users, which has facilitated its incorporation in higher education pedagogical processes. Recent research shows that generative models have the potential to foster critical and creative thinking, particularly when used as tools to support writing, assessment or complex problem solving in educational contexts.[3,4,5,6]

At the same time, decision-making in university students is an understudied dimension of academic and professional performance, especially in disciplines such as health sciences, where the ability to analyze information, evaluate alternatives, and act with clinical judgment has direct implications for patient safety and well-being.[7] This cognitive process, for Kaewrat[8] influenced by emotional, motivational and contextual factors, can be mediated by emerging technologies, which not only amplify access to information but also shape patterns of individual reasoning and judgment. Decision-making in complex academic environments requires scaffolding that balances human judgment with technological tools that offer accuracy, objectivity and personalized support.[9,10]

The confluence between generative artificial intelligence and student decision-making has begun to be explored by a number of researchers, especially in the context of predicting academic performance and personalizing learning. Albahli[11] points out that AI-based models, such as neural networks and explainable algorithms (XAI), can highly accurately anticipate student performance, facilitating timely pedagogical interventions and personalized learning strategies.

Furthermore, tools such as ChatGPT have been documented to not only provide effective automated feedback, but also to positively impact students' motivation and self-perception of their decision-making abilities.[12,13] However, there are still ethical, pedagogical and methodological challenges that require a rigorous evaluation of their impact on the training process, particularly in contexts where critical, jud personalized professional ethics are fundamental pillars, such as in the health sciences.[14,15]

In the context of higher education, the use of generative artificial intelligence has begun to have a direct impact on academic decision-making, offering predictive and analytical tools to optimize student planning and guidance.[16] For example, Farber[17] evidence how large-scale language models (LLMs) can effectively assist in the selection of scientific journals for academic publication by comparing AI-generated recommendations with high accuracy against expert human judgement.[18,19,20,21] This experience demonstrates that AI systems not only simplify complex tasks, but also strengthen users' analytical capabilities, enabling them to evaluate multiple criteria in greater depth for informed and efficient decision-making.[22,23,24,25]

In addition, recent research highlights that the design of decision support systems, integrated with data mining techniques, can facilitate the early identification of academic risk factors, enabling timely interventions by institutions. Maniyan et al.[26] propose a hybrid system based on associative rules and supervised algorithms to predict students' academic performance before the start of the course, providing a powerful tool for planning personalized learning trajectories and making sound curricular decisions. In addition, Usher y Barak[27] demonstrated that explicit-reflective AI ethics training modules significantly strengthen ethical decision-making skills in science and technology students, showing an improvement in their ability to identify dilemmas, assess risks and propose solutions in AI-mediated educational scenarios.[28,29,30,31]

In this scenario of educational transformation driven by emerging technologies, this study aims to analyses the impact of generative artificial intelligence on the academic decision-making processes of university students in health sciences. The research is framed in a cross-sectional design with a quantitative approach, aimed at examining how interaction with AI tools, such as generative language models, influences students' ability to select learning strategies, manage academic resources and make informed decisions during their professional training.[32,33] Based on these, the following research questions are posed:

RQ1: To what extent does the use of generative artificial intelligence affect the criteria used by health science students for academic decision-making?

RQ2: Is there a significant relationship between the level of interaction with generative AI tools and self-perceived efficacy in academic decision-making in university contexts?

METHOD

Approach

This study was developed under a quantitative approach, as it allowed us to obtain measurable and objective data on the use of generative artificial intelligence in academic contexts.[34] This approach sought to analyze relationships between variables by means of statistical procedures, guaranteeing rigorous treatment of the information collected.

A cross-sectional and correlational study was conducted. Data collection was carried out at a single point in time, which allowed for the observation of variable behaviour without intervention. In addition, multiple linear regression analysis was applied, which allowed the degree of influence exerted by certain independent variables on a dependent variable to be identified, providing a deeper insight into the factors that affect artificial intelligence-assisted decision-making.

Participants

The population consisted of 500 undergraduate medical students from two nationally recognized higher education institutions in Ecuador: The Technical University of Ambato and the Polytechnic School of Chimborazo. From this universe, a final sample of 210 students was selected through random convenience sampling. The inclusion criteria considered to obtain the final sample were belonging to the morning session and studying in the fourth, fifth or sixth semester, with the aim of ensuring that participants had sufficient academic background and relevant training experiences for the study.

To ensure the ethical compliance of the process, institutional consent was obtained from both universities and participants were informed in detail about the objectives and characteristics of the study. All students agreed to participate voluntarily, and the respective informed consent form was shared with them, guaranteeing respect for their privacy, the confidentiality of the data and their right to withdraw from the study at any time without repercussions.

