*Hunan Daxue Xuebao/Journal of Hunan University Natural Sciences*
*ISSN：1674-2974 | CN 43-1061 / N*

DOI: 10.5281/zenodo.16308302
Vol: 62 | Issue: 07 | 2025

# OPTIMIZING PHYSICS TEACHING: TOWARDS A SYNERGY BETWEEN MARKOV MODELS AND KOLB MODELS

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***Abstract***

*This paper explores the optimization of learning in physics by applying Markov models, taking into account the learning styles defined by Kolb. We conducted a study with 115 university students to evaluate the influence of different teaching methods on the transitions between these learning styles. Using Markov models, we identified three learning states: initiation, understanding, and application. A transition matrix was developed to show the probabilities of moving from one state or style to another. The analysis was performed by machine learning algorithms. The results show that active methods, such as group projects and experiential laboratory activities, promote better understanding of concepts. This study highlights the importance of adapting teaching practices to students' learning styles, allowing for increased personalization to maximize student engagement and success. The results offer practical recommendations for teachers to improve the effectiveness of physics teaching.*

***Keywords:*** *Optimization, Kolb Model, Markov Model, Adaptation, Personalization.*

## INTRODUCTION

Teaching physics in high school faces significant challenges, especially due to the complexity of abstract concepts and physical laws. These concepts require not only theoretical understanding, but also the ability to apply them in real-world situations. (Hake, RR, 1998). Therefore, it is crucial to adapt teaching methods to students' different learning styles in order to maximize their engagement and improve knowledge retention, which contributes to their success. Previous research has clearly shown that teaching methods adapted to students' learning styles promote this engagement and strengthen memorization (Felder & Silverman, 1988; Dunn & Dunn, 1993). In addition, personalized learning environments have been associated with improved knowledge retention (Pashler et al., 2008; Bess et al., 2021). However, recent studies are beginning to examine how students can transition from one learning style to another, highlighting the importance of educational interventions in this process. Zhang et al. (2022) found that students who have a good understanding of their own learning style do better in varied learning environments. Despite these advances, there remains a significant gap in the literature regarding the analysis of transitions between these styles, an aspect that has been largely neglected until now. Indeed, few studies have delved deeper into how students can evolve from one style to another, although preliminary results indicate that educational interventions can play a crucial role.

DOI: 10.5281/zenodo.16308302
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This finding reveals the need to explore how pedagogical methods, such as project-based learning, lectures, hands-on work, and collaborative activities aligned with Kolb's experiential learning model, could be optimized using Markov models to better understand and predict learning behaviors, (González et al., 2017).

The objective of this research is therefore to examine how the integration of Kolb learning styles with Markov models allows to optimize pedagogical strategies. Based on experimental data collected from 115 physics students, this study aims to identify the most effective learning pathways for each style, while providing practical recommendations for teachers. By integrating Kolb's key concepts, our research strengthens its credibility by grounded in a proven theory, (Kolb, D. A. 2005). while filling existing gaps in the literature on transitions between learning styles.

Markov models, as analytical tools, offer a relevant framework for modeling these transitions by quantifying the probabilities of moving from one learning state to another, which makes it possible to analyze the evolutionary dynamics of students through different phases of their learning (Norris et al., 2014). Ultimately, our research enriches the understanding of learning mechanisms and effective pedagogical strategies, while contributing to the improvement of educational outcomes in physics. The framework of this study is fundamental to understanding learning dynamics and transitions between learning styles. It is based on two key concepts namely, Kolb's (1984) experiential learning model is one of the most influential frameworks for understanding learning styles. According to Kolb, learning is a cyclical process that is based on two dimensions: perception and information processing. According to Coffield, F., Moseley, D., Hall, E., & Ecclestone, K. (2004). This model emerges four learning styles, each representing a unique approach for the divergent. They excel in situations that require reflection and idea generation, whether assimilators favor theoretical understanding and abstract concepts, seeking to deepen their knowledge, while convergents are oriented towards practical problem-solving and apply their knowledge concretely, while accommodators learn through experimentation and action, they adapt quickly to challenges.

This dynamic can be influenced by the pedagogical methods employed, the importance of this model lies in its ability to offer a global perspective on learning, emphasizing that each learner has distinct preferences. This is directly related to our goal of analyzing how an intervention can influence these learning styles. However, the issue of transitions between learning styles has been less explored.

In this context, Markov models, on the other hand, are powerful tools that allow to model the transitions between different learning states, (Markov, A. A. 1906). A learning state can be characterized by the degree to which a concept is understood or applied. By quantifying the probabilities of transition from one state to another, the initiation, understanding and application phases were used to model these dynamics. (Wang et al., 2019; Norris et al., 2014). These models allow for exploring how students evolve through the different phases of their learning and provide an effective way to model these transitions. (Butkovic et al., 2019), we can identify three states where the student:

State 1 (Initiation): discover new concepts through easy exercises.

State 2 (Comprehension): Begins to connect these concepts through medium-difficulty exercises.

State 3 (Application): Autonomously applies knowledge by solving complex problems.

Each transition between these states is associated with a probability, determined by historical observations of learning behaviors. This approach makes it possible to analyse how students evolve through different phases of their learning and to identify the factors that facilitate or hinder these transitions (Norris et al., 2014).

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Finally, the integration of the Markov model with the Kolb model offers an effective approach to analyze and predict learning behaviors. This combination allows for the development of more targeted teaching strategies tailored to the specific needs of each student. The different stages of learning according to Kolb correspond closely to the learning states defined by Markov models (Wang et al., 2019). This connection highlights the importance of each step in the learning process and can guide educators in designing learning experiences that promote smooth progression through these states. By incorporating these steps into educational planning, it becomes possible to better support students in their learning journey. The following table illustrates the relationship between Kolb's learning stages and Markov learning states, illustrating their interconnections, this process demonstrates the continuous learning dynamics through these different stages:

**Table 1: Comparison between Markov states and kolb styles**

| Modes de Kolb | Markov States | Description of the relationship |
|---|---|---|
| Concrete Experience | Initiation | Learners have a first experience that introduces new concepts or skills. This corresponds to the state of initiation, where they begin to discover new ideas. |
| Reflective Observation | Understanding | After the experience, learners reflect on what they have experienced and begin to understand the underlying concepts. This helps them move from initiation to understanding. |
| Abstract Conceptualization | Understanding | Learners formulate theories or concepts based on their thoughts. This step strengthens their understanding and prepares them to apply their knowledge. |
| Active Experimentation | Application | Learners put into practice the concepts they have developed by applying them to real-life situations. This moves them from understanding to application. |

## RESEARCH METHODOLOGY

### 1. Sampling and Assessment of Learning Styles

This study is quantitative empirical research. The data was collected from a target group of first-year physics students at Abdelmalek Essaadi University, Morocco, with varied skills in this discipline. A total of 115 students who participated in the study, selected by random sampling. The research began with an assessment to determine each student's learning style using Kolb's Learning Style Inventory (ILS), a questionnaire that serves as a measurement instrument, followed by a pre-test to classify them into the categories of initiation, comprehension, and application. An intervention was then performed, followed by a post-test to measure the results of the summative assessment.

