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Physics Teaching with Artificial Intelligence (AI): A Personalized Approach for Accommodator-Style Learners According to Kolb

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This paper focuses on the integration of artificial intelligence (AI) applications in physics education, with the aim of improving the learning experience and performance of students identified as accommodative learners according to Kolb's model. We adopt a qualitative approach to integrate AI into the teaching and learning process, with an emphasis on pedagogical methods and the exploration of new perspectives. This work presents a case study on the evaluation of a physics assignment, involving a sample of 85 high school girls in science stream. To do this, we use tools such as questionnaires and interviews to collect information on the difficulties encountered during the assignment and in learning physics in general. Our results show that AI can offer personalized learning solutions, adapted to the specific needs and preferences of learners. We formulate concrete recommendations to optimize the use of AI, aimed at facilitating learning and developing students' skills. Finally, this approach highlights the importance of personalized pedagogy in physics teaching, opening the way to new perspectives to meet the unique needs of students.

Keywords: artificial intelligence (AI), personalization, AI applications, secondary physics, Kolb accommodator style

INTRODUCTION

Learning physics is essential in high school because it introduces fundamental theoretical concepts in key areas such as mechanics, electricity, optics, and nuclear energy. However, many learners have difficulty grasping these complex phenomena or interpreting experimental data (Freedman et al., 2015). The research problem of this article lies in the unsatisfactory performance of students, identified as accommodating learners, in the learning of physics. The study aims to identify the specific difficulties faced by these students and explore customized solutions to meet their learning needs. In this context, recent advances in artificial intelligence (AI) offer pedagogical and technological solutions to enrich the learning experience in physics. This topic is

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necessary to improve the academic performance of physics students, by providing personalized learning solutions through artificial intelligence. Responding to the diversity of learning styles David Kolb's experiential learning model provides a relevant framework for understanding individual preferences in terms of knowledge acquisition (Kolb, 1984). The tool used to identify kolb styles is the Learning Styles Inventory (KLSI 4.0) (Kolb & Kolb, 2005).

This study focuses specifically on the accommodating style, characterized by a preference for active experimentation and hands-on experience, making it particularly suitable for scientific and technical learners. Our aim is to explore the use of artificial intelligence (AI) applications in physics education to improve the learning experience and performance of students identified as accommodating learners, in order to identify the specific challenges faced by learners in their learning environment, and to optimize learning conditions and better meet their needs (Ayeni, 2021). To achieve this objective, we will conduct a survey among learners in science options in order to identify the main difficulties they encounter. We will then develop a questionnaire based on a LIKERT scale to assess their preferences regarding activities incorporating AI. Based on a literature review, we will examine how these technologies can address the identified challenges. Finally, we will refine our recommendations based on the feedback collected, thus consolidating our argument on the potential of AI to enrich physics learning at the secondary level. This research aims to pave the way for innovative pedagogical approaches, adapted to learners' learning styles.

Background and Literature Review

This theoretical framework establishes a solid foundation for the practical part of our study, integrating the experiential Kolb cycle and the accommodating learning style, emphasizing the preferences and characteristics of these learners, whose problem lies in the unsatisfactory performance identified in the learning of physics. The study aims to identify the specific difficulties faced by these students and explore customized solutions to meet their learning needs. Recent literature underlines the importance of adapting teaching methods to the specific characteristics of these learners, in order to promote a better assimilation of concepts (Honey & Mumford, 2000), The integration of artificial intelligence (AI) in the educational field represents a significant advance that makes it possible to personalize learning even more. Because it offers powerful tools to analyze learning preferences and adjust educational content accordingly. However, the relationship between AI and education deserves further exploration. Recent studies show that AI can enrich the learning experience by providing real-time feedback and tailoring educational pathways to students' individual needs (Luckin et al., 2016). Nevertheless, there is a lack of research focused on the application of AI to specifically address the needs of accommodating learners in the context of physics education. To fill this gap, our study aims to examine how AI tools can be integrated to tailor learning activities to the preferences of physically accommodating learners. Building on recent research, we aim to demonstrate how AI can not only support student engagement, but also transform traditional teaching methods into innovative solutions. A critical review of the literature will highlight the potential benefits of this integration while identifying the challenges to be overcome for effective implementation. In short, this theoretical framework demonstrates that the adoption of adapted pedagogical strategies, based on AI, can transform the learning experience of accommodating students, while providing concrete recommendations for their integration into physics teaching. This research aspires to articulate contemporary knowledge and identify areas of innovation, highlighting the potential of AI to enrich physics learning in high school.

