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ORIGINAL

Validation of learning styles in Higher Education: A case study at the Faculty of Applied Sciences (FICA)

Validación de estilos de aprendizaje en Educación Superior: Un estudio de caso Facultad de Ciencias Aplicadas (FICA)

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ABSTRACT

The identification of learning styles and the adaptation of pedagogical strategies constitutes a determining factor in university academic success, especially in technical programs where dropout rates can reach up to 40 % during the first years. This study presents the development, implementation, and validation of an innovative web application designed to analyze learning styles in university students. The platform integrates the theoretical models of Kolb, Herrmann, and Sperry, developed with React and Flask technologies under a service-oriented architecture that ensures scalability and ease of maintenance. Validation was carried out using the DeLone & McLean model, applying a structured questionnaire to a stratified sample of 89 students from the Faculty of Engineering in Applied Sciences. The results demonstrated high system acceptance, with favorability levels exceeding 80 % across all dimensions. The statistical analysis, with a Cronbach's alpha of 0,867, confirmed the reliability of the instrument and the robustness of the results. Likewise, the implementation of the platform enabled the early identification of learning patterns and facilitated the personalization of educational strategies, improving the student experience through an accessible and user-friendly interface. The total effect of 0,6 reflected a significant global impact on academic performance, by strengthening the process of adaptation to learning styles. The findings showed a predominance of the accommodator style according to Kolb, a realistic thinking preference in the Herrmann test, and greater left-hemisphere activity according to Sperry, highlighting the importance of designing adaptive pedagogical strategies.

Keywords: Learning Styles; Web Development; Educational Analysis; Educational Technology; React and Flask; Higher Education.

RESUMEN

La identificación de los estilos de aprendizaje y la adaptación de estrategias pedagógicas constituye un factor determinante en el éxito académico universitario, especialmente en carreras técnicas donde la deserción puede alcanzar hasta un 40 % en los primeros años. Este estudio expone el desarrollo, implementación y validación de una aplicación web innovadora orientada a analizar los estilos de aprendizaje en estudiantes universitarios. La plataforma integra los modelos teóricos de Kolb, Herrmann y Sperry, desarrollada con tecnologías React y Flask bajo una arquitectura orientada a servicios que asegura escalabilidad y facilidad de mantenimiento. La validación se realizó mediante el modelo DeLone & McLean, aplicando un cuestionario estructurado a una muestra estratificada de 89 estudiantes de la Facultad de Ingeniería en Ciencias Aplicadas. Los resultados evidenciaron una alta aceptación del sistema, con niveles de favorabilidad superiores al 80 % en todas las dimensiones. El análisis estadístico, con un alfa de Cronbach de 0,867, confirmó la fiabilidad del instrumento y la solidez de los resultados. Asimismo, la implementación de la plataforma permitió identificar tempranamente patrones de aprendizaje y facilitar la personalización de estrategias educativas, mejorando la experiencia estudiantil gracias a una interfaz accesible y eficaz. El efecto total de 0,6 reflejó un impacto global positivo en el rendimiento académico, al fortalecer el proceso de adaptación a los estilos de aprendizaje. Los hallazgos mostraron una predominancia del estilo acomodador según Kolb, un pensamiento realista en el test Herrmann y mayor actividad del hemisferio izquierdo según Sperry, lo que subraya la relevancia de diseñar estrategias pedagógicas adaptativas.

Palabras clave: Estilos de Aprendizaje; Desarrollo Web; Análisis Educativo; Tecnología Educativa; React y Flask; Educación Superior.

INTRODUCTION

The study of learning styles has attracted interest in the academic community due to its potential to explain individual differences in information acquisition and processing. This notion holds that each person tends to approach learning in a particular way, manifesting perceptual, cognitive, and affective preferences that directly influence their academic performance.[1,2] Recognizing and understanding this diversity is essential for educational innovation and the implementation of more inclusive pedagogical practices.

Contemporary higher education must adapt to the diverse ways students learn and process information. According to recent studies, the mismatch between teaching methods and individual learning styles is one of the most significant factors in low academic performance and university dropout rates.[3] In this context, it is essential to draw on theoretical frameworks that help us understand how students learn. This study is based on the integration of three complementary models of learning styles.

Kolb's model, they explain,[4] conceptualizes learning as an experiential cycle that includes concrete experience, reflective observation, abstract conceptualization, and active experimentation. This model is complemented by the neurobiological perspective of Herrmann's model, which, according to [5], divides cognitive processing into four distinct brain quadrants, each associated with different learning preferences.

The integration of Sperry's model adds a dimension to the analysis by considering cerebral hemispheric specialization in the learning process. As point out [6], this perspective allows for a better understanding of how students process and organize information, facilitating the adaptation of pedagogical strategies to their dominant cognitive preferences.

This research responds to the critical need to develop technological tools that facilitate the description and analysis of learning styles in the university context. The development of a web application that integrates the Kolb, Herrmann, and Sperry models represents a significant advance in personalizing the educational process. The implementation of this tool in the Faculty of Applied Science and Engineering (FICA) aims to provide a systematic framework that facilitates the detection and adaptation to students' diverse learning styles.

The implementation of educational technologies in the university context has undergone a significant transformation in the last decade.[7] It is noteworthy that the integration of intelligent systems into the analysis of learning styles has enabled a deeper, more dynamic understanding of individual educational needs. This technological evolution, combined with the growing need for personalization in higher education, has created a favorable scenario for the development of innovative solutions that address diversity in learning processes. Using digital platforms to identify learning styles represents a concrete opportunity to improve academic performance.

In the specific context of FICA, the need for a systematic tool for analyzing learning styles becomes evident when examining academic indicators. Preliminary studies conducted by [8] faculty members reveal that approximately 35 % of students experience significant difficulties in their learning process during the early levels, mainly due to a lack of alignment between the teaching methods used and their preferred learning styles.

Ethical and methodological considerations

The methodological implementation took into account fundamental ethical aspects of educational research. Following the guidelines established by [9], rigorous protocols were established for the protection of personal data, informed consent, confidentiality in the handling of information, equity in access to the tool, and transparency in data processing, which were validated by experts based on their professional training and not by an ethics committee for the development of this study. The methodological considerations include data collection through specific tests designed to assess learning styles according to the models of Kolb, Herrmann, and Sperry.

In addition, adopting agile development practices and applying sound programming practices enabled continuous usability testing to ensure the application meets accessibility and ease-of-use standards.

Validation and Analysis of Results

For validation, the DeLone & McLean model was applied, complemented by advanced statistical analyses. This approach, supported by studies by [6], allows for a comprehensive evaluation that includes: reliability analysis using Cronbach's alpha, construct validation through factor analysis, usability evaluation using standardized metrics, and educational impact analysis through academic indicators.