### 2. Student Progress

Score evaluation and improvements provide an overview of learners' performance. By analyzing average performance based on scores, one can identify areas that need specific improvements. In addition, by considering performance according to learning styles, it becomes possible to customize pedagogical approaches to better meet individual needs.

Finally, a performance assessment by level provides a better understanding of progress over time and adjusts learning objectives accordingly. This holistic approach promotes continuous and targeted improvement in educational outcomes.

### 3. Data Collection

The data is collected through a pedagogical approach that includes a structured test, integrating four pedagogical methods adapted to each learning style.

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This approach aims to maximize engagement and learning effectiveness by taking into account individual student preferences:

Assigning methods according to learning style

- Divergent: Participation in group projects.
- Assimilators: Followed by in-depth theoretical courses.
- Convergent: Practical problem solving.
- Accommodators: Engaging in hands-on activities.

**4. Instructional Design**

Students were actively involved in a pre-test, which focused on fundamental physics concepts and was administered prior to the intervention. Then, the participants were followed up to collect data on their learning paths and the methods used. To conclude, a summative test was performed after the intervention to measure progress.

**5. Knowledge Assessment**

Pre-test: A knowledge test on physics concepts will be administered before the procedure. Post-test: A similar test will be administered after the intervention to assess progress.

Transition Tracking: Participants will be followed to collect data on their learning paths and the methods used.

**6. Data Analysis**

In this section, we will analyze the scores of students obtained during the pre-tests and post-tests to evaluate the effectiveness of the pedagogical intervention. We'll look at the different metrics, including Student Test Score (SET) and Average Student Test Score (SEMT), as well as performance by learning style and observed improvements.

These analyses will make it possible to measure not only individual progress, but also the overall performance of students at different levels of learning.

**7. Score Evaluation and Improvements**

- Pre-test, post-test scores, and improvements

(1) Student Test Score (SET):

$$\mathrm{SET} = \frac{\text{Correct test answers}}{\text{Total test questions}}$$

(2) Average Student Test Scores (SEMT):

$$\mathrm{SEMT} = \frac{\text{Sum of student scores}}{\text{Total number of students}}$$

(3) Absolute Improvement (AB):

$$\mathrm{AB} = \text{Score of } \mathrm{Post}_{\mathrm{test}} - \text{Score of Pre\_test}$$

(4) Relative Improvement (RA):

$$\mathrm{AR} = \frac{\text{Score Post\_test} - \text{Score Pre\_test}}{\text{Pre\_test}}\ \mathrm{x}100$$

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- Average student performance by learning style

(5) Percentage of Test Scores (%ST):

$$\%\,\mathrm{ST} = \frac{\text{Average test scores}}{\text{Sum of learning styles scores}} \mathrm{x}100$$

(6) Stability(s):

$$\mathrm{S} = \%\text{ of post}_{\text{test}} - \%\text{ of pre}_{\text{test}}$$

- Average performance by level

(7) Score Performance for Each Student (PSE):

$$\mathrm{PSE} = \frac{\text{Score obtained for each student}}{\text{Maximum student score}}$$

(8) Average Performance by Level (AMP):

$$\mathrm{PMN} = \frac{\text{Average performance of style x \% of' students validating the level}}{100}$$

(9) % of students validating the level (%EVN):

$$\%\mathrm{EVN} = \frac{\text{Number of students in the level x 100}}{\text{Total number of students}}$$

The evaluation of the test scores was analyzed and elaborated through a machine learning algorithm (Appendix 1).

**8. Comparison Graph**

Student performance was analyzed using machine learning tools in Python in Annex 2. This graph shows average performance by learning style, rated on a difficulty scale from 1 to 3, corresponding to easy, medium, and hard levels. The results highlight the variations in performance between Kolb's different learning styles, allowing for an in-depth understanding of the impact of pedagogical methods on each group of learners.

**9. Modeling Learning Paths: Markov Model**

Modeling learning paths using a Markov model provides a powerful framework for analyzing and optimizing learning. First of all, it is essential to clearly define the different learning states, which represent the learners' levels of competence or understanding (Initiation, Comprehension, Application). Next, we need to estimate the probabilities of transition between these states based on learner performance, which allows us to assess the probability that a learner will move from one state to another. The construction of the transition matrix is then a key step, as it synthesizes these probabilities and provides a structured representation of the learning dynamics from fictitious data to assess the probabilities of transition between states. Finally, establishing a transition matrix specific to learning styles allows educational pathways to be tailored to individual preferences, making learning more effective and personalized.

**10. Construction of The Transition Matrix**

The construction of the transition matrix, based on Markov state levels, is shown in Table 5 and the graph in Figure 5.

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This matrix illustrates the transitions between the learning states, namely 'Initiation → Understanding', 'Understanding → Application' and 'Understanding → Initiation'. The data was analyzed using machine learning tools in Python, as detailed in Appendix 3, thus allowing a clear visualization of the learning dynamics.

### 11. Transition Between Learning Styles According to Kolb

The transition between Kolb's learning styles, namely Concrete Experience (CE), Reflective Observation (OR), Abstract Conceptualization (AD) and Active Experimentation (EA), is summarized in Table 6 and the graph in Figure 6. This data was analyzed using machine learning tools in Python Annex 4. The transition matrix, which presents the probabilities of switching from one style to another, highlights the learning dynamics within these methods. Visualizing this matrix as well as simulating learning paths provides valuable insights into how learners evolve through different styles.

### 12. Identifying Learning Paths

Identifying learning pathways is a key process for personalizing education and ensuring that learners achieve their goals. This process is detailed in the Annex 5 algorithm, developed in Python. He starts by defining learning styles according to the Kolb cycle and creates a transition matrix with fictitious probabilities to model the transitions between these styles. Then, the learning path is simulated from an initial style, in this case the Concrete Experience, over a series of steps. Finally, the path thus generated is displayed, allowing you to visualize the evolution of learners through the different learning styles.

### 13. The Impact of Different Teaching Methods on Each Learning Style

The impact is crucial to understanding how to optimize teaching. This analysis helps to identify which approaches are most effective for each style, whether they are concrete experiments, thoughtful observations, abstract conceptualizations, or active experimentation. By assessing learners' outcomes based on the methods applied, it becomes possible to tailor instructional interventions to better meet individual needs and maximize student engagement and success.

### 14. Analysis Tools

Using Jumpy for mathematical operations, combined with Pandas for manipulating and displaying data as a Data Frame, provides an efficient approach to data processing. Jumpy allows mathematical calculations to be performed quickly and accurately, while Pandas makes it easy to organize and manage data, making it intuitive to handle. For the visualization of the results, Matplotlib and Seaborn are particularly useful.

Matplotlib offers flexibility to create varied graphics, while Seaborn, with its advanced features, allows for the production of aesthetically pleasing and informative visualizations. Together, these tools create a powerful environment for data analysis and presentation, enhancing the understanding of information.

## RESEARCH RESULTS

The sample studied includes 115 university students in physics, assessed using a standardized questionnaire (LSI), which classifies each student according to his or her predominant style as defined by Kolb: Divergent N=30, Assimilators N=23, Convergent N=35, and Accommodators N=27.