Instrument

Data collection was carried out using a questionnaire adapted from the instrument developed by Funda and Francke[10], which was contextualized to the Ecuadorian university educational environment. The instrument consisted of a demographic section and 25 items distributed in five constructs: Decision Support with items 7, 14, 15, 19, 20, 22 and 23 as dependent variable; and as independent variables: Efficiency with items 10, 11 and 12, Integration with items 6, 8, 9 and 21, User Satisfaction with items 1, 5, 24 and 25 and finally Scalability with items 13, 16, 17 and 18. Responses were collected using a five-level Likert-type scale, which facilitated the interpretation of student perceptions of the use of AI tools in their academic environment.

Information processing

The collected data was coded and analyzed using SPSS v.26 statistical software. A descriptive analysis was performed to observe general trends in the responses, as well as a correlational analysis using Pearson's coefficient to identify the strength and direction of relationships between variables. Finally, a multiple linear regression model was applied to determine the explanatory weight of the independent variables on Decision Support, thus providing relevant information on the factors that influence the effective use of generative artificial intelligence in university academic contexts.

RESULTS

In this section, we present the findings obtained after the statistical analysis of the information collected through the questionnaire applied to medical students from the participating universities. The results are organized according to the objectives of the study and allow us to observe both the general trends in student perceptions and the statistical relationships between the variables analyzed.

The socio-demographic characterization of the study showed that most of the participants are concentrated in the intermediate age range, with 39,5 % of students between 21 and 23 years of age, followed by 27,7 % in the lower age range, which is coherent with the formative cycle of the medical career in its middle levels. 22,7 % correspond to the youngest group in the sample and only 10 % belong to the oldest segment, indicating a predominantly young population in an active academic stage and exposed to emerging technological tools.

In terms of gender, the distribution shows a slight majority of female students 52,7 % compared to 47,3 % of male students, which reflects a balanced participation of both sexes. In institutional terms, the highest proportion of students comes from the Technical University of Ambato 55,5 %, while 44,5 % corresponds to the Polytechnic School of Chimborazo, which guarantees geographical and academic representativeness of both institutions participating in the study.

Regarding the level of training, 44,5 % of the students are in their sixth semester, followed by 30,5 % in their fourth semester and 25 % in their fifth semester, which ensures that the participants have already acquired a

sufficient academic basis to understand and interact with technological tools in their training process. Finally, it is important to note that 59,1 % of respondents expressed a high interest in artificial intelligence, compared to 38,6 % who indicated little interest and only 2,3 % who reported no interest at all. This favorable predisposition is a key element in understanding the receptiveness and potential impact of AI technologies in healthcare educational contexts.

Table 1. Sociodemographic data of the population

Characteristics		Frequency	Percentage
Age	19 years	50	22,7 %
	20 years	61	27,7 %
	21 years	87	39,5 %
	22 years or older	22	10 %
Gender	Female	116	52,7 %
	Male	104	47,3 %
Institutions	Escuela Superior Politécnica del Chimborazo	98	44,5 %
	Universidad Técnica de Ambato	122	55,5 %
Semester	Fourth	67	30,5 %
	Fifth	55	25 %
	Sixth	98	44,5 %
IntInterest in IA	A lot	130	59,1 %
	Little	85	38,6 %
	Nothing	5	2,3 %

The results of the descriptive analysis reflect a high valuation by students towards the use of generative artificial intelligence in their academic decision-making processes. The Decision Support dimension registered an average value of 30,27 out of a possible 35 points, which denotes a strong acceptance and positive perception regarding the functional impact of these tools in health training contexts. The standard deviation of 1,99 suggests a low dispersion of responses, which is evidence of a significant consensus among participants.

Regarding the independent variables, the User Satisfaction dimension presented the highest average, reaching a value of 17,98, followed by Scalability with 17,77 and Integration with 16,88. These results reflect a positive evaluation by the students in relation to the ease of use, adaptability and compatibility of the artificial intelligence system with their academic environments. Measures of central tendency, such as median and mode, were consistently close to the observed means, indicating a symmetrical and stable distribution of the data.

The efficiency variable obtained a mean of 12,62, the lowest among the dimensions analyzed, although within an equally favourable range. Despite being slightly lower, its low coefficient of variability suggests that participants maintain a constant perception of the system's ability to optimize resources and reduce time in their academic activities. Overall, the descriptive results allow us to affirm that students not only recognize the operational usefulness of generative artificial intelligence but also its potential as a complementary tool for the development of decisional competences in demanding and highly dynamic university environments.

