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Artificial Intelligence and Learning Analytics for Comparative Physics Education: Bridging the Didactic Gap between Moroccan and Scandinavian Higher Education

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Abstract

Physics is widely recognized as one of the most cognitively demanding disciplines, requiring students to integrate abstract mathematical reasoning with the interpretation of invisible physical phenomena. While Nordic higher education systems have successfully addressed this complexity through student-centered learning, formative assessment, and phenomenon-based pedagogy, massified higher education systems such as Morocco continue to face significant challenges related to large class sizes, limited individualized support, and linguistic barriers.

This study proposes a comparative didactic framework that integrates Artificial Intelligence (AI), Educational Data Mining (EDM), and Learning Analytics (LA) to support physics teaching in resource-constrained university environments. The proposed framework focuses on complex electromagnetism concepts and combines interactive virtual simulations with unsupervised machine learning techniques to analyze students' learning behaviors. A K-Means clustering model is employed to identify distinct misconception profiles from learners' interaction logs, enabling instructors to detect cognitive difficulties at an early stage and deliver targeted pedagogical interventions.

Rather than replacing teachers, the proposed AI-supported architecture extends formative assessment capabilities by providing continuous diagnostic feedback that would otherwise be impractical in large university classes. The framework also illustrates how learning analytics can reproduce key pedagogical characteristics commonly associated with Nordic educational practices while remaining compatible with the structural constraints of Moroccan higher education.

This work contributes to comparative physics education by establishing a conceptual bridge between educational systems through AI-supported learning analytics and offers a scalable framework for improving conceptual understanding, adaptive instruction, and evidence-based teaching in complex STEM disciplines.

Keywords: Physics Education; Comparative Didactics; Artificial Intelligence in Education; Learning Analytics; Educational Data Mining; Electromagnetism; Higher Education; Morocco; Nordic Education.

1. Contextual Challenges and the Role of Artificial Intelligence in Physics Education

1.1 The Intrinsic Complexity of Physics as a Discipline

Physics is widely recognized as one of the most cognitively demanding disciplines within STEM education. Unlike predominantly descriptive sciences, physics requires learners to integrate conceptual reasoning, mathematical formalism, graphical representations, and experimental observations to explain phenomena that are often invisible to direct human perception, such as electric fields, magnetic flux, or quantum wave functions (Redish, 2003; Duit et al., 2014). Students must therefore continuously translate between multiple representational systems, including physical intuition, mathematical equations, graphical models, and laboratory observations.

From the perspective of Cognitive Load Theory (Sweller, 1988), physics imposes a particularly high intrinsic cognitive load because learners are required to process several interdependent sources of information simultaneously. This complexity is further amplified by the abstract nature of many physical concepts, which frequently contradict learners' intuitive interpretations of the natural world. As demonstrated by Physics Education Research (PER), misconceptions concerning force, energy, electric fields, and electromagnetism remain remarkably persistent, even after formal instruction (McDermott, 2001; Hestenes et al., 1992; Guisasola et al., 2004). Consequently, effective physics instruction requires pedagogical approaches capable of reducing unnecessary cognitive load while promoting conceptual understanding through multiple representations and continuous formative support.

1.2 The Global Disparities in Supporting Physics Learning

Although the intrinsic complexity of physics is universal, students' learning outcomes are strongly influenced by the educational environments in which instruction takes place. Research has consistently shown that formative assessment, individualized feedback, and active learning strategies play a decisive role in helping students overcome persistent conceptual difficulties in physics (Black & Wiliam, 1998; Hattie, 2009). Consequently, differences in educational organization can substantially affect students' ability to construct meaningful scientific understanding.

Nordic higher education systems, particularly Finland, have gained international recognition for promoting student-centered pedagogies, phenomenon-based learning, and continuous formative assessment (Sahlberg, 2011; Halinen, 2018). Within such environments, instructors can closely monitor students' conceptual development, identify misconceptions at an early stage, and provide timely scaffolding that supports progressively deeper understanding of abstract topics such as electromagnetism.