Figure 1, shows the distribution of percentages of each kolb learning style, in a range between 27% and 35%, the close of the scores make the analysis of its results meaningful.

DOI: 10.5281/zenodo.16308302
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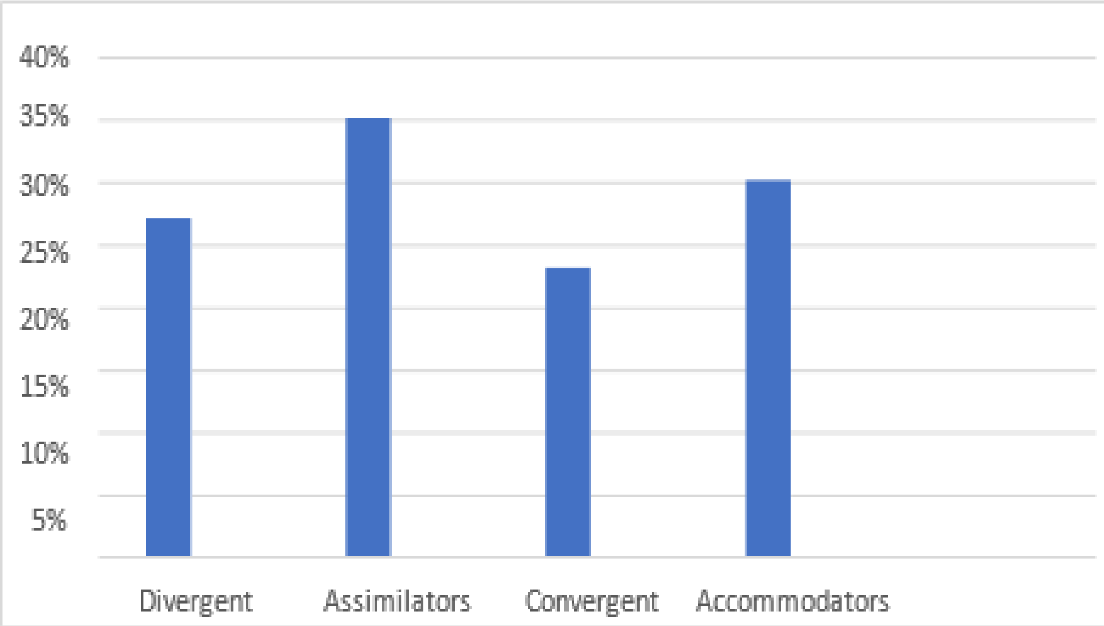


**Figure 1: Evaluation of the Sample's Learning Styles**

**1. Student Progress**

The analysis of student progress is based on several key dimensions. First, evaluating scores and improvements helps identify areas where learners have managed to progress and those that need attention.

Looking at average performance by score, one can observe overall trends and progress over time. In addition, an assessment of average performance by level provides a valuable perspective on the skills acquired according to the different stages of learning.

These combined analyses provide a holistic view of student progress, making it easier to optimize educational pathways and teaching strategies.

**2. Score Evaluation and Improvements**

The students' progress was assessed through the scores of the pre-test and post-test tests calculated by the relationship (1).

Table 1, presents the results of groups of learners based on the average test scores of students based on their learning style calculated by the relationship (2), this calculation provides information about how students of different styles interact with the content and progress in their learning.

The absolute and relative improvement calculated by relationships (3) and (4) showed an excellent improvement in their scores, reaching an average score of 85.00 for the post-test.

**Table 2: Pre and Post Test Scores**

| Group | Pre-test (average) | Post-test (average) | Improvement (Absolute) | Improvement (Relative) |
|---|---|---|---|---|
| Divergent | 55 | 79.75 | 24.75 | 45.00 |
| Assimilators | 60 | 70.00 | 10.00 | 16.67 |
| Converging | 65 | 90.00 | 25.00 | 38.46 |
| Accommodators | 58 | 85.00 | 27.00 | 46.55 |

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The figure 2, visually illustrates the improvements in the scores of the different groups.

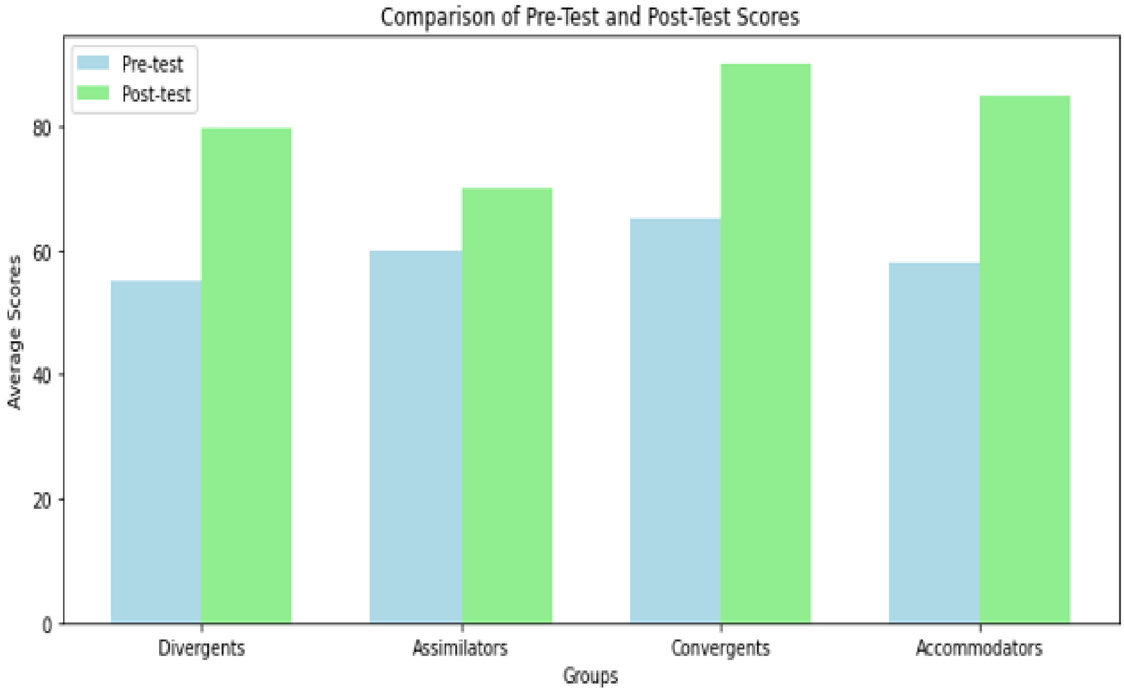


**Figure 2: Graph of score improvements**

**3. Average Student Performance by Learning Style**

The following results show students' performance in pre-test and post-test evaluations based on their learning style:

**Table 3: Average Performance by Learning Style**

| Learning styles | Number of students by style | % Pre-test | % Post | Stability % | Average performance | Increase in average score |
|---|---|---|---|---|---|---|
| Divergent | 30 | 23.10 | 24.55 | 1.45 | 0.38 | 24.75 |
| Assimilator | 23 | 25.21 | 21.55 | -3.66 | 0.43 | 10.00 |
| Convergent | 35 | 27.31 | 27.73 | 0.42 | 0.71 | 25.00 |
| Accommodator | 27 | 24.36 | 26.17 | 1.81 | 1 | 27.00 |
| Total | 115 | 100 | 100 | | | |

The table 2, calculated by applying relationships (5) and (6), indicates that an average performance of 0.38 and a stability of 1.45%, suggests a significant progression of the divergente, with an increase in their average score of 24.75 points, this means that the teaching methods were effective for this group. Although the Assimilators have also progressed, their improvement is relatively small compared to the other groups. Their average performance of 0.43 indicates that they have potential, but a 3.66% decrease in their stability suggests that they may have difficulty in certain learning situations. This could indicate that instructional strategies have not been as effective for these students, or that they require more support to move from theory to practice. The convergents show good progress, with a high post-test score. Their average performance of 0.71 shows that they have achieved a solid skill level, although a slight improvement of 0.42% indicates relative stability, indicating that they have achieved a higher skill level compared to the other groups, they have also shown a significant improvement, similar to that of the Divergente.