Theoretical Framework

The integration of AI into physics education is a personalized approach that aligns with Kolb's accommodating learning style, which emphasizes hands-on experiences and adaptability. (waladi & Khaldi, 2023). AI technologies can tailor educational experiences to meet the unique needs of learners, improving engagement and understanding. (Patero, J. L, 2023) This approach leverages AI's ability to adapt content and provide interactive and experiential learning opportunities, essential for accommodating learners who thrive through real-world experiences and active experimentation, (Kemouss, H., Abdannour, O., & Mohamed, K. (2024). The following sections detail how AI can be used effectively in this context. In addition, we hypothesize that the use of AI tools will create a more inclusive learning environment, where accommodating learners will feel valued and engaged in their learning process.

Kolb's experiential cycle

According to theorist David Kolb (1984), "learning is the process by which knowledge is created through the transformation of experience." Kolb states that the learning process is a four-stage cycle (concrete experience, reflective observation, abstract conceptualization, and active experimentation) where the combination of the two consecutive stages gives rise to a learning style (divergent, assimilative, convergent, and accommodating), which intervenes in a complementary way, expressed in Figure 1 below:

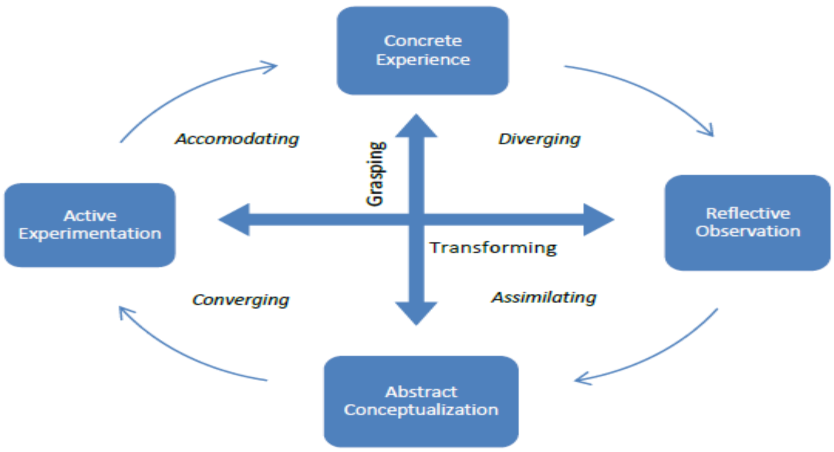


Figure 1
Kolb experiential learning cycle
Source: Kolb, B. (2008). Marketing research is a practical approach.

Description and Accommodating Kolb Learning Styles

David Kolb's theory of experiential learning remains a topic of interest to many educational researchers, including David A. Kolb, Alice Y. Kolb, Roger Fry, Bernice B. Wong, David B Swanson, Peter Senge, and Donna Gold Hawk. This theory remains relevant and continues to fascinate the field of education, due to its potential to improve the effectiveness of teaching and learning, while meeting the individual needs of learners. Indeed, research has shown that learners learn in different ways and that each learner has a preferred learning style (Harb, Durrant & Terry, 1993). The application of learning style theory builds on the work of Kolb, who identified a four-stage learning cycle, each corresponding to a particular style (Stice, 1987). Based on Kolb's (1984) theory of learning styles, accommodating learners show a marked inclination for practical experimentation and real-life experiences. They thrive in practical scenarios, where they can put their assumptions to the test and easily adapt to new circumstances. Additionally, they appreciate collaborative efforts and appreciate receiving quick feedback on their efforts.

AI and education

In 2020, Giraudon et al defined artificial intelligence as "the automation of processes and behaviors that we humans perceive as intelligent." This definition emphasizes the fact that AI aims to reproduce, by computer means, certain cognitive abilities specific to human beings (Giraudon et al, 2020).
In his article, Romero, M. et al, (2021) raised the issue of the uses of AI in education, which are at the intersection of AI, learning analysis, and technology-assisted learning. These uses can aim to create personalized learning paths, facilitate evaluation and increase the number and quality of feedback, as well as answer questions of varying complexity formulated by learners. Chen and his companions summarized these uses in Figure 3 below.