In contrast, many public universities in developing countries, including Morocco, operate under conditions of massification characterized by large lecture halls, limited opportunities for individualized interaction, and considerable linguistic challenges associated with French-medium scientific instruction. In these contexts, physics teaching often relies on transmissive instructional approaches in which students primarily receive mathematical derivations with limited opportunities for conceptual discussion or formative feedback (Bouziane, 2020). When these structural constraints are combined with the inherently high cognitive demands of physics, students frequently experience cognitive overload, contributing to low conceptual understanding and high failure rates during the first year of university studies.

1.3 Artificial Intelligence as a Didactic Bridge

Directly transferring educational practices from Nordic higher education systems to massified university contexts is neither pedagogically nor economically feasible. Structural constraints—including large class sizes, limited teaching resources, and heterogeneous student populations—restrict instructors' ability to provide the individualized formative feedback that is widely recognized as essential for learning complex scientific concepts.

Recent advances in Artificial Intelligence in Education (AIED), Educational Data Mining (EDM), and Learning Analytics (LA) offer promising opportunities to address this challenge by supporting evidence-based and adaptive instructional practices (Siemens, 2013; Baker & Inventado, 2014; Zawacki-Richter et al., 2019). However, despite the growing literature on AI-supported learning environments, relatively little attention has been devoted to their role as comparative didactic mechanisms capable of reproducing pedagogical practices across educational systems operating under fundamentally different structural conditions.

To address this gap, this study proposes an AI-supported comparative didactic framework in which students interact with virtual physics simulations while their learning behaviors are continuously analyzed through Learning Analytics techniques. By combining Educational Data Mining with unsupervised machine learning, the proposed framework identifies emerging misconception profiles and provides instructors with actionable diagnostic information that supports timely pedagogical interventions. Rather than replacing teachers, the proposed architecture extends their capacity to deliver individualized formative feedback within large university cohorts, thereby adapting key characteristics of student-centered Nordic pedagogies to the realities of Moroccan higher education.

2. Theoretical Foundations of Physics Learning and AI-Supported Scaffolding

2.1 The Epistemology of Physics Learning

Physics learning is fundamentally a process of conceptual reconstruction rather than simple knowledge acquisition. Unlike factual disciplines, physics requires students to progressively replace intuitive interpretations of natural phenomena with scientifically accepted conceptual models through observation, experimentation, mathematical reasoning, and abstraction. Consequently, learning physics involves profound epistemological change, in which learners continuously reorganize their existing mental models to accommodate increasingly complex scientific concepts (Redish, 2003; McDermott, 2001).

Physics Education Research (PER) has consistently demonstrated that students enter university with persistent misconceptions concerning force, energy, electricity, and electromagnetism (Hestenes et al., 1992; Guisasola et al., 2004). In electromagnetism, learners frequently struggle to visualize three-dimensional vector fields, distinguish magnetic field intensity from magnetic flux, and understand the causal relationships underlying Faraday's and Lenz's laws. These misconceptions often remain stable despite traditional lecture-based instruction because they originate from intuitive reasoning rather than simple factual errors.

From a constructivist perspective, conceptual understanding emerges through active cognitive conflict, continuous feedback, and the coordination of multiple representations, including mathematical equations, graphical models, experimental observations, and virtual simulations. These findings suggest that effective physics instruction should not merely transmit knowledge but should continuously diagnose learners' conceptual difficulties and provide adaptive support capable of facilitating conceptual change. This theoretical perspective provides a strong pedagogical rationale for integrating Learning Analytics and Artificial Intelligence into physics education.

2.2 Vygotsky's Zone of Proximal Development (ZPD) and AI

Vygotsky's (1978) ZPD dictates that optimal learning occurs when a student is guided by a "more knowledgeable other." In complex physics, when a student is stuck on the concept of Lenz's Law, they need immediate guidance. In Finland, the teacher is the guide. In Morocco's massified universities, AI systems must function as the guide.