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The increase in their average score of 25 points suggests that they have assimilated the knowledge well and are able to apply it effectively, and the accommodators show the largest percentage improvement. Their average performance of 1.00 underlines that they have integrated learning well, with a stability increase of 1.81%. Their ability to go from 58 to 85 points shows that they have managed to take advantage of hands-on activities, which is often crucial for their learning style.

The Figure 3, showing the average performance by performance by learning style of kolb, visually illustrates the improvements in the scores of the different groups.

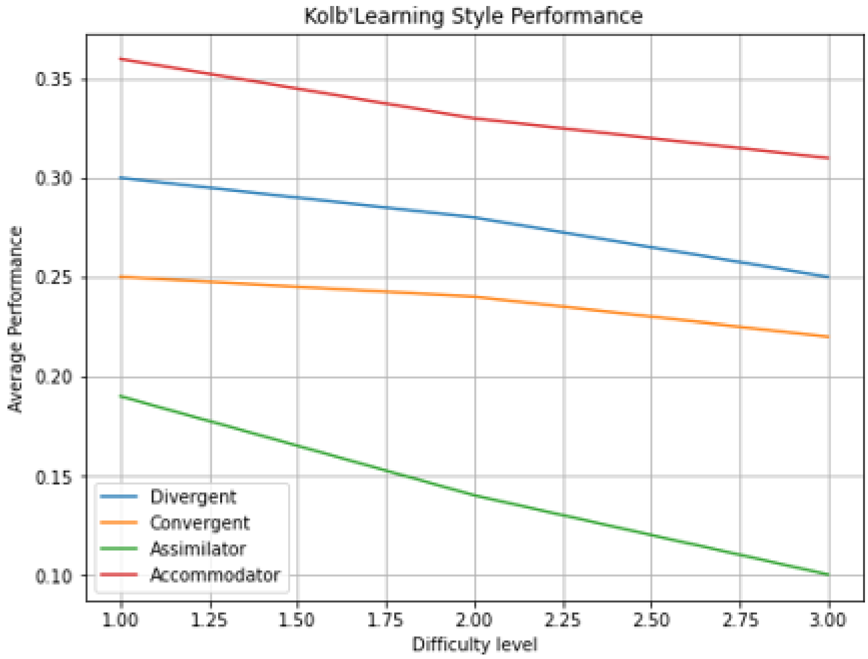


**Figure 3: Average performance by kolb style**

### 4. Average Performance by Level

The following results show the performance of learning styles by student level.

**Table 4: Learning Styles and Performance by Level**

| Learning styles | Number students by style | Number of students staying in level1 | Average Performance for Level 1 (Easy) | Number of students staying in level2 | Average performance for level 2 (Average) | Number of students staying in level3 | Average performance for level 3 (Hard) | Overall performance |
|---|---|---|---|---|---|---|---|---|
| Divergent | 30 | 11 | 0.30 | 10 | 0.28 | 9 | 0.25 | 0.83 |
| Assimilator | 23 | 10 | 0.19 | 8 | 0.14 | 5 | 0.10 | 0.43 |
| Convergent | 35 | 13 | 0.25 | 12 | 0.24 | 10 | 0.22 | 0.71 |
| Accommodator | 27 | 10 | 0.36 | 9 | 0.33 | 8 | 0.31 | 1.00 |

The table 3 presents the average performance of students by level calculated according to relationships (7), (8) and (9), for the three levels of learning: initiation, comprehension and application. The results show that the divergent show a high average performance of 0.83, although their scores decrease slightly with increasing difficulty. This could indicate a need for more adapted teaching methods for higher levels. In contrast, assimilators perform poorly across the board, with a significant drop as difficulty increases.

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This indicates that they may need more targeted support and tailored pedagogical approaches.

Convergents show relatively consistent performance across all three levels, although they are lower than divergent and accommodators. This suggests a solid approach but perhaps a potential need for improvement in more challenging contexts. While accommodators show the best overall performance across the board. Their ability to perform even at higher levels indicates that they benefit from a hands-on and interactive approach.

In conclusion, students' performance usually decreases with increasing difficulty, but accommodators maintain higher scores compared to other groups at each level. Accommodators have the best overall performance (1.00), followed by divergent (0.83) and convergents (0.71), while assimilators lag behind with an average of (0.43), indicating that they need additional support.

While the divergent and accommodators have a relatively high number of students in the higher levels, while the assimilators show a significant drop at each level. Its performance is summarized in kolb's performance graph by learning style. By identifying these performances, educators can adjust their teaching methods to better meet the needs of each group, promoting a better learning experience for all students according to their styles.

Its average performance by Markov state level is summarized in the following graph interpreted by a machine learning analysis under Phyton, on a scale of 1 to 3 of easy, medium and difficult (Appendix 2).