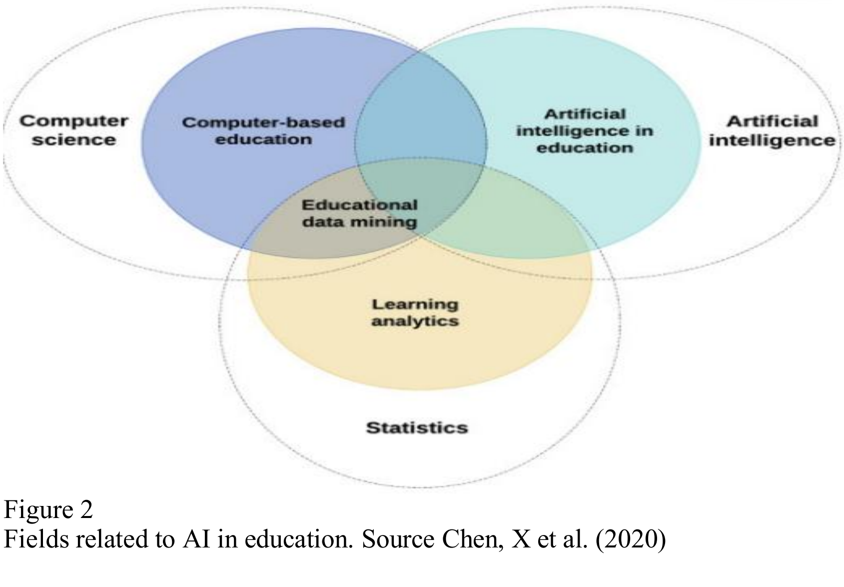


Figure 2
Fields related to AI in education. Source Chen, X et al. (2020)

To develop artificial intelligence solutions in education, it is essential to have both data and educational resources. The quality of this data depends on several key factors. Firstly, its relevance to the subject and the learning task addressed. Second, it must be consistent with the underlying learning model and pedagogical model used interchangeably to describe similar uses, as Rienties et al. point out in their work. (Rienties et al., 2019).

AI integration for accommodating style

Artificial intelligence (AI) is a powerful tool to support learners in their learning and problem-solving processes. According to Kolb's model, the accommodating learning style is characterized by a preference for concrete experience and active experimentation. Learners with this learning style learn best by actively engaging in practical tasks and by making trial and error (Kolb, 1984). This will allow us to define the most appropriate applications and guide the development of AI appropriately (Pruitt & Adlin, 2010). This analysis consists of clearly identifying the specific needs of the learners. Interviews, observations, and surveys help identify the tasks, workflows, and information that AI could have the most impact on, as well as the most accommodating features and interfaces (Dix et al., 2004). It is also necessary to define the objectives to be achieved by integrating AI, such as improving the user experience, optimizing certain tasks or providing personalized recommendations. These objectives should be prioritized according to their importance and feasibility (Maguire, 2001). Finally, it is essential to select use cases that align with learners' goals and needs, and to actively involve them throughout the AI design and development process. This will allow us to gather their feedback and suggestions for continuous improvement of the experience (Norman, 2023).

Using AI to adapt physical activities to accommodating people

AI offers many opportunities to adapt physics activities to accommodating learners, who prefer hands-on and experiential learning (KOLB, 1984). This requires a learner-centred approach and a thorough understanding of their needs, with active participation in the design and development process, as highlighted by Shinohara, K., and Wobbrock, J. O. (2011). A study by Treviranus and Roberts (2012) showed that AI can be a powerful tool for personalizing physics activities and making them more accessible to learners. AI makes it possible to analyze the performance and preferences of each learner and to adapt in real time the level of difficulty, visual or hearing aids and interaction methods. This contributes to greater inclusion and a more enriching and motivating learning experience (Burgstahler, 2012). However, the integration of AI into physics activities must be done in a thoughtful and ethical manner, taking care to respect data confidentiality, according to Desjardin and Deslauriers (2017). Close collaboration between designers, teachers and learners is essential to ensure the success of such initiatives (Mace, 1998).

Implementation and Practical Considerations

According to Kolb (1984), accommodating learners are characterized by a preference for practical situations, experimentation and rapid adaptation to change. Integrating AI into physics activities for these learners can be particularly beneficial. AI-powered recommender systems can analyze student performance, preferences, and learning styles to suggest interactive simulations, virtual lab experiments, or design projects (Schraw et al., 2006). Adapted from Bransford et al. (2000). The AI can also dynamically adjust the difficulty level and provide immediate, personalized feedback. Intelligent chatbots can also guide learners in carrying out practical activities and solving real-world problems (Graesser et al., 2005). Virtual and augmented reality, when combined with AI, can be used to create immersive learning environments where learners can manipulate and observe physical phenomena in an active and experiential way (Dede, 2009). AI can also be used to design learning-by-doing scenarios, proposing challenges to be solved in an active and collaborative way (Kolb & Kolb, 2005). However, the use of AI in these activities must be transparent and understandable to learners, in order to maintain their trust and engagement (Shneiderman & Plaisant, 2010). Adequate teacher training and regular follow-up of learners are also necessary to ensure the success of these initiatives. Finally, AI can help instructional designers design physics activities that are better suited to learners' needs, by generating suggestions for hands-on experiments, simulation scenarios, or projects based on real-world problem-solving (Reigeluth, 1999).