Table 2. Descriptive statistics

	Decision support	Efficiency	Integration	User satisfaction	Scalability
Mean	30,2682	12,6182	16,8773	17,9796	17,7682
Median	30,0000	13,0000	17,0000	18,0000	18,0000
Mode	30,00	12,00	17,00	18,00	17,00
Deviation	1,99449	1,13863	1,67943	1,75983	1,41933
Variance	3,978	1,296	2,820	3,097	2,015
Minimum	16,00	7,00	11,00	10,00	5,00
Maximum	33,00	14,00	20,00	20,00	20,00

Pearson's correlation analysis identified significant associations between the dependent variable Decision Support and the various independent factors assessed. The most robust relationship was observed with the Scalability variable, showing a correlation coefficient of 0,645, which represents a moderate to high positive

association. This result suggests that the greater the perceived scalability of the system, understood as its ability to adapt to changing contexts, foresee future situations and remain functional in complex scenarios, the greater the perceived usefulness of the system as a support tool in academic decision-making.

A significant positive correlation was also observed between decision support and efficiency, with a coefficient of 0,564. This association reveals that students tend to value generative artificial intelligence more positively as a support tool to the extent that they perceive that it contributes to a more efficient management of resources, time and learning processes. The Integration dimension also showed a significant relationship with decision support (r = 0,330), indicating that when the system is perceived as well articulated with existing academic routines and flows, it tends to be valued as an effective resource to support educational decisions. Along the same lines, user satisfaction, although with a more moderate correlation (r = 0,265), also showed a significant positive relationship, suggesting that user experience influences, albeit to a lesser degree, the perception of the system as a facilitator of decision making.

Regarding the interrelationships between the independent variables, there is a strong correlation between efficiency and user satisfaction, with a coefficient of 0,603. This finding indicates that students who perceive high efficiency in the system also tend to express high levels of satisfaction in their interaction with it. Similarly, efficiency has a significant relationship with integration (r = 0,484), which shows that the operational functionality of the system is related to its degree of integration into regular academic processes.

On the other hand, scalability showed significant relationships with both efficiency (r = 0,309) and user satisfaction (r = 0,291), although with less strength, suggesting that these dimensions contribute jointly but differently to the overall performance of the system. The lowest correlation, although statistically significant, was found between scalability and integration (r = 0,160), suggesting that the system's projective and adaptive capacity can operate relatively independently of its degree of structural integration with other platforms or institutional dynamics.

The significant and positive relationship between the independent variables and the dependent variable, especially between Scalability (r = 0,645) and Efficiency (r = 0,564), demonstrates that the greater the interaction with generative artificial intelligence tools, the greater the perception of effectiveness in decision-making processes. This finding confirms the existence of relevant associations that reinforce the link between the use of generative AI and self-perceived decision-making competence in the university environment.

Table 3. Correlation between variables

		Decision support	Efficiency	Integration	User satisfaction	Scalability
Decision support	Pearson	1				
Efficiency	Efficiency		1			
Integration	Pearson	0,330**	0,484**	1		
User satisfaction	Pearson	0,265**	0,603**	0,316**	1	
Scalability	Pearson	0,645**	0,309**	0,160*	0,291**	1

The multiple linear regression model showed a strong relationship between the predictor variables and the dependent variable decision-making support, evidenced by a multiple correlation coefficient of 0,811. The coefficient determination of 0,658 indicates that 65,8 % of the variance in the dependent variable is explained by the independent variables considered: scalability, efficiency, integration, and user satisfaction. The adjusted value (0,651) confirms the stability of the model when considering the number of predictors included.

The standard estimation error was 1,20126, indicating low dispersion of the residuals and, therefore, adequate precision in the estimates. The statistical significance of the model is high, as demonstrated by the F value (91,781) with a significance level of less than 0,001, which validates the joint contribution of the independent variables in predicting the dependent variable.

The Durbin-Watson statistics, with a value of 1,766, rules out the presence of autocorrelation in the residuals, guaranteeing the independence of the errors and reinforcing the validity of the estimates. Taken together, the indicators confirm the relevance of the proposed model for explaining the impact of the functional dimensions of the generative artificial intelligence system on academic decision-making processes.

The ANOVA applied to the multiple linear regression model confirms the statistical significance of the model as a whole. The sum of squares of the regression amounted to 529,769, representing a considerable proportion of the total variability of the dependent variable, in contrast to the sum of squares of the residuals, which was 275,618. This indicates that a substantial part of the variability in decision-making support can be attributed to the predictor variables included in the model.