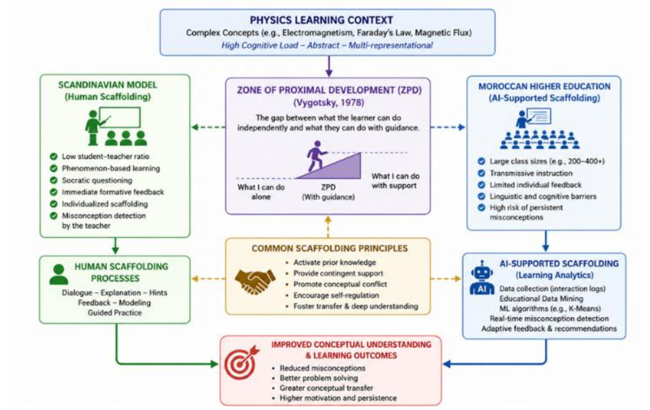

Figure 1. Conceptual framework linking Vygotsky's ZPD to human and AI scaffolding in physics education.

Figure 1 presents the conceptual framework of this study, illustrating how AI-supported Learning Analytics can reproduce key scaffolding mechanisms traditionally provided by instructors in Nordic educational systems while addressing the structural constraints of massified Moroccan higher education.

3. Comparative Gap Analysis in Physics Education

Before proposing an Artificial Intelligence-supported solution, it is essential to identify the pedagogical and structural differences that characterize physics education across contrasting higher education systems. Comparative didactics provides a valuable analytical framework for examining how institutional organization, instructional practices, and assessment strategies influence students' conceptual understanding of complex scientific concepts.

The comparison presented in this study does not aim to rank educational systems but rather to identify transferable pedagogical practices that can be adapted to different institutional contexts. By comparing key characteristics of Nordic and Moroccan higher education, this analysis highlights the specific challenges associated with teaching abstract physics in large university cohorts and identifies the instructional dimensions that can potentially be supported through Learning Analytics and Artificial Intelligence.

Table 1 summarizes the principal pedagogical differences between the two educational contexts and illustrates how AI-supported Learning Analytics can contribute to reducing these disparities while preserving the central role of the instructor.

Table 1: Didactic Comparison between Scandinavian and Moroccan University Physics

Educational Dimension	Scandinavian Physics Education	Moroccan Physics Education	Moroccan System + AI Intervention
Handling Physics Complexity	Phenomenon-based, hands-on modeling	Abstract mathematical derivation on board	Interactive digital simulations (Visualizing the invisible)
Assessment Strategy	Formative, Continuous, low-stakes	Summative, Final Exam (High failure rate)	Continuous Learning Analytics tracking
Student/Teacher Ratio	Low (~15:1 to 30:1)	Extremely High (~150:1 to 300:1)	High physical ratio, 1:1 digital feedback ratio
Epistemological View	Physics is the study of nature	Physics is a set of hard equations	Physics is data-driven modeling of reality
Cultural Paradigm	Trust-based, high student autonomy	Competition-based, teacher-centric	Autonomy guided by algorithmic safety nets

As illustrated in **Table 1**, AI-supported Learning Analytics has the potential to enable large-scale implementation of formative assessment practices inspired by Nordic educational systems. By providing continuous diagnostic feedback and early identification of students' conceptual difficulties, the proposed framework supports the teaching of highly abstract physics concepts while reducing the dependence on substantial increases in instructional resources.

4. Methodology: An AI-Supported Framework for Physics Learning

This study adopts a design-oriented methodological approach aimed at developing and illustrating an Artificial Intelligence-supported framework for improving physics education in massified higher education contexts. Rather than evaluating a specific educational intervention, the proposed methodology integrates principles from Physics Education Research (PER), Learning Analytics (LA), Educational Data Mining (EDM), and Artificial Intelligence in Education (AIED) into a unified pedagogical architecture.