The integration of artificial intelligence (AI) tools in physics teaching and learning

Integrating artificial intelligence (AI) tools into physics teaching and learning requires a structured process that can be broken down into several key steps. First, an assessment of the needs of teachers and learners. This includes identifying difficulties students face in understanding physics concepts and varied learning styles. (BENAMAR, F., & BELHACHEMI, M. 2022). it is essential to train teachers in the use of AI technologies, so that they can effectively integrate them into their teaching practice (Kukulska-Hulme, 2020). This training may include workshops and online resources to familiarize teachers with the available tools and their pedagogical applications. Secondly, the creation of adapted educational content is crucial. Teachers should develop lessons and activities that harness the capabilities of AI tools, such as interactive simulations and smart tutoring systems, to enrich students' learning experience (Heffernan & Heffernan, 2014). For example, adaptive learning platforms can be used to customize exercises based on student performance, which promotes more focused and effective learning. Finally, these tools must be integrated seamlessly into regular course sessions. This involves planning activities where students can interact with AI technologies, thereby stimulating their engagement and motivation to learn complex concepts in physics (Luckin et al., 2016). Finally, the onboarding process includes a feedback phase, where teachers and students share their impressions on the use of AI tools. This allows adjustments to be made to continuously improve the learning experience. By following these steps, the integration of AI tools can transform physics education by making learning more interactive, personalized, and effective.

Concrete Examples of Educational Activities Using AI

Accommodating learners prioritize activities that allow them to explore, experiment, and actively engage in their learning, while benefiting from personalized coaching and feedback. They value experiential learning and practical application of concepts, and the proposed activities are grouped according to these five axes, and presented in Table 6 above:

- Hands-on Experiments and Interactive Simulations

Students can use wave simulators to experiment with concepts such as diffraction and interference. For example, a simulator like PhET allows students to visualize how waves propagate in different environments, thus strengthening their understanding through virtual experimentation (PhET, n.d.).

- Adaptive Learning Applications

Tools like Smart Sparrow allow teachers to create interactive lessons that adjust to students' needs. For example, a module on energy conservation could offer personalized problems based on students' past performance, thus encouraging better assimilation of concepts (Smart Sparrow, n.d.).

- Data Analysis and Visualization

Students can use AI-based data analysis tools to explore experiments in physics, such as the movement of projectiles. Applications such as DataCamp provide environments where students can analyze real-world datasets and visualize the results, making it easier to understand scientific principles (DataCamp, n.d.).

- Smart Tutoring Systems

Platforms like Carnegie Learning offer smart tutoring systems that adapt to each student's pace and level. These tools provide personalized exercises and instant feedback, helping students master complex concepts such as Newton's laws, at their own pace (Carnegie Learning, n.d.).

Results of Integration of AI tools in physics

The integration of artificial intelligence (AI) tools into physics education has shown positive results in terms of engagement and understanding of concepts. Studies, such as that of Karam et al. (2021), reveal that students using interactive simulations improved their comprehension, with a 25% increase in exam scores compared to those without access to these tools. Student testimonials, especially on platforms like PhET, highlight that these simulations make learning more interactive and engaging.

Students have mentioned that the simulations will help him visualize difficult concepts, making learning more fun. According to research by Essel, H. B et al. (2022), smart tutoring systems, such as those from Carnegie Learning, offer immediate feedback that helps students identify and correct their mistakes. One student expressed appreciation for the instant guidance, which makes it easier to understand. Adaptive learning tools also allow for self-directed progression, with one student noting that they can review difficult topics without pressure, which promotes mastery of complex concepts. Finally, data analysis environments, such as those offered by DataCamp, encourage collaboration between students, enriching the collective learning experience. These results and testimonials illustrate the tangible impact of AI tools on physical learning, providing an enriching and personalized educational experience. One student said, "I appreciate getting instant advice. It helps me understand my mistakes on the spot. »

Adaptive learning tools allow students to progress at their own pace. A testimonial from a Smart Sparrow user revealed, "I can review topics that I find difficult without feeling rushed. It really helped me master complex concepts. »

Data analytics environments, like those offered by DataCamp, encourage collaboration between students. One student noted, "Working on group projects with these tools allowed us to learn from each other while applying our knowledge in a practical way."