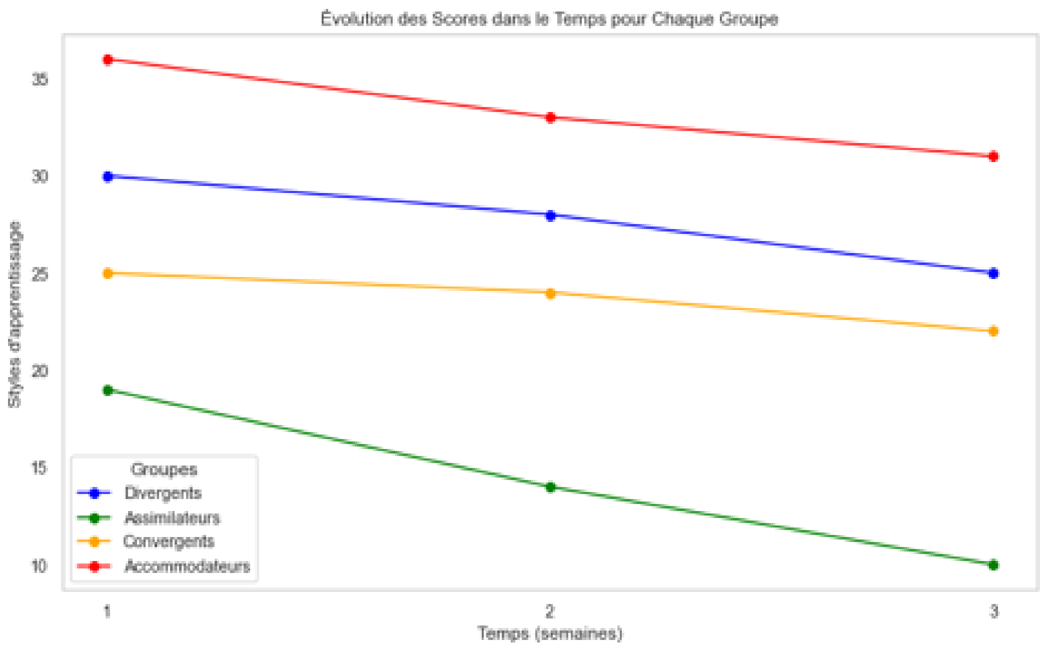


**Figure 4: The evolution of scores over time**

### 5. Markov Chain Modeling of Learning Paths

Markov chain modeling offers a powerful analytical framework to explore Kolb learning styles, allowing a more nuanced and applicable understanding in the pedagogical field, in this study we will first identify Markov states, then the construction of the transition matrix and the transition between learning styles according to Kolb for identification of learning paths and finally a discussion on the impact of the different teaching methods on each learning style.

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### 5.1 Markov states

For this study, we will identify three learning states: Initiation, comprehension and application.

**Table 5: Student Transition by Markov State**

| Styles | Students | remaining in the Initiation state | move to the comprehension state | students move to the application state |
|---|---|---|---|---|
| Divergent | 30 | 11 | 19 | 9 |
| Assimilators | 23 | 10 | 13 | 5 |
| Convergents | 35 | 13 | 22 | 10 |
| Accommodators | 27 | 10 | 17 | 8 |
| Total | 115 | 44 | 71 | 32 |

The table 4 presents the students' transition through Markov states: Initiation, understanding and application.

Total Transitions to the Initiation State: A total of 44 students transitioned to the "Initiation" state, representing approximately 38.26% of the students. This indicates that a significant proportion of students remain in this first state of learning

### 5.2 Transitions to Understanding

The total transitions to "Understanding" is 71, which shows that the majority of students are successful in progressing after initiation. This progress is encouraging and is a testament to the effectiveness of the teaching methods applied to help students gain a better understanding of the concepts.

Transitions to Application: With only 32 transitions to "Application", which suggests that students are experiencing more difficulties in reaching this level, which could indicate a need for additional support and adapted pedagogical strategies to facilitate this crucial stage of learning.

### 5.3 Construction of the transition matrix

The results of the transitions between learning styles according to the Kolb cycle are presented in Table 5, which presents the possible transitions between Markov states and kolb styles, they are represented by a transition matrix between the three learning states: Initiation (Starting level), Comprehension (Intermediate level.), Application (Advanced level) and learning styles according to kolb.

This matrix demonstrates insight into the students' learning dynamics where the divergent show a good number of transitions to the "Comprehension" state, suggesting that they are successful in moving to a higher level of learning after initiation, as well as accommodators. While convergents show a good balance between transitions to the three states, with a strong propensity to move to "Understanding". Assimilators have fewer transitions to each state, which could indicate difficulties in progressing to more advanced levels of learning.

**Table 6: Percentage distribution of students by number by style and condition**

| Learning state | Divergent | Assimilators | Converging | Accommodators |
|---|---|---|---|---|
| Staying at the initiation | 0.36 | 0.43 | 0.37 | 0.37 |
| Initiation → Understanding | 0.63 | 0.56 | 0.62 | 0.62 |
| Understanding → Application | 0.30 | 0.21 | 0.28 | 0.29 |
| Understanding → Initiation | 0.33 | 0.34 | 0.34 | 0.33 |

From table 5, we obtain the following transition matrix:

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**Table 7: Transition matrix**

| Learning state | Divergent | Assimilators | Converging | Accommodators |
|---|---|---|---|---|
| Initiation → Understanding | 63 | 56 | 62 | 62 |
| Understanding →Application | 30 | 21 | 28 | 29 |
| Understanding → Initiation | 33 | 34 | 34 | 33 |

The transition matrix shows that learners have a strong tendency to move from the "Initiation" state to "Understanding", especially for the "Divergent". This highlights the importance of fostering understanding before application, while taking into account different learning styles, these results have been represented in the Figure 5.

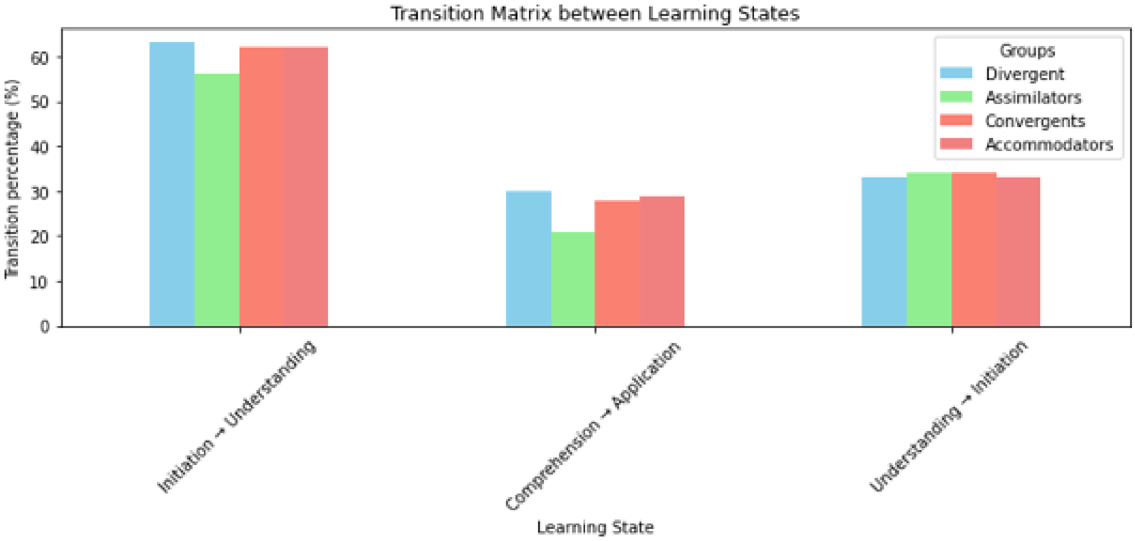


**Figure 5: Improvements in the scores of the different groups**

The Figure 5, visually illustrates the improvements in the scores of the different groups and represents the behavior of the transitions and identifies the states that are more likely to be achieved, it represents the evolution of the scores over time for each group after a six-week intervention, it is a valuable tool for visualizing the results of the intervention. It helps identify the states that benefited the most from the intervention, those that are at risk of regression, and those that need special attention to maintain or improve scores.

An in-depth analysis of these transitions can offer clear insights into the effectiveness of the strategies being implemented.

