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Physics Didactics in the Era of Artificial Intelligence: A Machine Learning Framework for Conceptual Modeling in Mechanics

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Abstract

Teaching introductory mechanics in higher education remains challenging because students often struggle to develop genuine conceptual understanding beyond procedural problem-solving. The abstraction of mathematical formalism frequently overshadows the physical intuition necessary for engineering practice. This paper proposes a pedagogical framework that integrates computational modeling and machine learning to support conceptual learning in physics. The approach centers on a nonlinear damped pendulum a canonical system rich in dynamical behavior yet analytically intractable to shift student focus from symbolic derivation to physical exploration. Students construct Python-based computational models, generate numerical datasets across parameter regimes, and train a Multilayer Perceptron to predict the next state dynamics from simulated trajectories. This inversion of the traditional learning sequence positions the Multilayer Perceptron as a pattern discovery tool that students must interpret physically. The instructional design is grounded in Cognitive Load Theory, Constructionism, and Didactic Transposition, each addressing a distinct dimension of the learning process: managing cognitive demands, learning through model-building, and reconciling formal physics with executable representations. We present a proof-of-concept instructional design and propose an experimental evaluation protocol combining pre-test and post-test conceptual assessments, cognitive load measurements, and qualitative analysis of student computational artifacts. Expected outcomes include reduced extraneous cognitive load, improved conceptual mapping between simulation parameters and physical behavior, and stronger epistemic connections between academic physics and engineering practice. By framing artificial intelligence as a cognitive amplifier rather than a replacement for scientific reasoning, this work advances a human in the loop paradigm for physics instruction and offers a replicable model for integrating data driven methods into science, technology, engineering, and mathematics curricula.

Keywords: Physics Didactics; Machine Learning; Computational Modeling; Conceptual Learning; Cognitive Load; Python Programming; Mechanics Education; Artificial Intelligence.

Introduction

- **The Global Challenge of Physics Education**

Physics education has long been recognized as one of the most challenging domains in science education. Despite decades of research in Physics Education Research (PER), a persistent gap remains between students' ability to manipulate mathematical expressions and their genuine conceptual understanding of physical phenomena (McDermott, 1991; Redish, 2003). Numerous studies have shown that many students successfully solve numerical exercises while still holding fundamental misconceptions about the underlying physical principles.

Mathematics is unquestionably the universal language of physics and provides the formal framework for describing natural phenomena. However, from a didactic perspective, mathematical formalism may itself become a cognitive barrier rather than a learning facilitator. As emphasized by Viennot (1996), excessive attention devoted to algebraic manipulations and analytical derivations can obscure the physical meaning of a problem. Consequently, students often allocate most of their cognitive resources to solving equations such as systems of differential equations or integral formulations while devoting little attention to interpreting the associated physical mechanisms (Mazur, 1997).

This challenge has become even more significant in modern engineering education. Contemporary scientific and industrial problems increasingly rely on computational modeling, numerical simulation, and data-driven approaches rather than purely analytical solutions. Nevertheless, introductory physics courses continue to emphasize manual mathematical derivations, creating a growing gap between traditional instructional practices and the computational competencies required in engineering and scientific professions.

This mismatch highlights the need to rethink physics instruction by integrating computational thinking and Artificial Intelligence as complementary learning tools capable of promoting conceptual understanding while reducing unnecessary cognitive demands.

- **The Moroccan Educational Context: Linguistic and Cognitive Challenges**

Within the Moroccan higher education system, the conceptual difficulties commonly encountered in introductory physics are further amplified by a complex linguistic environment. Morocco is characterized by a multilingual educational system in which students are exposed to Darija, Modern Standard Arabic, French, and increasingly English throughout their academic trajectory.

Although scientific subjects are predominantly taught in Arabic during secondary education, students entering university STEM (Science, Technology, Engineering, and Mathematics) programs generally experience a rapid transition toward French as the primary language of instruction (Bouziane, 2020). Consequently, many first-year students are required to simultaneously process unfamiliar scientific terminology, mathematical formalism, and new physical concepts.