The framework focuses on complex electromagnetism concepts, particularly Faraday's Law of Electromagnetic Induction, which has been extensively documented as one of the most conceptually challenging topics in undergraduate physics due to its reliance on three-dimensional spatial reasoning, abstract vector representations, and the coordination of multiple conceptual models (Guisasola et al., 2004; Redish, 2003).

To facilitate conceptual understanding, students interact with interactive virtual laboratories based on PhET Interactive Simulations. These simulations provide an authentic learning environment in which students manipulate physical variables, observe the consequences of their actions in real time, and progressively construct conceptual understanding through exploration. Simultaneously, every learner interaction is recorded to generate behavioral data that constitute the basis for subsequent Learning Analytics and machine learning analyses.

4.1 Learning Analytics Data Generation

Unlike traditional Moroccan physics assessments, which only evaluate the correctness of the final numerical answer, the proposed AI-enhanced learning environment continuously captures the learner's interaction with the virtual laboratory. Rather than considering only the outcome of the problem-solving process, the system records a sequence of behavioral indicators describing how conceptual understanding is progressively constructed.

These interaction logs constitute the primary dataset used for Educational Data Mining (EDM) and Learning Analytics. They provide fine-grained evidence of students' cognitive strategies, conceptual difficulties, and problem-solving behaviors while exploring Faraday's Law of Electromagnetic Induction. Such process-oriented data allow AI models to diagnose misconceptions that remain invisible in conventional paper-based assessments.

Table 2 summarizes the principal variables extracted from the simulation environment and their corresponding didactic interpretations.

Table 2. Learning Analytics Variables Collected from the Physics Simulation

Tracked Variable	Data Type	Educational Interpretation	AI-Based Pedagogical Use
Time_Magnet_Motion	Continuous (s)	Measures the time spent manipulating the magnetic source, reflecting exploratory behavior and spatial reasoning.	Detects insufficient experimentation and exploratory learning patterns.
Toggle_Field_Lines	Boolean	Indicates whether the learner activates magnetic field visualization to support conceptual understanding.	Estimates dependence on visual scaffolding and abstract reasoning difficulties.
Equation_View_Time	Continuous (s)	Measures the duration devoted to mathematical equations compared with experimental exploration.	Distinguishes mathematically driven strategies from concept-oriented learning.
Error_Rate_Lenz	Percentage (%)	Quantifies incorrect predictions of the direction of induced current according to Lenz's Law.	Detects persistent misconceptions requiring adaptive feedback.

The collected variables are not intended merely for descriptive statistics. Instead, they constitute multidimensional learning traces that feed AI-based predictive models capable of identifying conceptual misconceptions, estimating learners' cognitive profiles, and generating personalized pedagogical interventions in real time. Consequently, the educational focus shifts from evaluating students' final answers toward understanding the reasoning processes that produced them.