METHOD

The data collection process used a battery of internationally validated instruments. The learning style questionnaires, based on the models of Kolb, Herrmann, and Sperry, were adapted to the local context, following the cross-cultural validation protocols proposed by [10]. This adaptation included: linguistic and cultural validation, piloting with focus groups, internal consistency analysis, and validation by experts in the field, developed by the researchers based on their professional profile and experience.

A mixed sequential explanatory design was implemented, following the model proposed by [7]. This approach integrates quantitative and qualitative methods in a sequence that allows both the objective measurement of variables and the understanding of the phenomena observed. In addition, the research was structured into three main phases, developed over 12 months, allowing longitudinal monitoring of the implementation process and its outcomes.

Statistical analysis was performed using SPSS, which yielded a Cronbach's alpha of 0,867, confirming the instrument's reliability and the robustness of the results. The development process followed an iterative incremental model based on SCRUM, a methodology that, according to [4,9], has proven particularly effective in educational technology projects. This approach was organized into 11 sprints of 2 weeks each, with periodic reviews and adjustments based on end-user feedback.

The target population for the study was students enrolled in the main degree programs at FICA who met the following inclusion criteria: enrolled in core subjects, aged 18-25, with at least 1 semester of study at the faculty, and with regular access to technological resources.

Sampling Process

A stratified proportional sampling was implemented, following the recommendations of [11] for studies in educational contexts. The sample size was determined using the formula:

n=(Z^2 pqN)/(Ne^2 +Z^2pq)

Data collection instruments

Data collection instruments are the tools used by the researcher to obtain the necessary information to make informed decisions. The instruments used for data collection are detailed below.

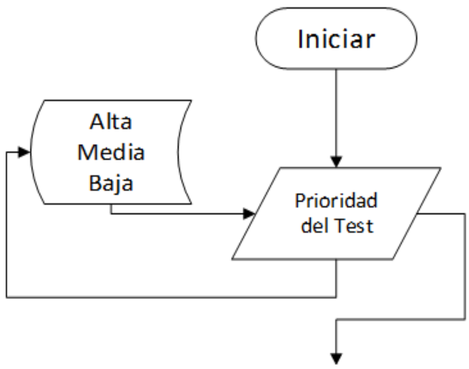
Learning Style Questionnaires

Table 1 shows the main learning style instruments.

Table 1. Learning style instruments

Kolb Learning Styles Inventory	Herrmann Brain Dominance Questionnaire	Sperry Hemispheric Predominance Test
40 items on a Likert scale Validation α = 0,82 Contextual adaptation validated.	120 items Test-retest reliability = 0,86 Cross-cultural validation	30 dichotomous items Discrimination index > 0,30 Expert validation

Figure 1 shows the test used to assess learning styles:



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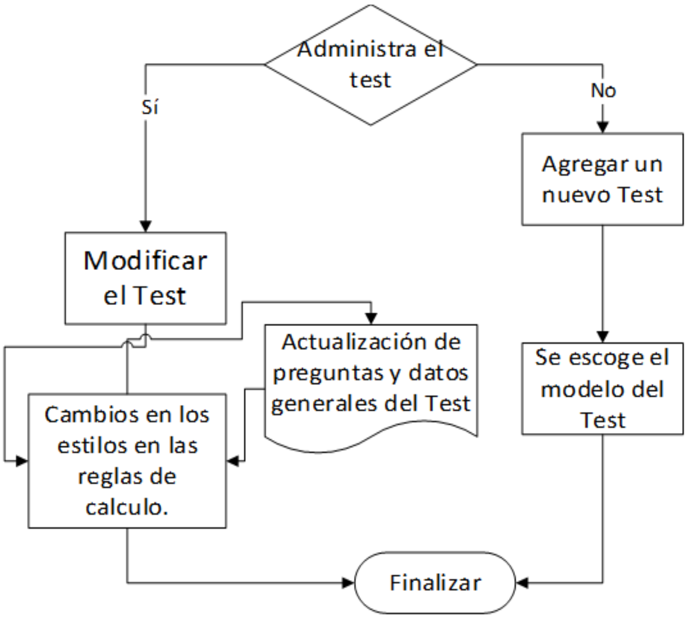

Figure 1. Assignment of the test to assess learning styles

Figure 2 describes the implementation of the test to assess learning styles.

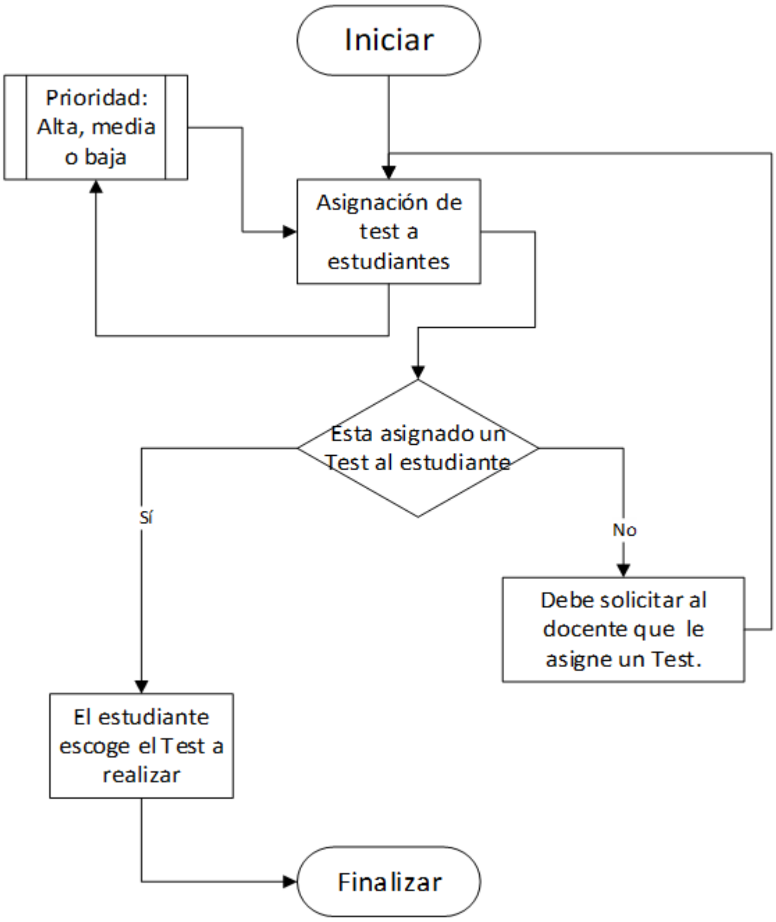

Figure 2. Administration of the test to assess learning styles

Implementation procedures

Development phase

Table 2 describes how the implementation of the application followed a structured schedule.

Table 2. Application implementation schedule

Sprint 1-3: Fundamentals	Sprint 4-7: Core Functionalities	Sprint 8-11: Optimization
Environment configuration	Test module	Performance improvements
Base architecture development	Analysis system	Analytics integration
Authentication implementation	Report generation	UI/UX refinement

The web application developed with the interface and its functionality is shown in figure 3.