From the perspective of Cognitive Load Theory, this linguistic transition introduces an additional source of extraneous cognitive load, reducing the cognitive resources available for constructing meaningful conceptual schemas. Students may therefore devote substantial effort to interpreting the language of a problem before engaging with its underlying physical principles.

This dual challenge combining linguistic adaptation with the mathematical complexity inherent to university physics may contribute to learning difficulties frequently observed during the first year of undergraduate physics programs. Beyond the Moroccan context, similar challenges have been reported in multilingual educational systems where language transitions coincide with increasing disciplinary complexity, highlighting the broader relevance of developing instructional approaches capable of reducing unnecessary cognitive load while promoting conceptual understanding.

- **Bridging the Gap between Physics Education and Engineering Practice**

A second limitation of traditional physics education lies in the growing disconnect between academic instruction and contemporary engineering practice. To preserve analytical tractability, introductory physics courses frequently rely on highly idealized systems, such as frictionless motion, small-angle approximations, or negligible aerodynamic effects. Although these simplifications facilitate mathematical derivations, they often provide only a partial representation of the complex physical systems encountered in modern engineering.

In contrast, engineering applications routinely involve nonlinear dynamics, dissipative phenomena, coupled multiphysics interactions, and computationally intensive models that cannot be solved analytically. Instead, engineers increasingly rely on numerical simulation, computational modeling, data-driven methods, and Artificial Intelligence to investigate, predict, and optimize physical systems.

This discrepancy creates an epistemological gap between the knowledge taught in introductory physics courses and the professional practices expected in engineering and scientific careers. According to Chevallard's theory of didactic transposition (1985), the transformation of scholarly knowledge into teachable content inevitably requires simplification. However, excessive simplification may distance students from authentic scientific reasoning and limit their ability to transfer conceptual knowledge to real world engineering problems.

Integrating computational tools into physics education offers an opportunity to reduce this gap by allowing students to investigate realistic physical systems while maintaining a strong emphasis on conceptual understanding rather than purely analytical calculations.

1. Research Questions and Objectives

Motivated by these pedagogical, linguistic, and epistemological challenges, this study proposes a proof of-concept instructional framework that combines computational modeling, Python programming, and Machine Learning to support conceptual learning in introductory mechanics. Rather than replacing traditional physics instruction, the proposed framework aims to complement analytical reasoning by introducing computational thinking as an additional pathway for understanding complex physical phenomena.

The study addresses the following research questions:

RQ1. How can computational modeling using Python reduce extraneous cognitive load and facilitate conceptual understanding in bilingual physics education?

RQ2. How can Machine Learning be integrated into introductory mechanics to promote an inductive understanding of nonlinear physical systems?

RQ3. To what extent can computational thinking contribute to bridging the gap between traditional physics education and contemporary engineering practice?

To answer these questions, this paper develops a proof-of-concept pedagogical framework based on the numerical simulation of a nonlinear damped pendulum and the training of a Machine Learning model capable of learning the system's dynamics from simulated data. The proposed methodology is grounded in Cognitive Load Theory, Constructionism, and Didactic Transposition, providing a coherent theoretical foundation for integrating Artificial Intelligence into undergraduate physics education.

1.1. Cognitive Load Theory (CLT) in Physics

John Sweller's Cognitive Load Theory (Sweller, 1988; Sweller et al., 1998) is paramount to understanding student failure in physics. CLT divides working memory load into three categories: Intrinsic (inherent difficulty of the topic), Extraneous (caused by poor instructional design or language barriers), and Germane (effort devoted to schema construction). In traditional bilingual physics education, the Extraneous load (deciphering French text and performing manual calculus) completely overwhelms the working memory, leaving zero capacity for Germane load (conceptual understanding) **Figure 1**.