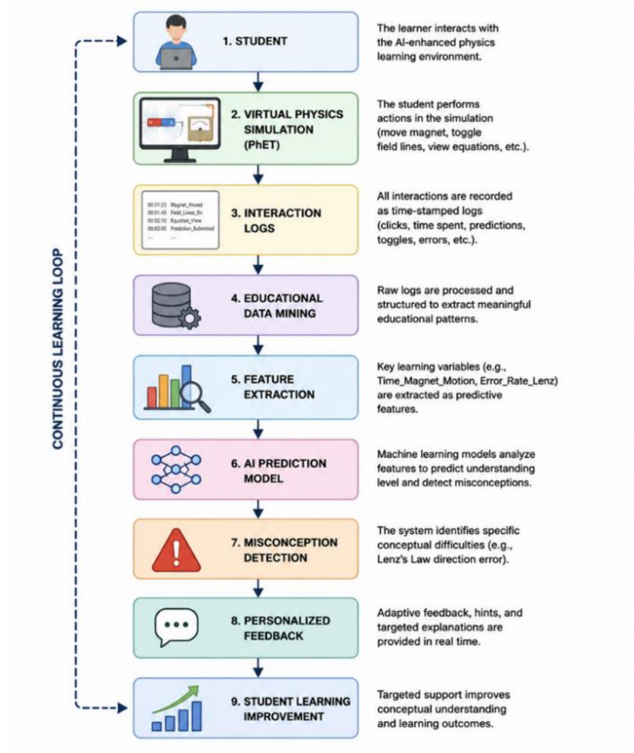

Figure 2. AI-Based Learning Analytics Pipeline for Physics Learning

Figure 4 illustrates the complete Learning Analytics pipeline implemented in the proposed AI-enhanced physics learning environment. The process begins with students interacting with a virtual physics simulation, where every action such as manipulating the magnet, activating magnetic field visualizations, consulting equations, or making predictions is automatically recorded as interaction logs. These raw data are subsequently processed through Educational Data Mining techniques to extract meaningful behavioral features. Machine learning models then analyze these features to detect conceptual misconceptions, estimate students' understanding levels, and generate personalized pedagogical feedback. This continuous feedback loop enables adaptive instruction by transforming low-level interaction data into actionable educational insights, thereby supporting conceptual learning beyond traditional outcome-based assessment.

4.2 Unsupervised Machine Learning for Misconception Profiling

To identify latent patterns in students' conceptual understanding, the collected interaction logs are analyzed using an unsupervised machine learning approach. Unlike supervised learning, which requires manually labeled datasets, unsupervised clustering automatically discovers groups of learners exhibiting similar behavioral characteristics during the virtual physics experiment.

Among the available clustering techniques, **K-Means clustering** (MacQueen, 1967) was selected because of its computational efficiency, interpretability, and widespread use in Educational Data Mining and Learning Analytics. Prior to clustering, all numerical variables are standardized using the **StandardScaler** algorithm to eliminate differences in measurement scales and ensure equal contribution of each feature to the clustering process.

The clustering process considers the four behavioral variables introduced in Table 2:

- Time_Magnet_Motion
- Toggle_Field_Lines
- Equation_View_Time
- Error_Rate_Lenz

The algorithm partitions students into three clusters representing distinct misconception profiles. Rather than assigning grades, the AI system identifies groups of learners exhibiting similar interaction patterns, allowing instructors to design targeted pedagogical interventions adapted to each conceptual profile.

The overall clustering workflow is illustrated in **Figure 5**.

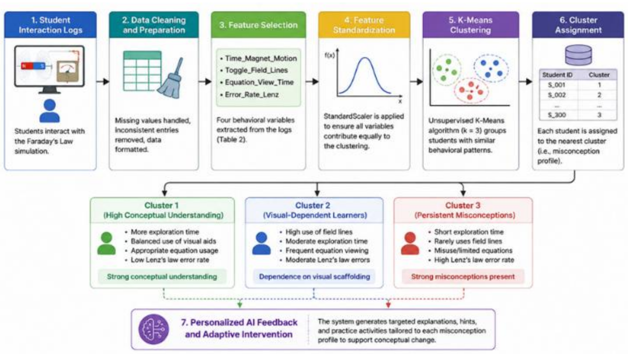

Figure 3. AI-Based K-Means Clustering Workflow for Automatic Identification of Physics Misconception Profiles

4.3 AI-Generated Physics Learning Profiles

Following the K-Means clustering process, the AI system automatically identifies groups of students exhibiting similar behavioral patterns during their interaction with the Faraday's Law simulation. Rather than evaluating students solely on the correctness of their final answers, the proposed approach characterizes learners according to their exploration strategies, conceptual reasoning, and interaction behaviors. These AI-generated learning profiles provide valuable insights into the underlying misconceptions that hinder conceptual understanding and enable the delivery of personalized formative feedback.