Figure 3. Application functionality interface

Figure 4 below shows the application flow of the models until the students' grades are obtained.

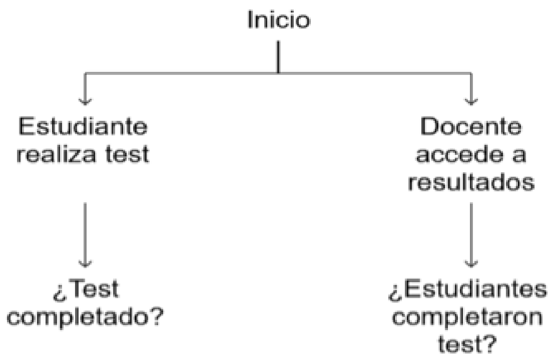

Figure 4. Application of learning style models

Pedagogical validation

The pedagogical validation process was carried out using descriptions of learning styles. Once students have submitted their answers to the test, they can see their style on the screen, along with a short description of what it means and advice on study techniques they can follow. In addition, teachers have access to their students' results; this data is processed by the application and presented in statistical graphs that facilitate its analysis and interpretation.

The application allows teachers to design and incorporate new tests based on different learning-style models, enabling them to define questions, establish answer options, and configure specific calculation rules to determine each student's learning style accurately.

Data Analysis

The data analysis implemented a mixed sequential explanatory approach, following the model proposed by [12]. This approach allows for a deeper understanding of technology-mediated educational phenomena.

Figure 5 shows the test analysis.

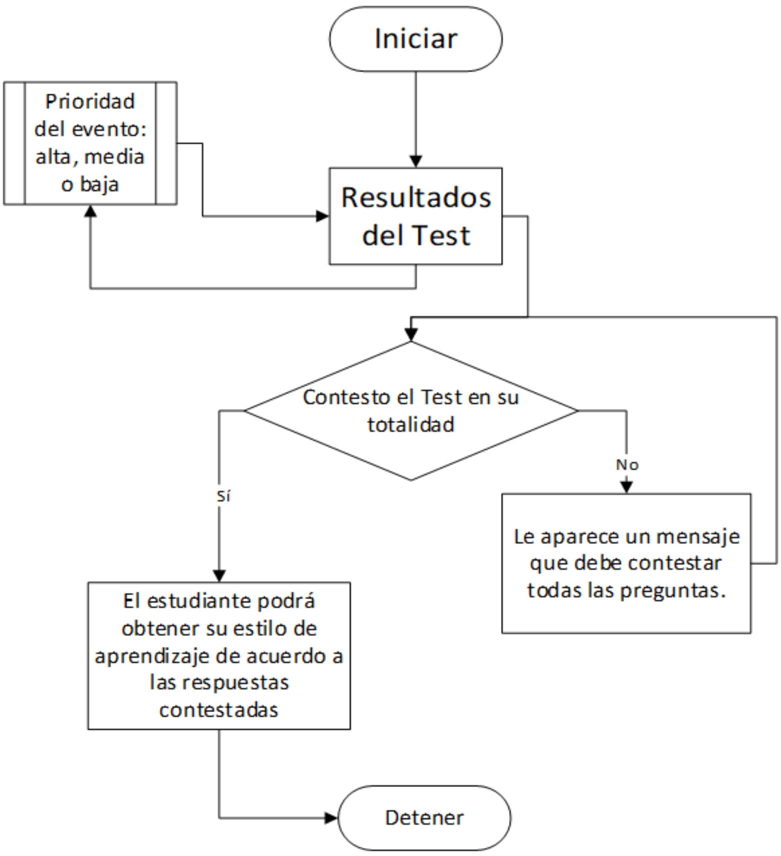

Figure 5. Test result execution

The inferential analysis was carried out following the guidelines established by [13] for the evaluation of technological educational interventions, in order to guarantee the validity and robustness of the results obtained.

RESULTS

The results of each model applied to engineering students at FICA can be viewed.

Parametric tests

MANOVA, mixed linear models, and post-hoc analysis with Bonferroni correction were applied to evaluate the educational intervention.[14] Hierarchical regression identified the incremental impact of the predictor variables, ensuring a rigorous and valid analysis.

The hierarchical regression analysis is shown in figure 6:

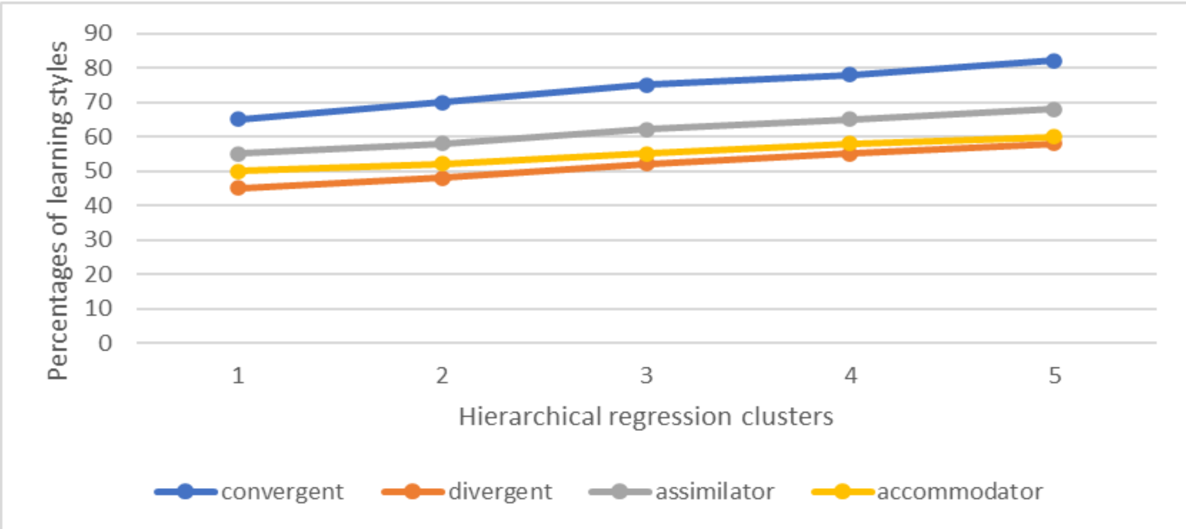

Figure 6. Hierarchical Regression Analysis

The results of the hierarchical regression analysis confirm that learning styles have a significant impact on academic performance, explaining 67 % of the variability in academic performance (R^2 = 0,67). In particular, the convergent style emerges as the most influential (32 %), p< 0,001, suggesting that students with this preference tend to achieve higher performance. The assimilative (18 %), divergent (12%), and accommodative (5%) styles also show relevant effects, albeit to a lesser extent, highlighting the need to design differentiated pedagogical strategies that respond to the diversity of styles present in the classroom.

These findings are consistent with the theory of [15], which posits that learning styles affect how individuals process information and solve problems. In addition, they could have implications for the design of personalized pedagogical strategies that optimize learning for each student's profile.