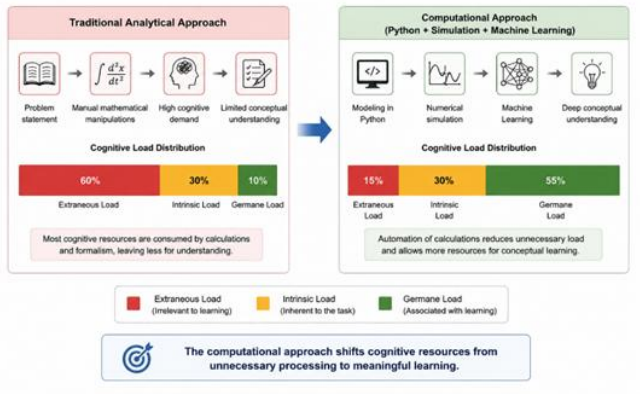

Figure 1: Evolution of Cognitive Load distribution using the computational approach.

1.2. Epistemological Obstacles

The notion of the epistemological obstacle, introduced by Gaston Bachelard (1938), refers to the intellectual barriers that hinder the construction of scientific knowledge. Rather than arising solely from learners' misconceptions, these obstacles may also originate from the very methods used to represent scientific phenomena.

In university level physics, mathematical formalism can paradoxically become such an obstacle. Although mathematics provides the formal language through which physical laws are expressed, increasingly sophisticated analytical techniques may divert students' attention from the interpretation of the underlying physical processes. When solving a problem requires lengthy algebraic manipulations or advanced differential equations, students often focus on procedural correctness rather than conceptual reasoning. Consequently, mathematical formalism may function as a "black box" that conceals the physical mechanisms it is intended to describe.

The computational approach proposed in this study seeks to overcome this epistemological obstacle by transferring repetitive analytical calculations to numerical computation. This shift enables students to devote greater cognitive resources to model interpretation, hypothesis formulation, and conceptual reasoning, thereby restoring physics as the primary object of learning rather than mathematics itself.

1.3. Didactic Transposition and Engineering Reality

According to Yves Chevallard (1985), didactic transposition describes the transformation of scholarly knowledge into knowledge suitable for teaching. In introductory physics, this transformation has traditionally relied on simplifying assumptions that render physical systems analytically solvable, including idealized conditions such as frictionless motion, linear approximations, or negligible dissipative effects.

While these simplifications facilitate instruction, they may also create a substantial gap between classroom activities and contemporary engineering practice. Modern engineers rarely rely exclusively on analytical solutions; instead, they routinely employ computational modeling, numerical simulation, optimization techniques, and Artificial Intelligence to investigate complex nonlinear systems.

Integrating computational methods into physics education therefore redefines the process of didactic transposition. Rather than simplifying physical reality to fit analytical mathematics, computational tools allow authentic engineering problems to become accessible while preserving their physical complexity. In this perspective, programming and numerical simulation become mediating instruments that reconnect academic physics with professional engineering practice.

1.4. Constructionism and Artificial Intelligence in Education (AIED)

The proposed instructional framework is grounded in Constructionism, developed by Seymour Papert (1980) from the constructivist foundations established by Jean Piaget (1970) and the sociocultural perspective introduced by Lev Vygotsky (1978). Constructionism argues that learners develop deeper understanding by actively constructing meaningful artifacts that can be explored, tested, and refined.

Within this framework, programming serves not merely as a technical skill but as a cognitive tool for scientific inquiry. Students construct computational models, explore alternative hypotheses, visualize system behavior, and iteratively improve their representations of physical phenomena. This active process promotes conceptual understanding through experimentation rather than passive reception of knowledge.

The integration of Machine Learning further extends this constructivist perspective. Instead of following the traditional deductive sequence (physical law → mathematical equation → predicted behavior), students adopt an inductive learning process in which simulated data are analyzed to identify underlying physical relationships. By training a neural network on numerical simulations, learners experience how Artificial Intelligence extracts patterns from data, thereby connecting computational thinking, data driven modeling, and scientific reasoning. In this context, Artificial Intelligence is not intended to replace physics knowledge but to serve as a cognitive partner that supports conceptual exploration and model construction (Baker & Inventado, 2014).