### 6. Transition Between Learning Styles According to Kolb

The transition matrix below illustrates the probabilities of switching from one learning style to another, calculated from the data collected:

**Table 8: Matrix of Transition between styles**

| Learning state | Divergent | Assimilators | Converging | Accommodators |
|---|---|---|---|---|
| Concrete Experience | 0.63 | 0.56 | 0.37 | 0.37 |
| Reflective Observation | 0.36 | 0.43 | 0.62 | 0.62 |
| Abstract Conceptualization | 0.30 | 0.21 | 0.28 | 0.29 |
| Active Experimentation | 0.33 | 0.34 | 0.34 | 0.33 |

Table 6 presents Kolb's matrix of transition between learning styles, offering crucial information for the design of adapted educational programs.

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The transition probabilities reveal that the Concrete Experience (CE) state is particularly effective, with a high probability for divergent (0.63) to establish themselves there. This state also favors Assimilators, Convergents, and Accommodators, indicating balanced support for multiple styles. In contrast, the state of Reflective Observation (OR) shows a tendency toward Assimilators (0.43), although transitions toward divergent are significant (0.36). The state of Abstract Conceptualization (AB) has lower probabilities, suggesting a limited transition dynamic. Finally, the Active Experimentation (EA) state shows an equilibrium in transitions, but with a moderate probability towards divergent (0.33). To maximize the effectiveness of instructional interventions, it is recommended to strengthen transitions from the CA state and maintain positive transitions from the CE state.

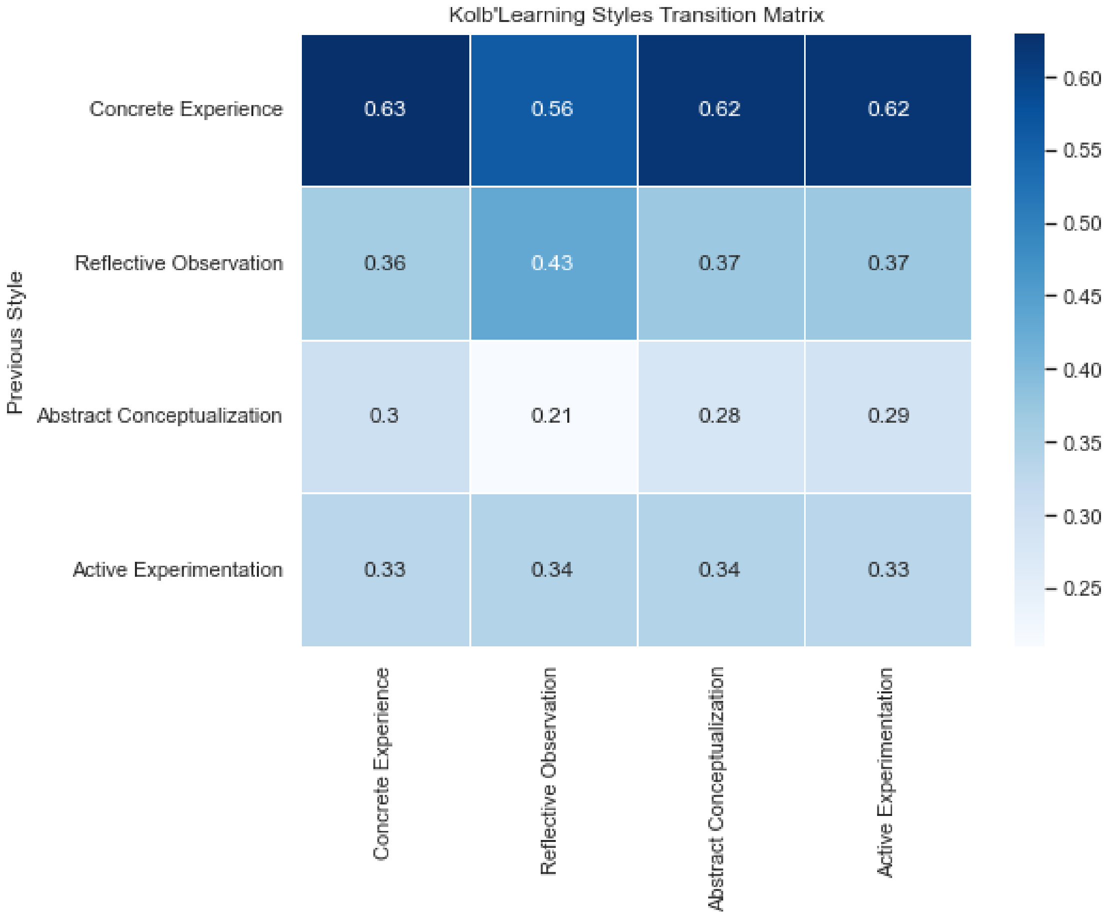


**Figure 6: Transition Matrix between kolb styles**

### 6.1 Identifying Learning Paths

Using data on learning behaviors, it is possible to plot individual pathways. This helps to understand how learners navigate between the different stages and which learning style predominates.

Figure 7, presenting the simulated learning path revealed that the students, from the initial state Concrete Experience, have mostly evolved towards Active Experimentation, thus illustrating the possible transitions between learning styles, then a reflection on the actions to be carried out in order to give meaning to the actions, Abstract conceptualization and plan the actions to be carried out and go through the cycle with a new action to be carried out by the students with an experience Concrete. By identifying the most frequent or least frequent transitions, teaching methods can be better adapted to meet the specific needs of personalization of learning and pedagogical adaptation. By analyzing

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transitions and pathways, it is possible to assess the effectiveness of different pedagogical strategies. Markov chains can help quantify the impact of educational interventions on the development of learning skills.

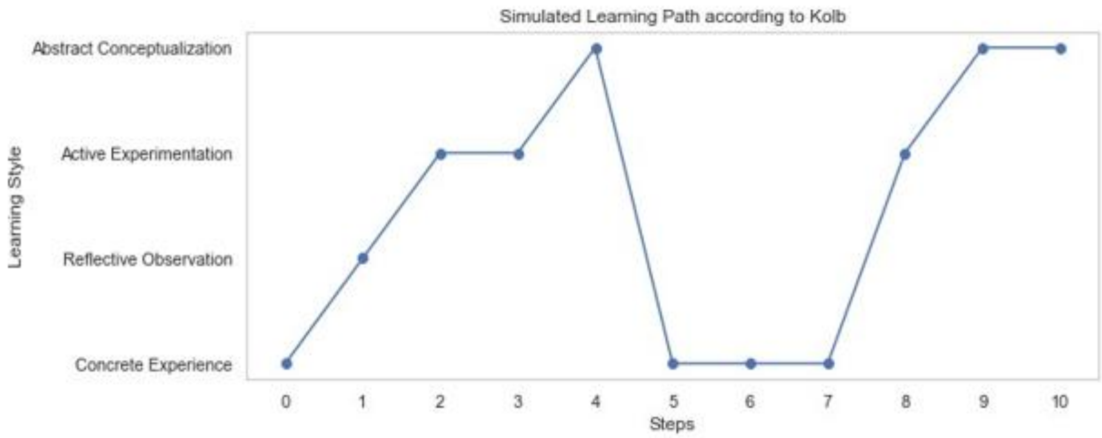


**Figure 7: Simulated learning path according to kolb**

The learning path shows the learner using Kolb's model iteratively, frequently alternating between "Active Experimentation" and "Concrete Experience". This dynamic indicates a preference for hands-on learning, where concrete experience reinforces theoretical understanding. The Markov model illustrates that each transition between styles is probabilistic, reflecting the adaptive nature of learning choices. The repetition of certain styles suggests a cyclical learning process, essential for integrating abstract concepts. These findings highlight the importance of creating flexible learning environments that allow learners to explore different styles fluidly.