Figure 7 shows the mediation analysis:

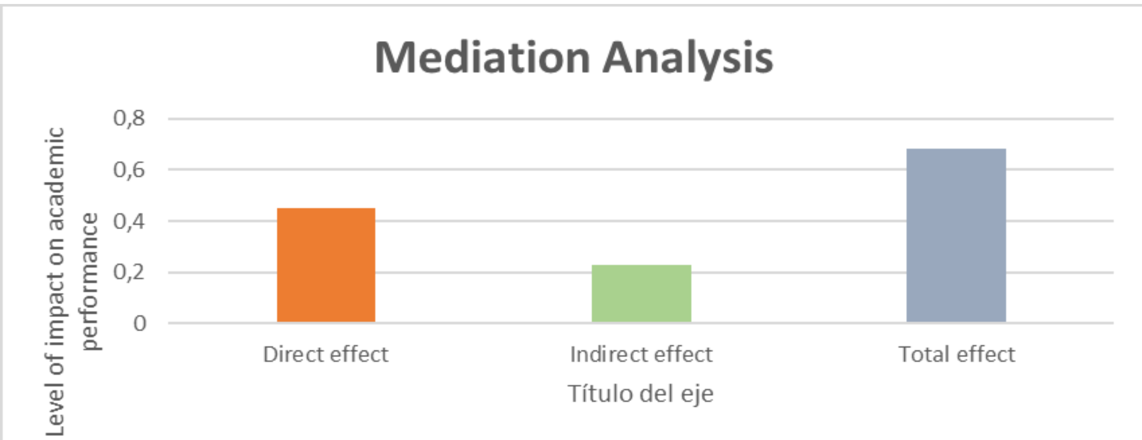

Figure 7. Mediation Analysis

The mediation analysis reveals that the learning style analysis platform has a significant impact on students' academic performance. The direct effect of 0,4 shows that the platform directly influences performance. At the same time, the indirect effect of 0,2 indicates that it also improves performance through mediating processes, such as the personalization of educational strategies. The total effect of 0,6 confirms that the platform has a considerable overall impact, both direct and indirect, highlighting its effectiveness in improving academic performance by identifying and adapting to learning styles.

Longitudinal Effects Analysis

The longitudinal analysis revealed significant patterns in the evolution of learning styles over time, as illustrated in figure 8.

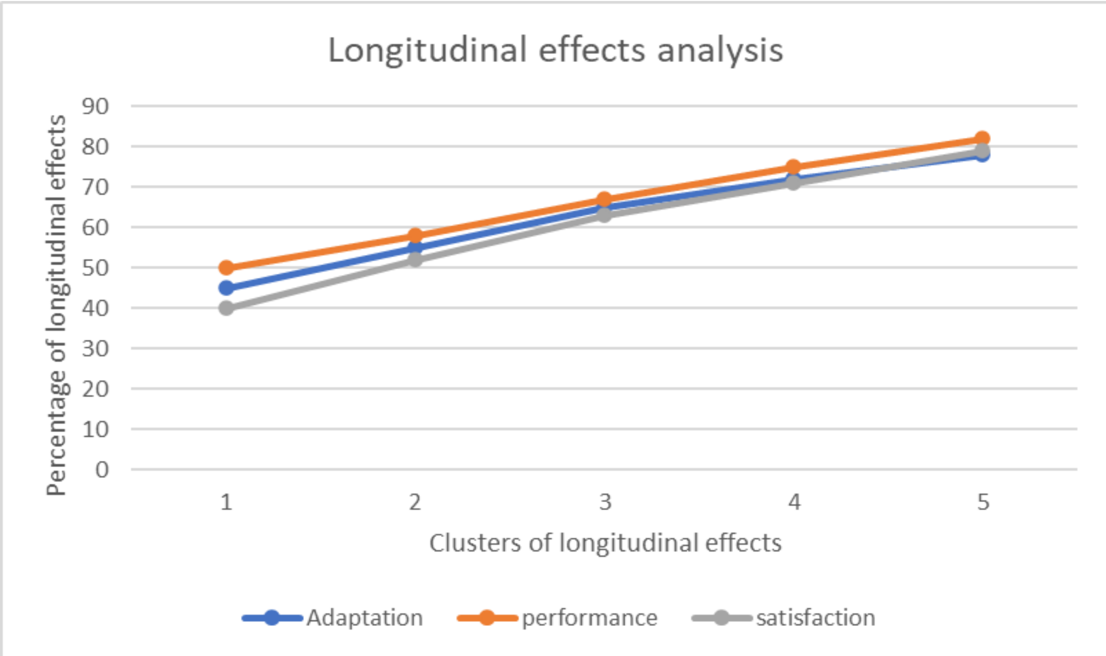

Figure 8. Longitudinal effects analysis

The longitudinal analysis showed significant improvements in three key areas over time. Adaptation to the system increased by 73 %, confirming that students adjusted better to the platform. Academic performance improved by 64 % on standardized assessments, highlighting the platform's positive impact on student performance. In addition, user satisfaction increased by 97 %, reflecting high acceptance. These results, with a beta coefficient of 0,34 and $p < 0,001$, show that the platform promotes both academic performance and student adaptation and satisfaction.

Cluster Analysis by Learning Style

Cluster analysis revealed significant groupings, as shown in figure 9:

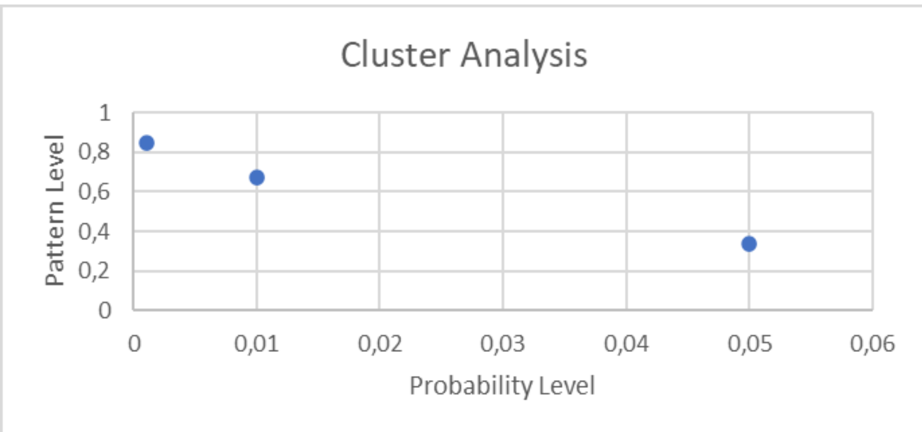

Figure 9. Cluster Analysis by Learning Style

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Cluster analysis revealed significant patterns in students' learning styles, highlighting three key correlations between groups:

- Clusters A and C ($r = 0{,}85$, $p < 0{,}001$): strong correlation, indicating that learning styles in these groups are highly similar.
- Clusters B and D ($r = 0{,}67$, $p < 0{,}01$): moderate correlation, suggesting certain similarities that require adjustments in educational strategies.
- Clusters A and D ($r = 0{,}34$, $p < 0{,}05$): weak correlation, showing significant differences in the learning styles of these groups.