METHOD

Background and samples

The physics module in Moroccan high schools covers options A and B of mathematical sciences as well as the physics curriculum, is structured in four fundamental parts: waves, nuclear transformations, electricity and mechanics. This program, which lasts a total of 118 hours, aims to establish a solid understanding of basic concepts and notions, in accordance with official guidelines from the Ministry of Education. The sample of this study includes 85 learners divided into three options: Mathematical Sciences A (2SMA), Mathematical Sciences B (2SMB) and Physical Sciences (2SPhy). The sampling process was carried out using a stratified selection method. This means that we have made sure to include representatives from each option to ensure a diversity of learning styles and skill levels within our sample. Participants were selected based on their availability and willingness to participate in the study, ensuring that the sample is both representative and accessible. This approach provides a better understanding of how the integration of artificial intelligence in physics education can influence different groups of learners, while taking into account their specificities.

Data collection

For this study, we developed a research tool based on a mixed approach, combining qualitative and quantitative methods. This tool is designed to assess the impact of integrating artificial intelligence on learners' engagement and performance in the physics module:

1. Identification of learning styles: An online questionnaire (Learning Style Inventory, ILS) Based on an adaptation of the Kolb model, which aims to identify the predominant learning style of each participant (accommodating, assimilating, convergent, divergent).

2. Classroom Observations: A survey will be conducted among students and their physics teachers to identify the difficulties encountered and collect qualitative data to understand how learners interact with the AI tools integrated in the physics module, taking into account: Interaction with technologies, participation in activities, collaboration between peers, and attitudes towards the concepts taught. This survey will assess satisfaction with a variety of factors that influence learning, including:

- Language of instruction
- Overload of educational content
- Lack or forgetfulness of prior knowledge

- Superficial understanding of abstract concepts
- Inadequate practical work and tutorials
- Inconsistency between the mathematical tools learned and those used in physics
- Teacher-cantered teaching

3. Assessment of preferences for learning activities: (ANNEX, Table 6)

Interviews aimed at deepening our understanding of learners' individual experiences with AI of the topics covered such as experience with AI tools, perception of their usefulness, impact on learning and suggestions for improvement, where learners will be asked to rate their level of preference for various learning activities based on artificial intelligence (AI) applications,

The goal is to provide a concrete and engaging learning experience, tailored to the accommodating style of high school physics students, to enhance both teaching and learning. His activities were selected according to specific criteria, and we also drew on a body of previous research (Cheng, M. T., Lin, Y. P., & Lin, S. S. J. 2013, Hmelo-Silver, C. E., 2004, Kuhn, D., & Hemberger, L. 2014, Almpanis, T., & Kynigos, C. 2010, Linn, M. C., Davis, E. A., & Bell, P. 2004).

Data analysis

Quantitative data from the questionnaires will be statistically analyzed to identify significant correlations between AI use, engagement, and academic performance. The qualitative results of the observations and interviews will be processed through advanced statistical analysis to identify relevant trends and insights. This combination of research tools will provide a general view of the impact of artificial intelligence on physics learning, while taking into account the specificities of learners. The reliability of the test was measured by Cronbach's alpha which measured the degree of consistency between the 5 items on a sample of 19 accommodating students.

FINDINGS AND DISCUSSION

The Kolb Learning Styles Inventory (LSI) tool is a questionnaire that assesses people's learning preferences across four dimensions: concrete experience, reflective observation, abstract conceptualization, and active experimentation (Pashler, H et al., 2008).

After analysing the results of the inventory, our samples are grouped in the following table:

Table 1
Learning styles based on sample options

	Physics Science	Mathematical Sciences A	Mathematical Sciences B	The Somme	%
Divergent	7	3	5	15	17.64
Assimilator	17	6	2	25	29.41
Convergent	15	7	4	26	30.58
Accommodating	9	5	5	19	22.35
The Somme	48	21	19	85	100

According to the analysis in Table 1, which represents the distribution of the 85 learners according to the kolb style:

- 17.64% of the sample is divergent in style
- 29.41% of the sample is assimilative style
- 30.58% of the sample is convergent
- 22.35% of the sample is accommodating