Three distinct learner profiles emerged from the clustering analysis, each representing a specific pattern of conceptual understanding and instructional needs:

- **Cluster 0 – Equation-Oriented Profile:** Students in this cluster spend most of their time consulting mathematical equations while interacting minimally with the virtual experiment. Although they are familiar with the mathematical formulation of Faraday's Law, they exhibit persistent conceptual errors regarding the direction of the induced current (Lenz's Law), suggesting insufficient spatial reasoning. These learners primarily require visual and conceptual scaffolding to strengthen their understanding of electromagnetic phenomena.

- **Cluster 1 – Conceptual Exploration Profile:** Learners in this cluster actively manipulate the virtual magnet and frequently use visual representations of magnetic field lines, demonstrating good qualitative understanding of magnetic flux. However, they experience difficulties translating these observations into the mathematical formalism of electromagnetic induction. Instructional support should therefore emphasize the connection between physical intuition and mathematical representation.

- **Cluster 2 – Low-Engagement Profile:** Students assigned to this cluster spend little time interacting with the simulation and perform very few exploratory actions. Their behavior suggests cognitive overload, low confidence, or insufficient engagement with the learning activity. These learners benefit from simplified instructional guidance, motivational support, and progressively structured learning tasks before engaging with more advanced concepts.

Figure 6 summarizes the three AI-generated learning profiles and illustrates how each misconception profile is associated with a specific pedagogical intervention. This personalized profiling enables the AI system to recommend targeted instructional strategies rather than providing identical feedback to all learners, thereby supporting adaptive learning and improving conceptual understanding.

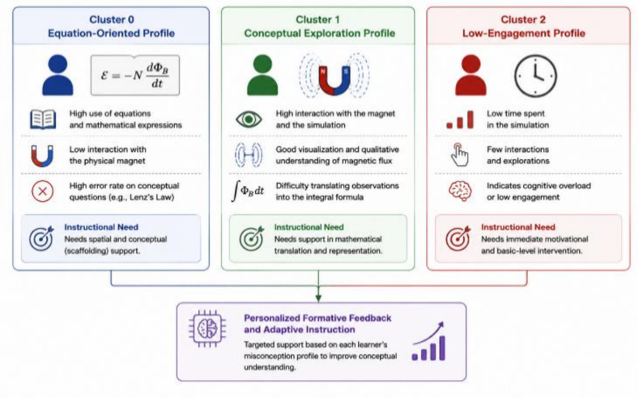

Figure 4. AI-Generated Physics Learning Profiles and Their Corresponding Pedagogical Intervention

5. Proposed Implementation and Expected Outcomes

5.1 Empowering Moroccan Instructors Through Early Intervention

The proposed AI-supported framework is designed to provide Moroccan physics instructors with timely and actionable information about students' conceptual difficulties. Through a Learning Analytics dashboard, the instructor can monitor the distribution of learner profiles identified from students' interactions with the virtual simulation.

For example, if the clustering model indicates that 60% of students belong to the Equation-Oriented Profile during the second week of instruction, the instructor can infer that a substantial proportion of the class is relying on mathematical formulas without sufficiently understanding the spatial and conceptual foundations of Lenz's Law. This information can then be used to modify the following lecture by introducing additional visual demonstrations, magnetic-field representations, guided simulations, or qualitative reasoning activities.

In the traditional assessment model, such misconceptions may remain undetected until the final examination, when opportunities for corrective instruction are limited. In contrast, the proposed AI-enhanced approach supports continuous formative assessment by identifying conceptual difficulties during the learning process. It therefore enables the instructor to move from reactive remediation to proactive pedagogical intervention.