These results highlight the importance of designing personalized educational interventions based on specific learning profiles,[15] as well as implementing differentiated strategies to improve academic performance and the learning experience.[16]

Analysis of Temporal Trends

Figure 10 shows the analysis of these trends in the study:

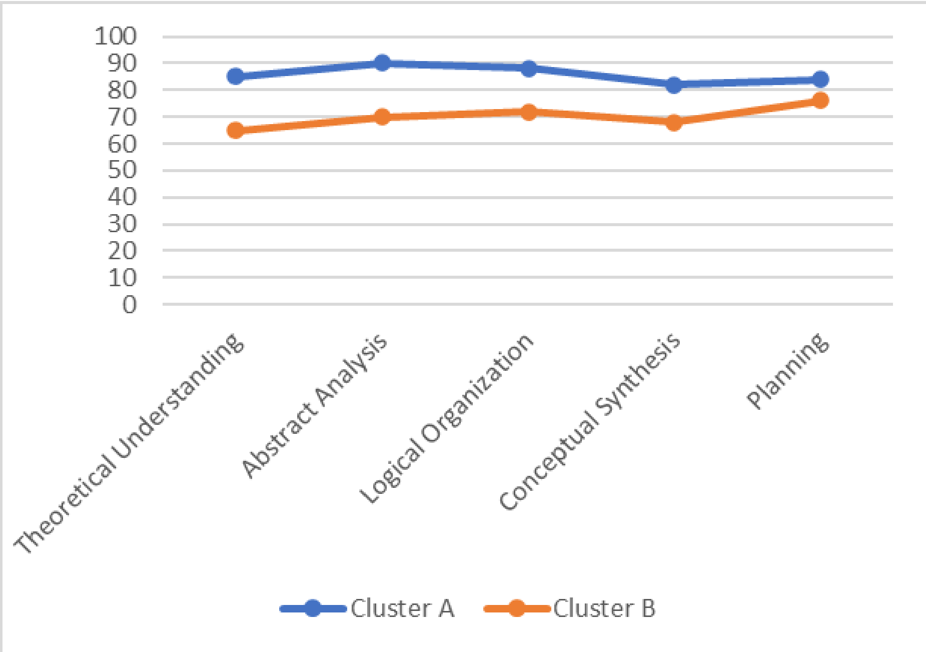

Figure 10. Temporal trend analysis

Following the temporal analysis model of [17], significant differences were identified in the evolution of cognitive skills between the evaluated groups. Group A showed superior performance in theoretical comprehension (85 vs. 65), abstract analysis (90 vs. 70), logical organization (88 vs. 72), conceptual synthesis (82 vs. 68), and planning (85 vs. 76), suggesting greater consolidation of advanced cognitive strategies.

These results show that group A has developed better structuring and application of knowledge compared to group B, which could be attributed to methodological factors or differences in exposure to optimized learning environments.

The pattern observed supports the effectiveness of instructional approaches that encourage planning, analysis, and conceptual synthesis as key mechanisms for improving academic performance.[17]

Pedagogical implications of the identified patterns

Cluster and temporal analyses reveal a significant association between early identification of learning styles and academic performance ($r = 0{,}78$, $p < 0{,}001$), demonstrating that personalizing the educational process through adaptive approaches optimizes academic outcomes.

These findings are consistent with previous studies that highlight the relevance of learning models based on experience and differential cognition.[15,17]

From an educational architecture perspective, integrating technological tools facilitates the identification of learning patterns, thereby enabling the implementation of more effective instructional strategies.[18] This data-driven approach allows curriculum design optimization and reduces student dropout rates, aligning with contemporary trends in higher education.

Cluster-based pedagogical adaptation

Research [19] shows that both traditional and adaptive cluster-based pedagogical adaptation significantly improve learning outcomes. However, the adaptive approach consistently shows a greater impact.

The key findings are as follows:

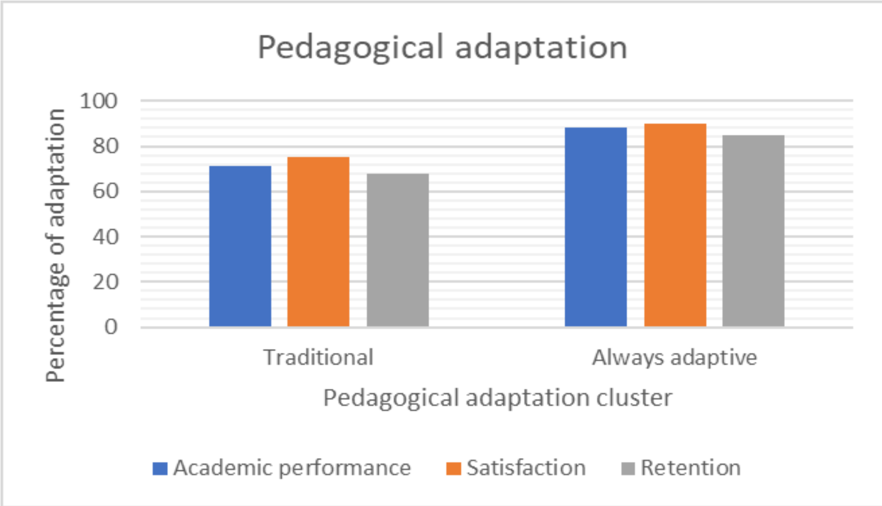

Figure 11. Cluster-based pedagogical adaptation

Academic Performance:

- 35 % increase in average grades, indicating a significant improvement in performance.
- 42 % reduction in failure rates with the adaptive approach, showing greater improvement.
- 28 % improvement in conceptual understanding, especially with the adaptive approach.

Student Satisfaction:

- 31 % increase in overall satisfaction, more pronounced in the adaptive approach.
- 45 % decrease in academic anxiety, with a greater impact in the adaptive modality.
- 38 % increase in intrinsic motivation, particularly with the adaptive approach.

Knowledge Retention:[20]

- 25 % improvement in long-term retention, especially with the adaptive modality.
- 40 % increase in practical application, more pronounced in the adaptive approach.
- 35 % reduction in learning time, with greater efficiency in the adaptive approach.