### 6.2 The Impact of Different Teaching Methods on Each Learning Style

**Table 9: Impact observes pedagogical methods**

| Learning styles | Teaching methods | Observed impact (Improved score) |
|---|---|---|
| Divergent | Group projects | High |
| Assimilators | Theoretical courses | Moderate |
| Converging | Practical issues | Very high |
| Accommodators | Hands-on activities | High |

Finally, Table 7 shows the impact of different teaching methods on each learning style:

The interpretation of the results should make it possible to draw conclusions about the effectiveness of teaching methods according to learning styles. By identifying trends in learning pathways and assessing the impact of methods, we can make recommendations to improve physics education and better meet learners' needs. It can also contribute to the design of more tailored and personalized educational programs.

### Recommendations

Numerous previous studies have explored learning styles according to the Kolb model, emphasizing the importance of pedagogical adaptation to meet the varied needs of learners (Prud'homme, 2007). The results of these studies highlight the need to adjust teaching strategies according to the learning styles identified.

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Studies have shown that 'Convergent' and 'Active' learners particularly benefit from hands-on activities and collaborative projects (Prince, M. (2004), , Meyer, J. H. F., & Land, R. (2006), which our study confirms by revealing a high probability of transition from 'Convergent' to 'Active' style.

In contrast, our results suggest that divergents and accommodators show good transition abilities. It could be useful to strengthen the methods and practices that have worked for these groups to further improve their performance, Convergents with a good balance in transitions, could benefit from additional challenges to stimulate their learning and prepare them for more advanced levels of application, they could benefit from more challenging tasks to develop their skills to higher levels. While the results of the assimilators have shown difficulties in progressing. It would be beneficial to introduce pedagogical strategies adapted to their learning style to help them move to higher levels and improve their engagement and understanding, which aligns with the work of Felder, R. M., & Brent, R. (2005). Since the transition to the implementation state is more difficult for all groups, targeted interventions, such as practical exercises or projects, could be put in place to facilitate this transition.

In addition, the integration of a variety of approaches, practical for the "Divergents" and theoretical for the "Assimilators", could enrich the learning dynamic, Hattie, J. (2009). It is important to carry out regular assessments to monitor progress and adjust teaching methods in real time to meet the specific needs of each group. These findings provide valuable insights for adjusting teaching methods and improving learning transitions for all styles and guide future teaching efforts to personalize instructional approaches to maximize learning for all learners. Linking our findings to previous work, we can conclude that adapting teaching methods to different learning styles is not only beneficial, but essential to maximizing each student's potential. Finally, this study paves the way for future research that could examine more deeply the contextual and psychological factors influencing transitions between learning styles, thus contributing to a finer understanding of personalized learning.

## CONCLUSION

This work highlighted the importance of integrating Kolb and Markov learning models to better understand and adapt learning processes. By applying machine learning algorithms, we have been able to analyze and visualize data from different tests that enrich our understanding of the learning dynamics of the four distinct learning styles, revealing the specific preferences and behaviors of students. The analysis of the probabilities of transition between these styles has made it possible to highlight specific behavior’s, such as the flexibility of the "divergent" and the preference for thinking of the "Assimilators".

These findings have significant pedagogical implications, highlighting the need to adapt teaching methods to meet the varied needs of learners. By designing customized learning paths, we have demonstrated how it is possible to foster more engaging and effective learning, taking into account individual preferences. This work paves the way for future research and practical applications, enabling educators to create inclusive and dynamic learning environments that maximize each student's potential. Thus, the integration of these models and techniques represents a significant step towards a more personalized and learner-centered pedagogy. In conclusion, this work demonstrated the importance of integrating Kolb and Markov learning models to improve students' learning paths with pedagogical methods.

The analysis of the probabilities of transition between styles has highlighted interesting dynamics. These results shed light on crucial pedagogical implications, encouraging the adoption of different teaching methods and the creation of personalized training paths. By tailoring instructional approaches to individual styles, we promote more engaging and effective learning, while meeting the

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varied needs of students. This work paves the way for future research and practical applications. While the integration of these models represents a significant step towards a more inclusive and dynamic education. Finally, this study clearly demonstrated that adapting teaching methods to students' learning styles has a significant impact on the understanding of physics concepts. The results highlight the need to use a variety of approaches to meet the diverse needs of learners. This will improve the effectiveness of physics education and optimize student learning.

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**Appendix 1**: The evaluation of the test scores was analyzed and elaborated through a machine learning algorithm, defined as follows: (Table 2 and Figure 2)

```
import numpy as np
import pandas as pd
import matplotlib. pyplot as plt
# Set learning styles and initial scores
styles = ['Divergents', 'Assimilators', 'Convergents', 'Accommodators']
pre_test_scores = [55, 60, 65, 58] # Pre-test averages
improvement_percentages = [45, 16.67, 38.46, 46.55] # Percentage Improvements
# Calculate Post-Test Scores
post_test_scores = [
    np.round(pre_score+(pre_score*(improvement/100)), 2)
    for pre_score, improvement in zip (pre_test_scores, improvement_percentages)
]
# Create a DataFrame to display the results
results = pd. DataFrame ({
    'Group': styles,
    'Pre-test (average)': pre_test_scores,
    'Post-test (average)': post_test_scores,
    'Improvement (%)': improvement_percentages
})
# Displaying results
print(results)
# Visualization of test results
plt.figure(figsize=(10, 5))
```

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```
bar_width = 0.35
index = np.arange(len(styles))
# Bars for pre-test and post-test
plt.bar(index, pre_test_scores, bar_width, label='Pre-test', color='lightblue')
plt.bar(index + bar_width, post_test_scores, bar_width, label='Post-test', color='lightgreen')
# Adding labels and title
plt.xlabel('Groups')
plt.ylabel('Average Scores')
plt.title('Comparison of Pre-Test and Post-Test Scores')
plt.xticks(index + bar_width/2, styles)
plt.legend()
# View Chart
plt.tight_layout()
plt.show()
```

**Appendix 2**: Its performance is summarized in the following graph interpreted by a machine learning analysis under Phyton, on a scale of 1 to 3 of easy, medium and difficult.(Figure 3)