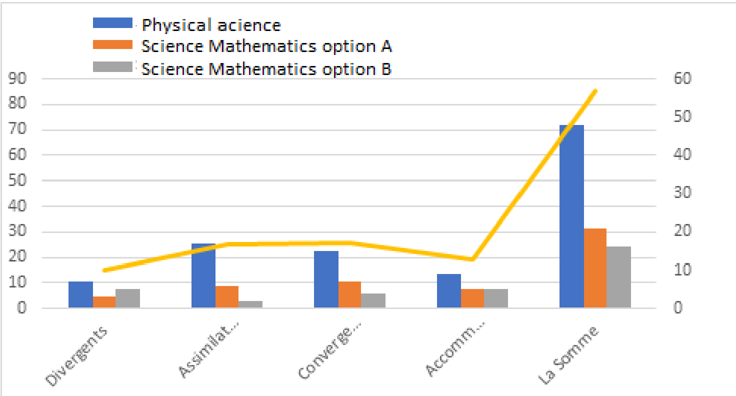


Figure 3
Representation of Kolb's style

Data analysis reveals significant differences in learning styles among physical science learners. As shown in Figure 4, students in the Physical Sciences stream have a strong tendency towards the accommodative style. They emphasize the practical application of theoretical concepts to solve physical problems, which emphasizes their orientation towards the experimental and technical sciences. This trend is consistent with the findings of Cheng et al. (2013), who highlight the importance of experiential learning for learners with an accommodative style.

On the other hand, students in Option A in mathematics show a lesser preference for this style, favoring theoretical learning based on logic and the application of abstract concepts. This observation is in line with the official orientations that position these learners as future theorists (Hmelo-Silver, 2004).

For Option B in mathematics, accommodative and divergent styles stand out as the most dominant. These results suggest that students in this course are not only oriented towards experimentation and observation, but also towards proposing hypotheses, which is characteristic of technical education focused on practical skills (Kuhn & Hemberger, 2014).

Physics Assessment Learning Disability

Learners are asked to express the degree of difficulty encounter by secondary school students and their teachers when learning physics, as detailed in the table below: The sample of 85 students is divided into a flow Number of learners who responded, Yes out of 85 students

Table 2
The number of learners who responded to the proposals and their percentages

Prepositions	Lerner number	%
Q1: The concepts of physics are abstract and is there a deep understanding?	63	74,12%
Q2: Is the language of instruction an obstacle?	78	91,76%
Q3: Is forgetting prior knowledge a factor in learning physics?	80	94,12%
Q4: Overload of course content, are you a problem?	83	97,65%
Q5: Is there a shortage of tank destroyers?	75	88,24%
Q6: Is there a shortage of TP?	85	100%
Q7: Is teaching teacher-centered and dominated by exposure?	72	84,71%
Q8: Are the mathematical tools used in physics difficult?	62	72,94%

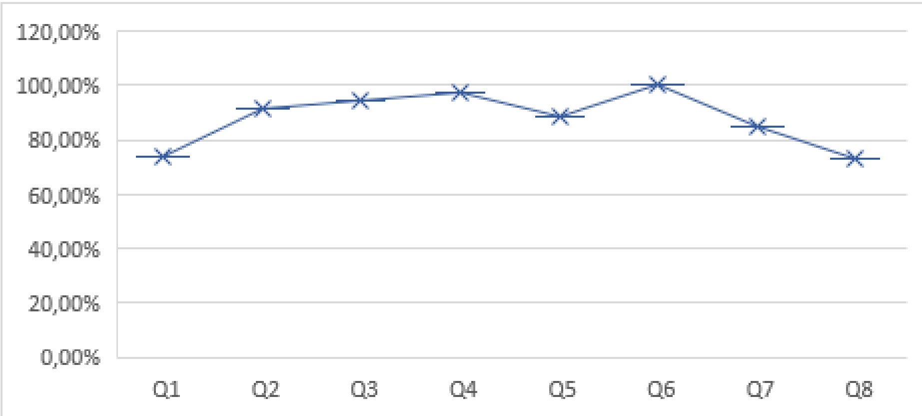


Figure 4
The percentages of difficulty proposed by the learners

The survey conducted to assess the difficulties expressed by learners and their physics teachers in high school in learning physics aims to identify the difficulties encountered. According to the results shown in Table 2 and Figure 5, the collection of information focuses on the percentage of dissatisfaction with its factors according to a Likert scale in Table 2, and which present the most encountered problems in the teaching and learning of physics means that there are actually problems expressed by its learners as shown in Figure 5, which represents the percentages of difficulties proposed by the learners in a range of 80% to 100%, According to Table 2, the Q6 proposal represents 100%, all the learners have a lack of practical work, and 72.94% represents the Q8 proposal which designates the coherence of the mathematical tools used in physics and their difficulties, this is due to the mathematical aspect of the learners, This problem will be mitigated by collaboration between teachers, whether in physics or mathematics.