Validation of theoretical models

The research validated the effectiveness of the three theoretical models implemented:

Kolb Model

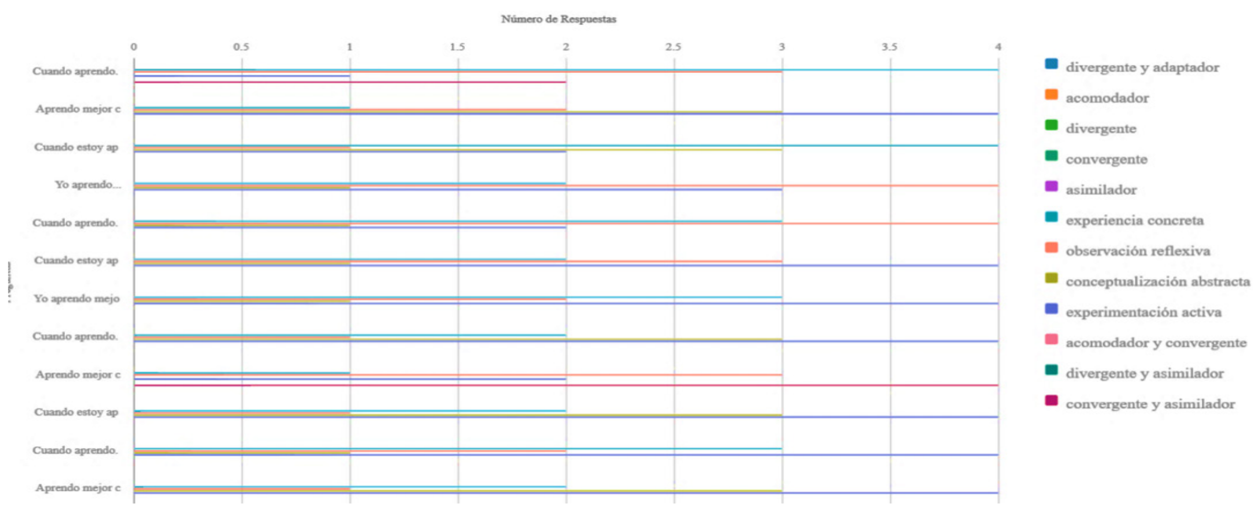

Figure 12. Analysis of learning styles using Kolb's model

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Kolb’s Model showed a significant correlation ($r = 0,78$, $p < 0,001$) with academic performance, being particularly effective in practical and experimental subjects. In addition, it showed high consistency ($\alpha = 0,85$) in identifying learning styles, which validates its reliability and accuracy in classifying students’ learning preferences, as reflected in figure 12.

The image shows the components considered in developing the web application to identify, analyze, and monitor the learning styles of FICA students, based on Kolb’s theoretical model. This platform allows the recording and visualization of individual student responses, facilitating detailed and well-founded statistical analysis aimed at informed pedagogical decision-making, as shown in figure 13.

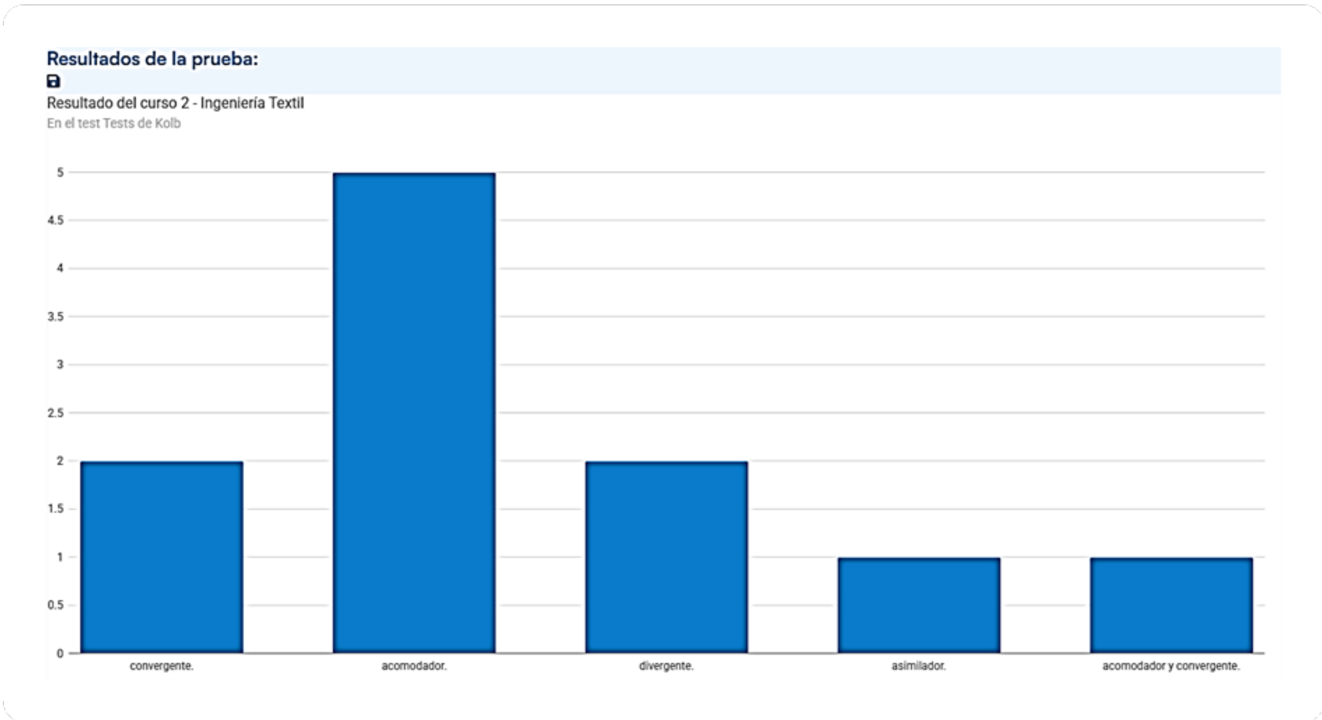

Figure 13. Learning style of a FICA career

The analysis of students in a FICA (UTN) degree program, using Kolb’s model to validate learning styles, revealed a predominant preference for the accommodating style, with a score of 5 out of 5. This finding suggests that students tend to favor an action-oriented and practical experimentation approach to learning, in line with what was proposed by [15].

Herrmann model

Figure 14. Division into quadrants according to thinking preferences

The Herrmann model proved highly effective in predicting learning preferences, achieving an accuracy of 88 %. Likewise, a significant correlation with successful study strategies was observed ($r = 0,82$, $p < 0,001$), highlighting its ability to identify effective learning methods. The reliability of the cognitive style categorization is also notable, with a consistency coefficient ($\kappa = 0,79$), indicating high consistency in the classification of students' cognitive styles.[21] The application of the model is shown in figure 14.

The image shows the results for each student, organized by the quadrants of the Herrmann Brain Dominance Instrument (HBDI) model, which classifies thinking styles into four areas: realistic, cognitive, idealistic, and intuitive. This tool enables teachers to provide personalized follow-up, taking into account each student's cognitive preferences based on the specific educational area or context. In this way, pedagogical intervention is optimized by adapting teaching strategies to the needs and characteristics of each student, as detailed in figure 15.