```
import matplotlib.pyplot as plt
# Average performance by learning style
divergent_performance = [0.30, 0.28, 0.25]
assimilator_performance = [0.19, 0.14, 0.10]
convergent_performance = [0.25, 0.24, 0.22]
accommodator_performance = [0.36, 0.33, 0.31]
# Performance visualization
x = [1, 2, 3] # Difficulty Levels
plt.figure(figsize=(8, 6))
plt.plot(x, divergent_performance, label='Divergent')
plt.plot(x, convergent_performance, label='Convergent')
plt.plot(x, assimilator_performance, label='Assimilator')
plt.plot(x, accommodator_performance, label='Accommodator')
plt.xlabel('Difficulty level')
plt.ylabel('Average Performance')
plt.title('Kolb\'Learning Style Performance')
plt.legend()
plt.grid()
plt.show()
```

ISSN：1674-2974 | CN 43-1061 / N

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**Appendix 3**: The evolution of scores over time (Figure 4)

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Dummy data representing scores over time for each group
data = {
    'Time (weeks)': [1, 2, 3],
    'Divergents': [30, 28, 25],
    'Assimilators': [19, 14, 10],
    'Convergents': [25, 24, 22],
    'Accommodators': [36, 33, 31]
}
# Convertir en DataFrame
scores_df = pd.DataFrame(data)
# Set Seaborn Style
sns.set(style='whitegrid')
# Create the chart
plt.figure(figsize=(10, 6))
# Tracing groups with custom colors
plt.plot(scores_df['Time (weeks)'], scores_df['Divergents'], marker='o', label='Divergents', color='blue')
plt.plot(scores_df['Time (weeks)'], scores_df['Assimilators'], marker='o', label='Assimilators', color='green')
plt.plot(scores_df['Time (weeks)'], scores_df['Convergents'], marker='o', label='Convergents', color='orange')
plt.plot(scores_df['Time (weeks)'], scores_df['Accommodators'], marker='o', label='Accommodators', color='red')
# Add details to the chart
plt.title("Evolution of Scores over Time for Each Group")
plt.xlabel("Time (weeks)")
plt.ylabel("Scores")  # Changed label to "Scores"
plt.xticks(scores_df['Time (weeks)'])
plt.legend(title='Groups')
plt.grid()
plt.tight_layout()
plt.show()
```

**Appendix 4:** (Table 7 and Figure 5)

```
import numpy as np
import pandas as pd
```

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```
import matplotlib.pyplot as plt
# Analyze transitions (fictitious data for example)
transition_data = {
    'Learning state': ['Initiation → Understanding', 'Comprehension → Application', 'Understanding → Initiation'],
    'Divergent': [63, 30, 33],
    'Assimilators': [56, 21, 34],
    'Convergents': [62, 28, 34],
    'Accommodators': [62, 29, 33]
}
# Create a DataFrame for Transitions
transition_df = pd. DataFrame(transition_data)
# Show the transition table
print ("\nTransition Matrix:")
print(transition_df)
# Visualization of learning transitions
transition_df.set_index('Learning state').plot(kind='bar', figsize=(10, 5), color=['skyblue', 'lightgreen', 'salmon', 'lightcoral'])
plt.title('Transition Matrix between Learning States')
plt.xlabel('Learning State')
plt.ylabel('Transition percentage (%)')
plt.xticks(rotation=45)
plt.legend(title='Groups')
# View Chart
plt.tight_layout()
plt.show()
```

**Appendix 5**: The transition between the learning style modes of kolb, EC, OR, CA and EA are summarized in Table 6 and the graph in Figure 6 by a machine learning analysis under Phyton (Table 8 and Figure 6):

```
import numpy as np
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns # Fixed import statement
# Definition of learning styles according to the Kolb cycle
styles = ['Concrete Experience', 'Reflective Observation', 'Abstract Conceptualization', 'Active Experimentation']
# Transition matrix (fictitious probabilities)
transition_matrix = np.array([
    [0.63, 0.56, 0.62, 0.62], # Probabilities of transition from CE
```

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```
    [0.36, 0.43, 0.37, 0.37], # Probabilities of transition from RO
    [0.30, 0.21, 0.28, 0.29], # Probabilities of transition from AC
    [0.33, 0.34, 0.34, 0.33] # Probabilities of transition from AE
])
# Convert to DataFrame for easy viewing
transition_df = pd. DataFrame(transition_matrix, index=styles, columns=styles)
# Show the transition matrix
print ("Transition Matrix:")
print(transition_df)
# Visualization of the transition matrix
plt.figure(figsize=(8, 6))
sns.heatmap(transition_df, annot=True, cmap='Blues', cbar=True, linewidths=.5)
plt.title('Kolb\'Learning Styles Transition Matrix')
plt.xlabel('Next Style')
plt.ylabel('Previous Style')
plt.show()
# Simulation of learning transitions
def simulate_learning(initial_style, num_steps):
    current_style = initial_style
    styles_sequence = [current_style]
    for _ in range(num_steps):
        current_style_index = styles.index(current_style)
        current_style = np.random.choice(styles, p=transition_matrix[current_style_index])
        styles_sequence.append(current_style)
    return styles_sequence
# Simulating a learning path
initial_style = 'Concrete Experience'
num_steps = 10
learning_path = simulate_learning(initial_style, num_steps)
# View Simulated Learning Path
print ("\nSimulated Learning Path:")
print (" → ". join(learning_path))
# Learning path visualization
plt.figure(figsize=(10, 4))
plt.plot(learning_path, marker='o')
plt.title('Kolb\'Simulated Learning Path')
```

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```
plt.xlabel('Steps')
plt.ylabel('Learning Style')
plt.xticks(range(len(learning_path)), range(len(learning_path)))
plt.yticks(styles)
plt.grid()
plt.show()
```

**Appendix 6:** Identifying learning pathways is an essential process for personalizing education and ensuring that learners achieve their goals, detailed in the following algorithm under Phyton (figure7)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Definition of learning styles according to the Kolb cycle
styles = ['Concrete Experience', 'Reflective Observation', 'Abstract Conceptualization', 'Active Experimentation']
# Transition matrix (fictitious probabilities)
transition_matrix = np.array([
  [0.25, 0.28, 0.24, 0.23], # Transition probabilities from CE
  [0.23, 0.30, 0.24, 0.23], # Transition probabilities from RO
  [0.28, 0.19, 0.26, 0.27], # Transition probabilities from AC
  [0.29, 0.21, 0.22, 0.28]   # Transition probabilities from AE
])
# Convert to DataFrame for easier visualization
transition_df = pd.DataFrame(transition_matrix, index=styles, columns=styles)
# Simulation of a learning path
def simulate_learning(initial_style, num_steps):
  current_style = initial_style
  styles_sequence = [current_style]
  for _ in range(num_steps):
    current_style_index = styles.index(current_style)
    current_style = np.random.choice(styles, p=transition_matrix[current_style_index])
    styles_sequence.append(current_style)
  return styles_sequence
# Fix the random seed for reproducibility
np.random.seed(42)
initial_style = 'Concrete Experience'
num_steps = 10
```

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```
learning_path = simulate_learning(initial_style, num_steps)
# Show simulated learning path
print ("\nSimulated learning journey:")
print (" → “. join(learning_path))
# Visualization of the learning path
plt.figure(figsize=(10, 4))
plt.plot(learning_path, marker='o')
plt.title('Simulated Learning Path according to Kolb')
plt.xlabel('Steps')
plt.ylabel('Learning Style')
plt.xticks(range(len(learning_path)), range(len(learning_path)))
plt.yticks(styles)
plt.grid()
plt.show()
```