Table 1. Educational theories underpinning the proposed computational framework for physics education.

Educational Theory	**Main Principle**	**Contribution to the Proposed Framework**
Cognitive Load Theory **(Sweller)**	Reduce unnecessary cognitive effort	Python automates complex calculations, allowing students to focus on conceptual reasoning
Epistemological Obstacles **(Bachelard)**	Scientific knowledge may be hindered by inappropriate representations	Computational modeling prevents mathematics from becoming an obstacle to understanding physics
Didactic Transposition **(Chevallard)**	Adapt scholarly knowledge into teachable knowledge	Numerical simulation enables authentic engineering problems to be introduced into undergraduate physics
Constructionism **(Papert)**	Learning occurs through creating meaningful artifacts	Students build computational models and train Machine Learning algorithms to investigate physical systems

Although these educational theories originate from different research traditions, they converge toward a common objective: promoting meaningful conceptual learning while reducing unnecessary cognitive demands. The proposed computational framework builds upon these complementary theoretical foundations, as summarized in **Table 1**.

The relationships among these theoretical foundations and their contribution to the proposed instructional framework are illustrated in **Figure 2**.

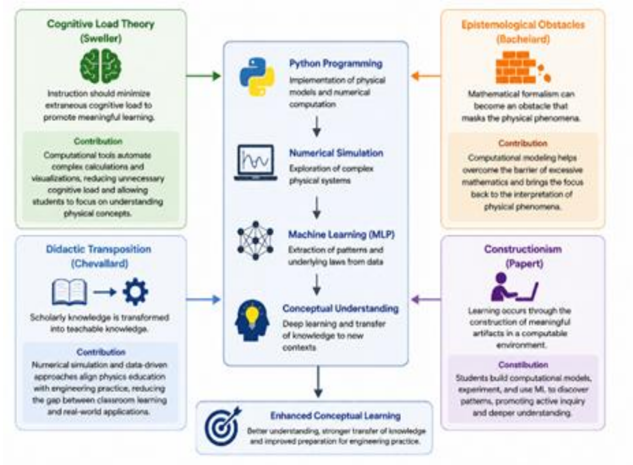

Figure 2. Theoretical Foundations of the Proposed AI-Based Computational Framework for Physics Education

2. Methodology: A Proof-of-Concept Computational Learning Framework

This study proposes a proof of concept (PoC) pedagogical framework that integrates computational modeling, Python programming, and Machine Learning to enhance conceptual learning in introductory mechanics. Rather than replacing traditional analytical methods, the proposed framework complements them by enabling students to investigate complex physical systems through numerical simulation and datadriven modeling.

The instructional design is organized as a three-hour laboratory session during which students progressively move from physical modeling to computational implementation and finally to Artificial Intelligence based prediction. The overall methodological workflow of the proposed framework is illustrated in **Figure 3**.

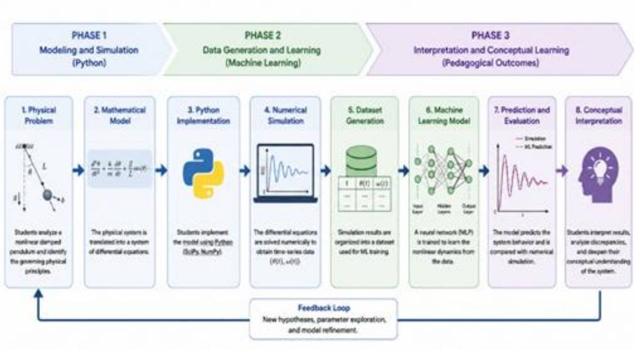

Figure 3. Overall Workflow of the Proposed AI-Based Computational Learning Framework

2.1. Justification of the System Choice: The Nonlinear Damped Pendulum

The nonlinear damped pendulum was selected as the reference physical system because it represents an ideal benchmark for introducing computational modeling and Artificial Intelligence in undergraduate mechanics. Unlike the simple pendulum commonly presented in introductory physics courses, the nonlinear damped pendulum exhibits realistic dynamical behavior that cannot generally be described by closed-form analytical solutions.