The mean square of the regression was 132,442, while that of the residual was 1,443. This substantial difference is reflected in an F statistic of 91,781, which has a significance level of 0,000. This value confirms that the model is statistically significant and that the independent variables considered together make a

relevant explanatory contribution to the behavior of the dependent variable.

Table 4. Regression model analysis

Model	R	R squared	Adjusted R-squared	Standard error of the estimate	Change statistics					Durbin-Watson
					Change in R squared	Change in F	gl1	gl2	Sig. Change in F	
1	0,811[a]	0,658	0,651	1,20126	0,658	91,781	4	191	0,000	1,766

a. Predictors: (Constant), Scalability, Integration, User satisfaction, Efficiency
b. Dependent variable: Decision-making support

Table 5. Analysis of Variance

Model		Sum of squares	gl	Quadratic mean	F	Sig.
1	Regression	529,769	4	132,442	91,781	0,000[b]
	Waste	275,618	191	1,443		
	Total	805,388	195			

The multiple linear regression model shows that the variables scalability and efficiency are the most influential predictors of the dependent variable decision-making support. Scalability has a non-standardized coefficient of 0,814 and a beta coefficient of 0,581, making it the dimension with the greatest explanatory weight. Its high level of statistical significance confirms that the system's ability to adapt, anticipate, and respond effectively to various academic scenarios has a decisive influence on the perception of its usefulness for decision-making.

Efficiency also demonstrates a significant impact, with an unstandardized coefficient of 0,880 and a standardized beta of 0,500. This result indicates that students value the speed, functionality, and resource optimization offered by the system, which has a positive impact on their adoption of it as a decision-making tool. In contrast, the User Satisfaction variable has a negative relationship with the dependent variable, with a coefficient of -0,266 and a beta of -0,231, although statistically significant. This reversal in the direction of the effect suggests that the user's subjective experience, although valued, does not necessarily increase the perception of the system as a support for decision-making and may even be associated with a more superficial use or one that is disconnected from strategic academic goals.

The integration variable, with a low coefficient of 0,093 and a significance value above the accepted threshold, does not contribute significantly to the model, indicating that its effect on the dependent variable is minimal or statistically null. Overall, these results demonstrate that support for decision-making through generative artificial intelligence is mainly determined by functional factors, such as scalability and efficiency, while variables related to subjective perception or institutional compatibility have a limited or inverse impact in this academic context.

Finally, this analysis determined that scalability and efficiency significantly influence decision-making support, with beta coefficients of 0,581 and 0,500, respectively, which shows that students value the system's adaptability and functional optimization more than other factors when making academic decisions. Likewise, it indicates that the use of generative artificial intelligence has a direct and positive effect on the criteria used by students to make decisions in academic environments.

Table 6. Multiple Linear Regression Analysis

Coefficients[a] Model B		Non-standardised coefficients		Standardised coefficients	t	Sig.
		Desv. Error	Beta			
1	(Constant)	7,909	1,333		5,935	0,000
	Efficiency	0,880	0,103	0,500	8,574	0,000
	Integration	0,093	0,058	0,077	1,595	0,112
	User satisfaction	-0,266	0,062	-0,231	-4,308	0,000
	Scalability	0,814	0,063	0,581	12,903	0,000

a. Dependent variable: Decision support

DISCUSSION

This research confirms that generative artificial intelligence, particularly when applied as a support tool in

educational settings, has a significant influence on the academic decision-making processes of university students in the health field. As Chan[3] and Bellas et al.[2], have pointed out, these systems not only offer information resources, but also transform ways of thinking, organizing knowledge and dealing with complex dilemmas.[35,36,37] This study showed that students do not perceive these tools as a passive extension of information search, but as instruments that enhance their judgement and planning skills in cognitively demanding contexts, such as medicine.[38,39,40,41,42]

In line with the findings of Usher and Barak[27], interaction with generative language models has been found to enhance cognitive skills beyond information storage, promoting more strategic, adaptive, and situated learning.[43] Students highly value features that allow them to anticipate results, visualize multiple scenarios, and reorganize their decisions based on the specific contexts they face. This behaviour suggests a transition from a repetition-centred learning model to one oriented towards problem solving through intelligent technologies, which is consistent with the findings of Maniyan et al.[26] regarding hybrid academic prediction systems.

However, it has been observed that subjective experience of use does not always translate into greater decision-making capacity.[44,45] This highlights that simple user satisfaction, understood as comfort or enjoyment of the technological interface, is not sufficient to generate structural changes in decision-making. In this sense, as warned by Kétyi et al.[12] and Elbaz et al.[13], the transformative potential of artificial intelligence depends largely on its ability to integrate meaningfully into the user's thought processes, not just their superficial experience of use.