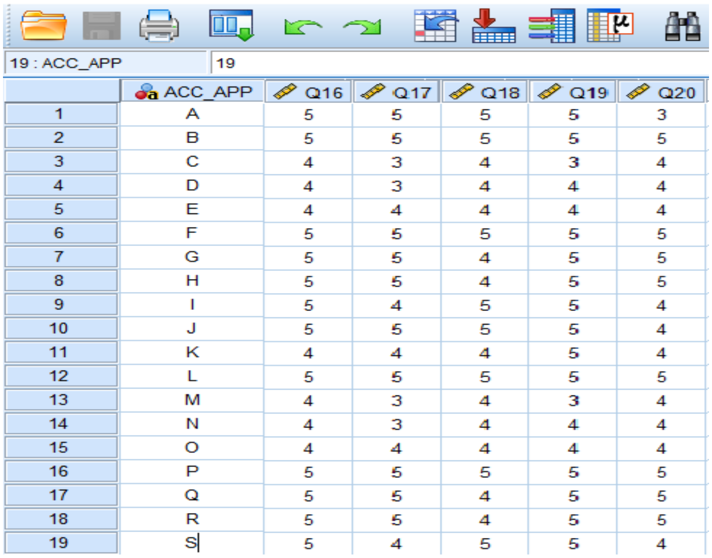
Statistical analysis

The results of activity preferences according to the Accommodator style. are presented in the following table.

Table 3
Summary of the processing of observations

		N	%
Feedback	Valid	19	100,0
	Excluded[a]	0	00,0
	Total	19	100,0

a. List-based deletion based on all variables in the procedure.



19 : ACC_APP 19

	ACC_APP	Q16	Q17	Q18	Q19	Q20
1	A	5	5	5	5	3
2	B	5	5	5	5	5
3	C	4	3	4	3	4
4	D	4	3	4	4	4
5	E	4	4	4	4	4
6	F	5	5	5	5	5
7	G	5	5	4	5	5
8	H	5	5	4	5	5
9	I	5	4	5	5	4
10	J	5	5	5	5	4
11	K	4	4	4	5	4
12	L	5	5	5	5	5
13	M	4	3	4	3	4
14	N	4	3	4	4	4
15	O	4	4	4	4	4
16	P	5	5	5	5	5
17	Q	5	5	4	5	5
18	R	5	5	4	5	5
19	S	5	4	5	5	4

Figure 5
The table of the responses accumulated by the accommodator

Measure the reliability of activity preferences based on accommodating style.

According to the questionnaire proposed in Appendix Table 7, the cumulative results are processed by the statistical analysis software SPSS for its variables which are of the ordinal qualitative type, the analysis was carried out on the numbers and the cross-tabulations of the multiple responses, but before ensuring the fidelity of the test it is necessary to measure the degree of coherence between the 5 items on a sample of 19 welcoming students, The test gave the result in the following table:

Table 4
Reliability statistics

Cronbach's alpha	Cronbach's alpha based on standardized elements	Number of elements
,743	,757	5

Among the existing methods, we chose one based on the internal coherence between questions and items, known as Cronbach's Alpha (Bertrand, R., et al, 2004). In practice, the homogeneity of the instrument is generally considered satisfactory when the value of the coefficient is at least equal to 0.70, whereas our accommodative style articles are acceptable with a coefficient of 0.757.

Descriptive statistical analysis

Descriptive statistical analysis was performed to analyze the learning activities and data, which allowed the learning data to be described, synthesized, and visualized in a clear and concise manner. It is an essential step in understanding learners' profiles, behaviors and performance, and in guiding pedagogical decisions and optimizing scheduled learning.

Table 5
$Accommodator frequencies

		Answers N	Percentage	Percentage of Comments
$Accommodator	Q16	8	19,0%	50,0%
	Q17	6	14,3%	37,5%
	Q18	12	28,6%	75,0%
	Q19	4	9,5%	25,0%
	Q20	12	28,6%	75,0%
Total		42	100,0%	262,5%

a. Group of dichotomies tabulated at value 1.

According to the statistical results in Table 5, learners have a preference for practical application projects and interactive experiential learning with 28.6%, followed by practical experiments with detailed instructions 19% and technological applications of physics 14.3%, while case studies and real-life examples are only 9.5%. which allows us to say that accommodating people are practitioners.