Its motion is governed by the following nonlinear second-order differential equation:

$$\frac{d^2\theta}{dt^2} + \frac{b}{m}\frac{d\theta}{dt} + \frac{g}{L}\sin(\theta) = 0$$

where:

θ denotes the angular displacement,

$\boldsymbol{\frac{d\theta}{dt}}$ is the angular velocity,

g is the gravitational acceleration,

L is the pendulum length,

m represents the pendulum mass,

b is the viscous damping coefficient.

Unlike the linear approximation **(sinθ≈θ)** frequently adopted in introductory mechanics, the complete nonlinear formulation accurately represents oscillatory motion at large amplitudes while incorporating continuous energy dissipation through viscous damping. As a result, no general analytical solution exists, and the system must be solved numerically.

From a pedagogical perspective, this physical system provides an excellent context for illustrating the transition from analytical reasoning to computational modeling. Students are introduced to authentic engineering practices in which numerical simulation replaces manual mathematical derivations for investigating complex physical phenomena. Moreover, the numerical simulations generate structured datasets that can subsequently be used to train Machine Learning models, thereby establishing a natural connection between physics, computational science, and Artificial Intelligence.

2.2. Computational Modeling Using Python

The first phase of the proposed framework introduces Python as a computational modeling environment through the **scipy.integrate.odeint** numerical solver. Instead of manually solving the nonlinear differential equation using lengthy analytical derivations, students translate the governing physical laws into executable computer code.

This shift redistributes cognitive effort from procedural mathematical calculations toward conceptual modeling. Rather than concentrating on symbolic manipulations, students identify the physical variables, define the forces acting on the system, and formulate the governing differential equations. Python therefore serves as an intermediate computational language that bridges mathematical formalism and physical reasoning.

The implementation of the nonlinear damped pendulum is illustrated below.

```python
import numpy as np
from scipy.integrate import odeint

def pendulum_derivs(state, t, g, L, b, m):
    """
    Compute the time derivatives for the nonlinear damped pendulum.
    state = [theta, omega] where theta is the angle and omega is the angular velocity.
    """
    theta, omega = state

    dtheta_dt = omega
    domega_dt = -(g / L) * np.sin(theta) - (b / m) * omega
    return [dtheta_dt, domega_dt]
```

Listing 1. Python Implementation of the Nonlinear Damped Pendulum Model

The computational process implemented in Python is summarized in **Figure 5**. Starting from the governing physical laws, the workflow translates the mathematical model into executable Python code, performs numerical integration using the odeint solver, and generates time-series data that constitute the dataset used for the subsequent Machine Learning phase.

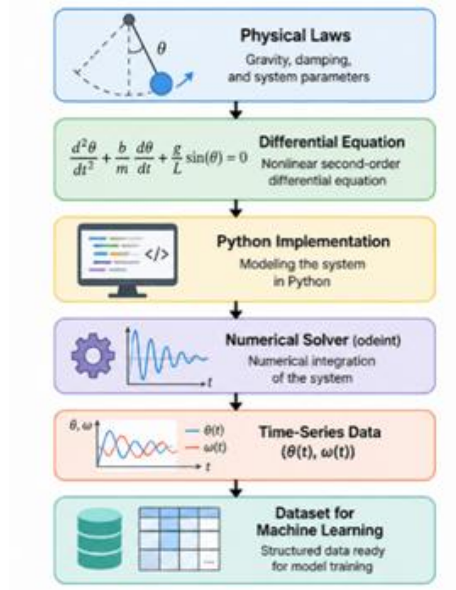

Figure 4. Computational workflow for numerical simulation and dataset generation.