Another relevant aspect is that the formal articulation of the system with institutional structures does not seem to be decisive in the perception of its usefulness. This reinforces the idea that students value the autonomy and functionality of the system more than its administrative or curricular integration.[46] In line with the views expressed by Ofem et al.[15], contemporary educational environments require more than technological adaptations; they need tools that support decision-making with precision, contextualization and anticipatory capacity, especially in disciplines where decision-making errors can have significant ethical or clinical consequences.

In short, generative artificial intelligence is emerging as a key player in the reconfiguration of educational processes, not only as a technological assistant, but also as a cognitive mediator that restructures the dynamics of analysis, reflection and decision-making in students in training.[28,47] Its impact goes beyond task automation: it redefines the criteria by which future professionals evaluate information, prioritize actions and construct knowledge, thus opening up a new horizon for technology-assisted professional learning in higher education.[8,48]

A recent study by Almarzouki et al.[7] has found substantial differences in the level of interaction and practical application of artificial intelligence in health science training contexts. While the study conducted in Saudi Arabia identified a marked gap between students' high level of interest and their limited formal training in artificial intelligence, our study is based on a context where students not only express interest but have also interacted directly with generative AI tools integrated into specific academic experiences. This methodological difference allows us to address not only general perceptions or expectations, but also tangible effects on the academic decision-making process, measured through functional variables such as efficiency, scalability and perceived support.[49,50,51,52]

Furthermore, while Almarzouki et al.[7] highlight that most Saudi students access knowledge about AI through informal sources such as social media, which limits their technical and critical understanding of the subject, our study emphasizes the influence that the structured use of AI platforms in real academic environments has on the development of decision-making skills. The key difference lies in the level of implementation: in the Saudi study, AI is still an aspirational component of the curriculum, while in our research it is analyzed as an active agent in the educational experience.[53,54]

CONCLUSIONS

The study concludes that generative artificial intelligence represents a highly strategic resource in the university education of health science students, as it not only acts as a computer supplement but also as a cognitive mediator that directly influences the development of complex skills linked to academic decision-making. Its implementation in educational settings shows that, when integrated in a functional and contextualized manner, it can help to stimulate critical thinking and strengthen students' intellectual autonomy.

Particularly strong when the tools that support it have robust operational qualities, such as adaptability, analytical accuracy, and responsiveness to diverse scenarios. This finding highlights the need to understand AI not only from a technological perspective but also as a support architecture that is articulated with the cognitive demands of the training process in highly demanding disciplines, such as medicine.

From a pedagogical perspective, it is concluded that simply incorporating digital technologies into the classroom does not guarantee a significant transformation of learning if it is not geared towards solving real problems and making informed decisions. It is therefore essential that higher education institutions design teaching strategies that integrate generative AI not as an end in itself, but as a tool situated within the logic

of professional thinking.

Furthermore, there is a recognised need to critically review traditional teaching approaches, especially in health science programmes, where diagnostic accuracy, clinical analysis and professional ethics are key elements. Generative AI has the potential to become a facilitator of these processes, provided that there is a curriculum structure that encourages its reflective, ethical use, geared towards improving decision-making in complex scenarios.

A methodological gap was identified that persists between the functional use of artificial intelligence and its formal incorporation into medical training. This gap must be addressed through future studies that longitudinally explore how sustained interaction with AI tools affects the evolution of students' clinical and academic judgement. This opens up a line of research aimed not only at measuring immediate impacts, but also at building long-range pedagogical models that integrate generative artificial intelligence as an essential part of the graduate profile of new health professionals.

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AUTORSHIP CONTRIBUTION

Conceptualization: Tania Lisbeth Chicaiza Zambrano.
Data curation: Darwin Marcelo, Varela Lascano.
Formal analysis: Eduardo Xavier, Macías Collahuazo.
Research: Yordan Ernesto, Calero Ocaña.
Methodology: Darwin Marcelo, Varela Lascano.
Project management: Tania Lisbeth Chicaiza Zambrano.
Resources: Yordan Ernesto, Calero Ocaña.
Software: Eduardo Xavier, Macías Collahuazo.
Supervision: Tania Lisbeth Chicaiza Zambrano.
Validation: Yordan Ernesto, Calero Ocaña.
Visualization: Tania Lisbeth Chicaiza Zambrano.
Writing – original draft: Darwin Marcelo, Varela Lascano.
Writing – review and editing: Tania Lisbeth Chicaiza Zambrano.