Figure 7 compares the intervention timelines of traditional and AI-supported physics instruction. The comparison illustrates how learning analytics can shorten the delay between the emergence of a misconception, its identification, and the implementation of an appropriate instructional response. Although the effectiveness of these interventions must be validated through empirical classroom experimentation, the proposed framework is expected to support earlier remediation, more responsive teaching, and improved conceptual understanding.

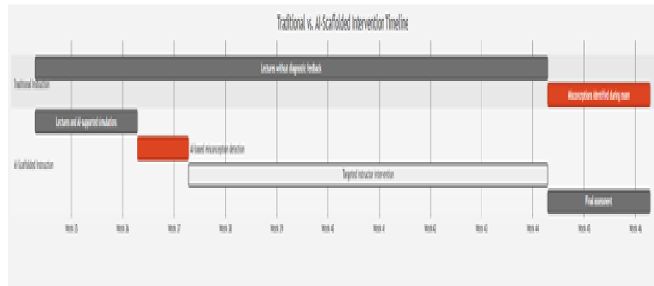

Figure 5. Comparison of Reactive and AI-Supported Proactive Intervention Timelines in Physics Instruction

5.2 Expected Educational Impact of AI-Supported Learning Analytics

The proposed framework is expected to improve learning outcomes by enabling early identification of conceptual misconceptions and timely instructional interventions. Previous studies in Learning Analytics and Intelligent Tutoring Systems have demonstrated that continuous formative feedback and adaptive instruction can significantly enhance student engagement, conceptual understanding, and course completion rates in STEM education (Kizilcec et al., 2013; Koedinger et al., 2015).

Although the present study does not report empirical classroom data, the proposed AI-supported approach is expected to outperform traditional summative assessment by providing instructors with continuous information about students' conceptual progress. The anticipated educational benefits are summarized in **Table 3**.

Table 3. Expected Educational Benefits of the Proposed AI-Supported Framework

Educational Indicator	**Traditional Instruction**	**Proposed AI-Supported Instruction**
Formative feedback	Limited (midterm/final exam)	Continuous and personalized
Misconception detection	After assessment	During learning activities
Teacher intervention	Reactive	Early and proactive
Student support	Uniform for all learners	Personalized according to learning profile
Expected conceptual understanding	Limited improvement	Enhanced conceptual understanding
Expected student engagement	Moderate	Higher through adaptive feedback

Note: *The numerical values presented are illustrative projections derived from findings reported in previous Learning Analytics and Intelligent Tutoring Systems studies. They are intended to illustrate the expected educational impact of the proposed framework and should not be interpreted as experimentally validated results.*

The expected educational impact of the proposed framework extends beyond the automation of data analysis. By combining continuous learning analytics with AI-driven learner profiling, instructors can identify conceptual difficulties at an early stage and implement targeted pedagogical interventions before misconceptions become deeply established. In contrast to traditional assessment practices, where corrective actions typically occur after formal examinations, the proposed approach promotes continuous formative assessment and adaptive instruction throughout the learning process. As illustrated in **Figure 8**, this shift from reactive to proactive teaching is expected to enhance conceptual understanding, increase student engagement, and support improved learning outcomes in challenging physics topics such as electromagnetism.

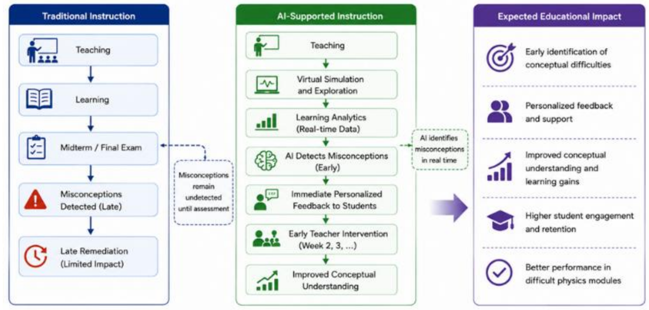

Figure 6. Expected Educational Impact of AI-Supported Learning Analytics in Physics Education

6. Discussion

The proposed AI-supported learning framework demonstrates how Learning Analytics and Artificial Intelligence can address persistent challenges in physics education within the Moroccan higher education context. Beyond improving the detection of conceptual misconceptions, the framework has the potential to transform the pedagogical relationship between instructors and students by shifting from summative evaluation toward continuous formative support.