The numerical solver automatically integrates the governing equations over time, generating the angular displacement and angular velocity of the pendulum. Consequently, students focus on constructing and interpreting the physical model rather than performing repetitive analytical calculations. From an educational perspective, Python acts as a computational language that supports conceptual reasoning while producing structured datasets suitable for subsequent Machine Learning training.

2.3. Machine Learning-Based Modeling

Following the numerical simulation, the generated time-series dataset containing the angular displacement (θ) and angular velocity (ω) is used to train a supervised Machine Learning model. This second phase introduces students to data driven modeling, enabling them to approximate the nonlinear behavior of the physical system directly from simulated data rather than from explicit analytical solutions.

The proposed framework employs a Multilayer Perceptron (MLP) Regressor implemented using the Scikit-Learn library (Goodfellow et al., 2016). The MLP learns the nonlinear mapping between the input variables and the target outputs through supervised learning. The overall architecture of the neural network is illustrated in **Figure 6.**

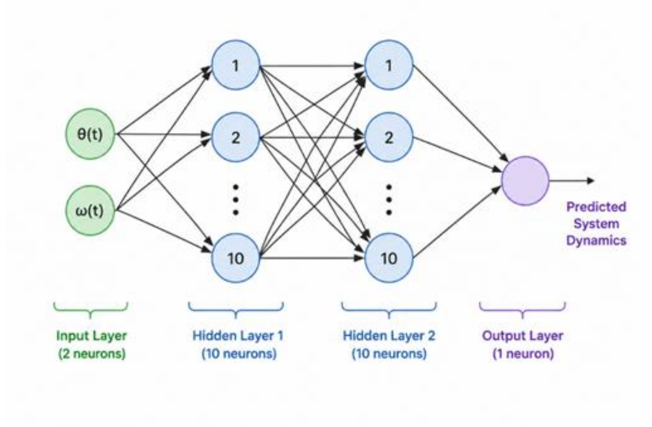

Figure 5. Architecture of the Multilayer Perceptron (MLP) Used for Modeling the Nonlinear Dynamics of the Damped Pendulum

The predictive model was implemented using a multilayer perceptron neural network consisting of two hidden layers, each containing ten neurons. The rectified linear unit (ReLU) activation function was selected because of its computational efficiency and its ability to facilitate the learning of nonlinear relationships between the input features and the target variable. The model configuration is presented below.

```python
MLPRegressor(
    hidden_layer_sizes=(10, 10),
    activation='relu'
)
```

The predictive model was implemented using a multilayer perceptron neural network consisting of two hidden layers, each containing ten neurons. The rectified linear unit (ReLU) activation function was selected because of its computational efficiency and its ability to facilitate the learning of nonlinear relationships between the input features and the target variable. The model configuration is presented below.

The Rectified Linear Unit (ReLU) activation function is selected because of its computational efficiency and its ability to mitigate the vanishing gradient problem during training. Model parameters are iteratively optimized through the backpropagation algorithm, which minimizes the prediction error between the simulated data and the network outputs.

From an educational perspective, this phase enables students to understand how Machine Learning can approximate complex nonlinear physical relationships using numerical data. Rather than replacing analytical reasoning, the neural network complements traditional physics instruction by providing a data-driven perspective on system dynamics and reinforcing conceptual understanding.

```python
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import train_test_split

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Define the MLP Regressor
mlp = MLPRegressor(hidden_layer_sizes=(10, 10), activation='relu',
      solver='adam', max_iter=1000, random_state=42)

# Train the model
mlp.fit(X_train, y_train)
# Make predictions on the test set
y_pred = mlp.predict(X_test)
```

Listing 2. Training the Multilayer Perceptron using Scikit-Learn.

The configuration of the Multilayer Perceptron used in this study is summarized in **Table 2**.