	N	Moyenne	Ecart type
Q1	19	2,53	1,073
Q2	19	2,42	1,305
Q3	19	2,11	1,197
Q4	19	1,84	,688
Q5	19	2,26	1,098
Q6	19	3,11	,809
Q7	19	3,79	,631
Q8	19	2,58	,692
Q9	19	3,89	,459
Q10	19	2,68	,749
Q11	19	1,84	,765
Q12	19	1,42	,507
Q13	19	1,68	,749
Q14	19	2,95	,970
Q15	19	1,53	,513
Q16	19	4,63	,496
Q17	19	4,32	,820
Q18	19	4,42	,507
Q19	19	4,58	,692
Q20	19	4,37	,597
N valide (liste)	19		

Figure 6
Descriptive statistics

According to the results of the descriptive statistics illustrated in Table 6, learners of the accommodative style answered questions Q16, Q17, Q18, Q19, Q20, with means of 4.32 to 4.63 with a normal or Gaussian distribution around The mean = 4.46 is the central value around which the distribution is symmetrical. this indicates that values close to the mean are the most frequent, The standard deviation (σ): it determines the spread of the distribution around the mean. Knowledge of the characteristics of the normal distribution is essential to understand and correctly use statistical tools based on this distribution. Practical experience with detailed instructions, technological applications of physics, practical application projects, case studies and real-world examples as well as interactive experiential learning are reliable and objective criteria for hosting style, as they allow hypothesis tests, confidence intervals and probability calculations to be performed.

The results observed provide tangible evidence that the integration of artificial intelligence techniques in the learning of physics in high school can effectively respond to the challenges identified in the study problem. They highlight the importance of these technologies in fostering more engaging, personalized and effective learning.

Practical implications

These findings have important practical implications for the integration of artificial intelligence into physical science education. It is essential to design learning activities that specifically cater to learners' preferences, especially those that have an accommodating style. For example, hands-on experiences and technology applications should be further integrated into the curriculum to foster student engagement.

RECOMMENDATIONS

Develop tailored learning modules: Teachers should use AI tools to create personalized learning modules that incorporate real-world experiences and technology applications, tailored to the needs of accommodating learners. Teacher training: It is crucial to train teachers in the use of AI technologies so that they can design activities that stimulate experiential learning and respond to diverse learning styles. Continuous Analysis: Implement continuous evaluation mechanisms to measure the effectiveness of AI-based teaching approaches and adjust methods based on learner feedback.

In sum, this discussion highlights the importance of adapting physical science teaching to students' learning styles, while highlighting the potential of artificial intelligence to transform this educational experience.

CONCLUSION

In conclusion, the integration of artificial intelligence (AI) technologies into high school physics learning represents a promising approach to meet the specific needs of accommodating learners, according to Kolb's model of learning. These students, who prioritize active experimentation and real-world experience, can benefit significantly from AI applications, such as interactive simulations, chatbots, and personalized feedback systems. These tools promote an engaging and hands-on learning environment, facilitating the understanding of complex physics concepts. These technologies also support the active application of knowledge and provide feedback tailored to students' individual needs. However, the successful integration of AI into high school physics learning requires careful consideration of the implementation and potential challenges. It is critical to ensure that these technologies are closely aligned with secondary school physics curriculum and objectives, while ensuring learner-centered design and seamless integration with existing classroom practices. Encourage teachers to adopt experiential learning approaches, promoting active experimentation and reflective observation of accommodators, and provide training and support to teachers to enable them to effectively integrate AI technologies into their teaching practices. By following these recommendations, practitioners will be able to successfully integrate AI applications into high school physics learning, addressing students' specific adaptation needs and improving their performance in the subject. To maximize the impact of AI applications, it is recommended that teachers be trained to adopt experiential learning approaches that encourage active experimentation and reflective observation. In addition, it would be beneficial to provide ongoing support to teachers to facilitate the effective integration of AI technologies into their teaching practices. Finally, while the judicious use of AI applications in high school physics education can significantly improve the learning and performance of host students, it is essential to proactively address the challenges. Critical reflection on these challenges and continuous adaptation of pedagogical approaches are needed to ensure that these innovations bring tangible benefits in science education.

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ANNEX

Table 6
Questionnaire of learning activities proposed for each style of kolb based on IA
How much do you prefer each proposition?

Kolb Styles	Proposed learning activities based on AI	1	2	3	4	5
Divergent	Q1. Experimentation and exploration of situation problems					
	Q2 Interactive virtual experiences					
	Q3. Visualization and modeling					
	Q4. Collaboration and sharing					
	Q5. Learning Personalization					
Assimilator	Q6. Interactive presentations					
	Q7. Personalized online resources					
	Q8. Modeling activities					
	Q9. Guided Discussions					
	Q10. Case Resolution Issues					
Convergent	Q11. Interactive virtual laboratories					
	Q12. Interactive problem solving					
	Q13. AI-assisted engineering projects					
	Q14. AI-assisted hands-on experiments					
	Q15. Interactive educational games					
Accommodator	Q16. Hands-on experiments with detailed instructions					
	Q17. Technological applications of physics					
	Q18. Practical application projects					
	Q19. Case studies and real examples					
	Q20. Interactive experiential learning					

1: Very Weak 2: Weak 3: Average 4: Fairly good 5: Excelent