One of the most significant contributions of the proposed approach is its ability to partially bridge the pedagogical gap between traditional Moroccan instructional practices and learner-centered educational models commonly observed in Scandinavian countries. Although the Scandinavian model is supported by a broader educational culture characterized by trust, collaboration, and low academic competition, the proposed AI framework reproduces several of its essential pedagogical mechanisms. By providing immediate, individualized, and non-judgmental feedback through virtual physics simulations, the system creates a psychologically safe learning environment in which students can experiment, make mistakes, and progressively refine their conceptual understanding without fear of social stigma or public evaluation. Such an environment is particularly beneficial for challenging topics such as electromagnetic induction, where abstract reasoning and spatial visualization frequently constitute major learning obstacles. Furthermore, reducing the affective barriers associated with repeated failure may be especially valuable for bilingual learners, whose conceptual difficulties may be amplified by linguistic constraints rather than by limited scientific reasoning (Krashen, 1982).

Despite these promising perspectives, the proposed framework also raises important methodological and ethical considerations. AI-based learner profiling should not be interpreted as an objective measure of students' cognitive abilities. The quality of the generated profiles depends directly on the representativeness of the collected interaction data and on the assumptions embedded in the clustering algorithm. If the training data contain hidden biases, the system may incorrectly attribute poor performance to cognitive overload or conceptual weakness when the actual difficulty originates from language barriers, socioeconomic factors, limited digital literacy, or unequal prior educational experiences (Ouyang & Jiao, 2021; Prinsloo & Slade, 2014). Consequently, the AI should be regarded as a decision-support system rather than an autonomous evaluator. Human instructors remain essential for interpreting learning analytics, contextualizing AI-generated recommendations, and making pedagogical decisions that account for the broader educational and social circumstances of each learner. Maintaining this human-in-the-loop approach is fundamental to ensuring transparency, fairness, and ethical use of AI in physics education.

7. Conclusion

Teaching physics remains a major challenge in higher education because many core concepts require advanced levels of abstraction, spatial reasoning, and conceptual integration. These difficulties are particularly pronounced in educational systems characterized by large class sizes and limited opportunities for individualized formative assessment. This paper has explored how Artificial Intelligence, Learning Analytics, and Educational Data Mining can contribute to addressing these challenges by supporting more adaptive and learner-centered physics instruction.

The proposed framework combines virtual physics simulations, continuous collection of student interaction data, unsupervised machine learning, and AI-generated learner profiling to identify conceptual misconceptions at an early stage of the learning process. Rather than replacing instructors, the proposed approach positions AI as an intelligent pedagogical assistant that provides timely diagnostic information and supports evidence-based instructional decisions. By enabling early detection of learning difficulties and personalized formative feedback, the framework promotes a shift from reactive remediation to proactive intervention.

Beyond its application to the Moroccan higher education context, the proposed methodology provides a transferable model for other educational systems facing similar constraints related to large student cohorts, limited teaching resources, and high failure rates in STEM disciplines. Although the educational benefits presented in this study remain conceptual and require validation through empirical classroom implementation, the framework demonstrates the potential of AI-supported learning analytics to enhance conceptual understanding, strengthen formative assessment practices, and improve the quality of physics education.

Future research will focus on implementing the proposed framework in undergraduate physics courses, evaluating its effectiveness using real classroom data, and comparing learning outcomes with those obtained through traditional instructional approaches. Additional investigations will also examine the ethical implications, fairness, and explainability of AI-generated learner profiles to ensure that intelligent educational systems remain transparent, equitable, and centered on human pedagogical decision-making.

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