As shown in Table 2, a relatively simple neural network architecture was intentionally selected to emphasize the pedagogical objectives of the proposed framework. The chosen hyperparameters provide sufficient modeling capability for the nonlinear pendulum while remaining easily understandable by undergraduate students. This allows learners to focus on the principles of Machine Learning and their application to physical systems rather than on the complexity of deep neural network architectures.

Table 2. Hyperparameters of the Multilayer Perceptron (MLP) Model

Parameter	Value	Description
Model	MLP Regressor	Supervised neural network used for regression
Input Variables	θ(t), ω(t)	Angular displacement and angular velocity generated by the numerical simulation
Output	Predicted system dynamics	Estimated nonlinear response of the damped pendulum
Hidden Layers	(10, 10)	Two fully connected hidden layers
Neurons per Hidden Layer	10	Number of neurons in each hidden layer
Activation Function	ReLU	Rectified Linear Unit activation function
Learning Paradigm	Supervised Learning	Learning from simulated labeled data
Optimization Algorithm	Backpropagation (Adam optimizer)	Iterative optimization of network weights
Maximum Iterations	1000	Maximum number of training iterations
Software Library	Scikit-Learn	Python Machine Learning library

3. Proposed Experimental Protocol and Expected Outcomes

To evaluate the educational effectiveness of the proposed proof of concept framework, a structured experimental protocol is proposed for implementation in Moroccan higher education institutions. The objective is to assess whether integrating Python programming and Machine Learning into introductory mechanics improves students' conceptual understanding while reducing unnecessary cognitive load. The proposed protocol is intended as a reproducible methodology that can be adapted to other multilingual STEM learning environments.

3.1. Participants and Experimental Design

The proposed experimental study is designed for first-year undergraduate students enrolled in introductory mechanics courses in Moroccan universities. Approximately 100 students are expected to participate and will be divided into two comparable groups:

- **Control Group (n ≈ 50):** Traditional analytical instruction.
- **Experimental Group (n ≈ 50):** Computational laboratory integrating Python programming and Machine Learning.

Both groups will receive the same theoretical instruction, differing only in the laboratory methodology **Figure 7**.

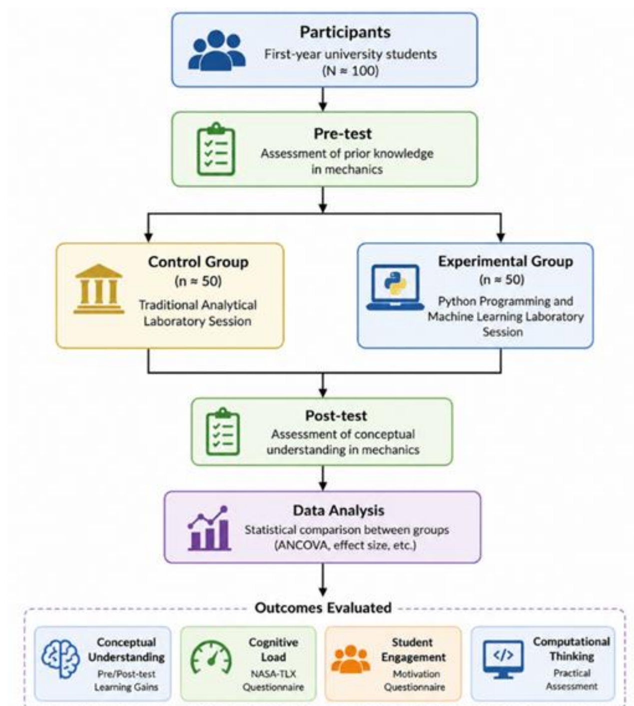

Figure 6. Proposed experimental design.

3.2. Evaluation Metrics

Learning effectiveness will be evaluated using complementary quantitative indicators including conceptual learning gains, normalized Hake's gain (Hake, 1998), cognitive load questionnaires, and student engagement measures.