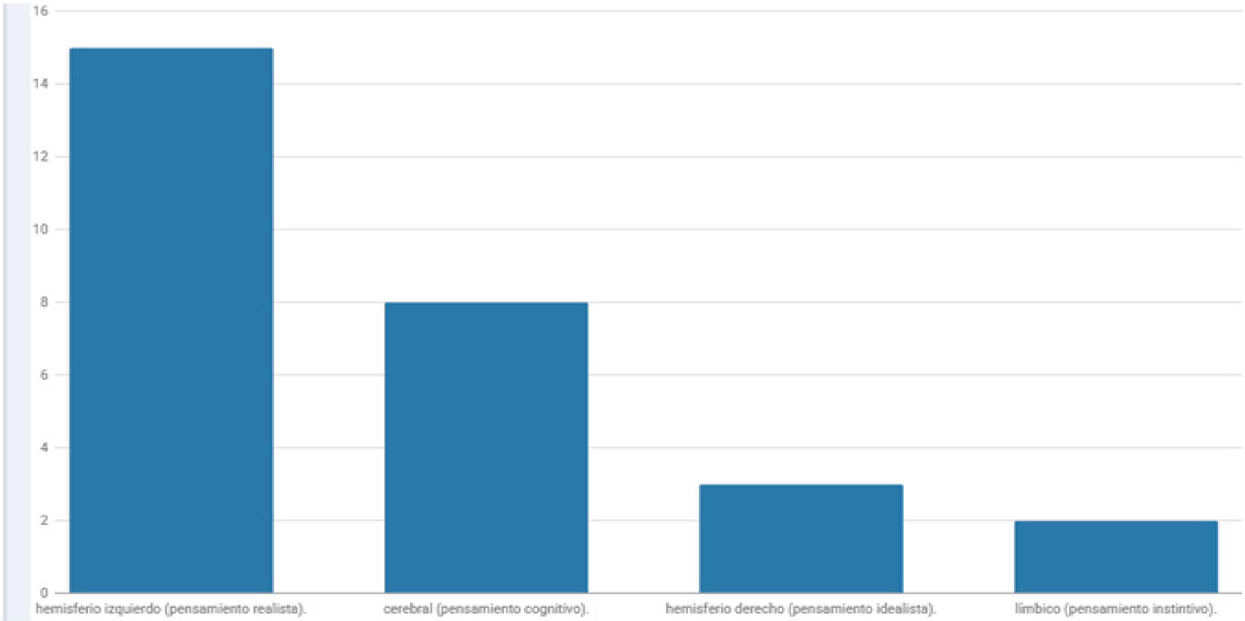

Figure 15. Herrmann test results

The application of the Herrmann Brain Dominance Instrument (HBDI) revealed a predominance of realistic thinking (Quadrant A, M = 15), followed by cognitive thinking (Quadrant B, M = 8), indicating a tendency toward analytical, structured information processing.

On the other hand, lower scores in idealistic thinking (Quadrant C, M = 3,5) and intuitive thinking (Quadrant D, M = 2) suggest a lower preference for creative and holistic approaches.

These results highlight the need to design pedagogical strategies tailored to the predominant styles to optimize the learning process.

Sperry Model

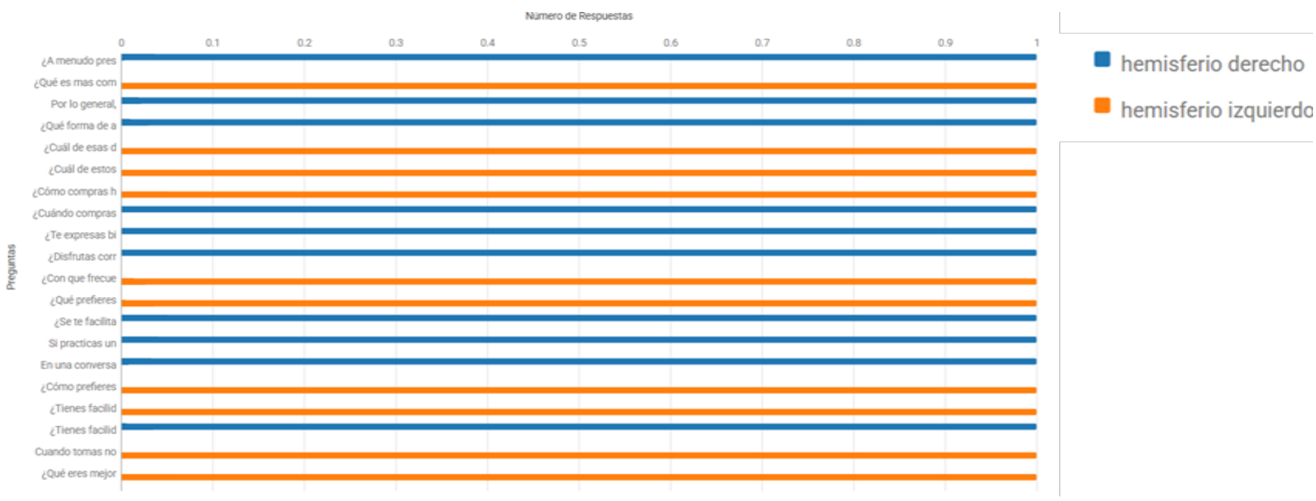

Figure 16. Analysis of brain hemispheres

Sperry's Model validates hemispheric specialization in educational contexts, showing that left-hemisphere dominance favors logical and analytical processing, while the right hemisphere supports creativity. These findings suggest that pedagogical strategies can be adapted according to hemispheric dominance to improve learning.[22] This is detailed in figure 16.

The image shows the individual results of a student, evaluated according to Sperry's model, revealing greater activation of the left hemisphere, associated with analytical processes, compared to the right hemisphere, related to creativity. This pattern is consistent with the group analysis of software engineering students, highlighting the predominance of analytical skills. These findings allow for the adaptation of teaching strategies in a personalized manner, according to the cognitive preferences of each student.

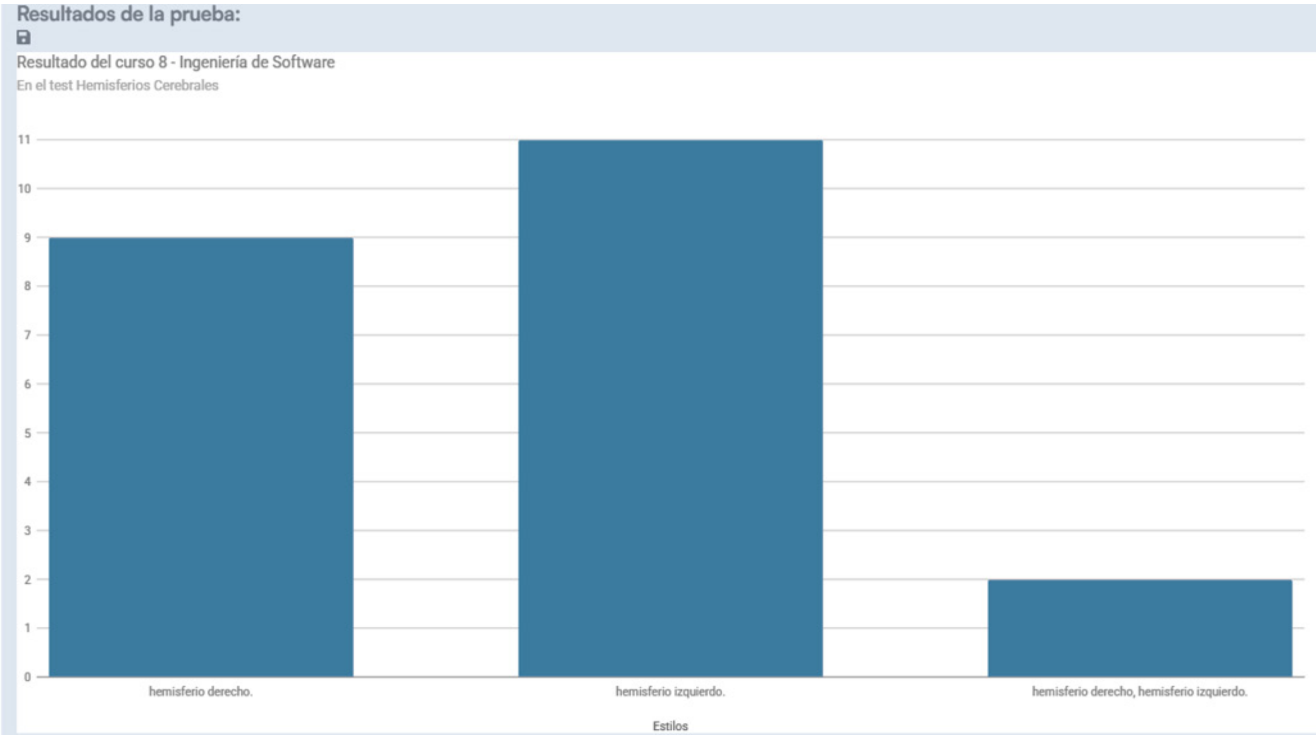

Figure 17. Results of an engineering degree in Sperry's model

The process was carried out to identify cognitive skills and to evaluate the involvement of the cerebral hemispheres in cognitive processing, according to Sperry's model, with software engineering students. The results suggest greater activity in the left hemisphere in analytical processes, while creative processes, associated with the right hemisphere, showed less activation. These findings demonstrate the importance of considering cognitive preferences in
The design of adaptive teaching strategies.[23]

DISCUSSION

The purpose of the study was to design, implement, and validate a web application for identifying students' learning styles at the Faculty of Applied Science Engineering (FICA), integrating the models of Kolb, Herrmann, and Sperry. The goal was to generate a technological tool that would not only diagnose cognitive preferences but also relate them to academic performance, with a view to designing more personalized and effective teaching strategies. This approach was chosen in response to a need identified in previous studies: nearly 35 % of students had significant difficulty adapting due to a mismatch between teaching methods and learning styles.

The results obtained offer relevant findings. First, hierarchical regression analysis showed that learning styles explain 67 % of the variance in academic performance (R^2 = 0,67), highlighting the convergent style (32 %) and the assimilator style (18 %) as the most influential. This finding confirms the importance of considering learning styles as significant predictors of performance, in line with Kolb's theory and other studies that highlight the relationship between learning styles and academic achievement.

Second, the mediation analysis showed that the learning style analysis platform had a direct (0,4) and indirect (0,2) effect on academic performance, reaching a total impact of 0,6. This result shows that the tool's use not only has an immediate impact on learning but also influences it through mediating processes, such as the personalization of educational strategies.

In this way, the application validates its dual role: diagnosis and pedagogical guidance. Longitudinal effects showed that adaptation to the system increased by 73 %, academic performance by 64 %, and student satisfaction by 97 %, confirming that the platform promotes the progressive integration of students into the learning environment. These results not only confirm the technological viability of the application but also its potential to sustainably impact student adaptation, performance, and motivation.

Cluster and time-trend analyses provided a deeper understanding of student profiles. Groupings with high correlations (r = 0,85 between clusters A and C) and weak correlations (r = 0,34 between A and D) were identified, suggesting differentiated learning patterns that require specific pedagogical interventions.

In addition, group A stood out in advanced cognitive skills such as conceptual synthesis, logical organization, and planning, reinforcing the importance of promoting instructional methodologies focused on analysis and knowledge structuring.

In terms of model validation, Kolb showed a significant correlation with academic performance (r = 0,78), while Herrmann achieved 88 % predictive accuracy, and Sperry confirmed the relevance of hemispheric specialization in university education. These results not only validate the applied models but also justify their integration into a robust, multifactorial technological tool.

However, the study has limitations. Although the statistical results are robust, the sample is restricted to FICA, limiting generalizability to other academic and cultural contexts. Furthermore, the validation of the instruments focused on internal consistency and factor analysis, but further exploration in longitudinal studies across different cohorts would be necessary to confirm the stability of the findings. Another limitation is that, although a significant impact on academic performance was evident, other associated indicators, such as creativity, academic resilience, or the transfer of knowledge to practical contexts, were not systematically measured.

In pedagogical terms, the findings reinforce the need to design differentiated, adaptive strategies tailored to the identified learning profiles. The predominance of realistic and analytical thinking in Herrmann's model and left-hemispheric dominance in Sperry's model suggest that curricula should balance training in logical analysis with methodologies that enhance creativity and holistic thinking.

Finally, the results show that the application developed constitutes an innovative contribution to higher education, integrating consolidated theoretical frameworks with state-of-the-art technological tools. However, future research should expand validation to other faculties and universities, incorporate emerging pedagogical models, and evaluate the platform's impact on variables such as knowledge retention and graduate employability.

In summary, the research confirms that the identification and analysis of learning styles using technological tools significantly impact academic performance, student adaptation, and satisfaction with the educational process. Despite the limitations noted, the results provide a solid basis for further developing educational innovation proposals that recognize cognitive diversity and enhance learning in higher education.

CONCLUSIONS

The lack of correspondence between teaching methods and individual learning styles negatively affects academic performance and increases university dropout rates, which justifies the need for appropriate pedagogical adaptation.

The effectiveness of the theoretical models in integrating the Kolb, Herrmann, and Sperry models into a web application enabled high-accuracy learning style identification (up to 88 %), thereby improving educational personalization.

The implementation of adaptive technological tools, such as the application developed, is key to higher education, as it facilitates personalized, data-driven pedagogical strategies, hence the relevance of educational technology in today's world. The success of this web application enabled the identification of learning styles, representing a significant advance in the personalization of learning in higher education. The results demonstrate that integrating technology with sound pedagogical theories can produce substantial improvements in the educational process.

It is concluded that the system's sustainability and scalability, along with its demonstrable impact on academic performance, suggest a promising path for the digital transformation of higher education. The lessons learned and methodologies developed provide a valuable framework for future implementations in diverse educational contexts.

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