To ensure a comprehensive evaluation of the proposed pedagogical framework, multiple complementary assessment measures are recommended. These measures are intended to capture not only students' conceptual achievement but also the cognitive and educational effects associated with the implementation of computational physics. As summarized in Table 3, the proposed experimental protocol combines knowledge assessment, cognitive evaluation, and statistical analysis to provide a multidimensional evaluation of learning outcomes.

The combination of pre-test and post-test assessments enables the measurement of conceptual understanding before and after the instructional intervention. Learning improvement can be quantified using Hake's normalized gain, which is widely employed in physics education research to evaluate instructional effectiveness. Cognitive load may be assessed through the National Aeronautics and Space Administration Task Load Index, allowing the investigation of learners' perceived mental demands during instructional activities. Furthermore, Cohen's *d* provides a standardized measure of the magnitude of the intervention effect, while Analysis of Covariance enables statistical comparison between experimental and control groups by accounting for initial differences in students' prior knowledge. Together, these complementary evaluation instruments provide a robust methodological framework for assessing both the educational effectiveness and the inclusiveness of the proposed computational physics approach.

Table 3. Assessment Metrics and Evaluation Instruments Used in the Proposed Experimental Protocol

Assessment Variable	**Measurement Instrument**
Conceptual understanding	Pre-test / Post-test
Learning gain	Hake's normalized gain
Cognitive load	NASA-TLX
Effect size	Cohen's d
Group comparison	ANCOVA

Learning effectiveness will be quantified using **Hake's normalized gain** (Hake, 1998), defined as:

$$<g> = \frac{<post> - <pre>}{100 - <pre>}$$

3.3. Statistical Analysis

Statistical analyses will include paired and independent-sample t-tests, Analysis of Covariance (ANCOVA), and Cohen's d effect size to compare the learning outcomes of the control and experimental groups while controlling for possible differences in prior knowledge.

Statistical analyses will first include descriptive statistics and checks of distributional assumptions, outliers, and missing data. Within-group changes will be examined using paired-sample tests, while between-group post-test differences will primarily be assessed using ANCOVA with pre-test score as a covariate. Effect sizes will be reported with 95% confidence intervals. The reliability of multi-item questionnaires will be examined using an internal consistency coefficient. If students are nested within intact classes, linear mixed-effects models will be considered to account for the hierarchical structure of the data. Statistical significance will be evaluated at $\alpha = 0.05$.

4. Discussion

The proposed computational framework demonstrates how the integration of Python programming and Machine Learning can contribute to addressing several longstanding challenges in introductory physics education. By transferring repetitive analytical calculations to numerical simulation, students are able to devote a greater proportion of their cognitive resources to understanding the physical mechanisms governing nonlinear systems. This redistribution of cognitive effort is consistent with Cognitive Load Theory, according to which reducing unnecessary cognitive demands facilitates the construction of meaningful conceptual knowledge (Sweller, 1988).

Beyond its cognitive benefits, the proposed framework also contributes to overcoming linguistic barriers frequently encountered in multilingual educational contexts. Rather than relying exclusively on complex mathematical derivations or lengthy textual problem statements, students express physical laws through a standardized computational language. In this sense, Python functions as a computational lingua franca, facilitating communication between mathematical formalism, physical reasoning, and programming while supporting conceptual understanding.

The framework also helps reduce the disconnect between traditional physics instruction and contemporary engineering practice. Modern engineers increasingly rely on computational modeling, numerical simulation, Artificial Intelligence, and data-driven approaches to investigate complex systems that rarely admit analytical solutions. Introducing these tools within undergraduate physics courses therefore brings academic instruction closer to authentic engineering practice while promoting computational thinking as an essential scientific competency.

From a pedagogical perspective, the proposed approach is consistent with Constructionism by positioning students as active constructors of computational models rather than passive users of mathematical formulas. Through numerical simulation and Machine Learning, learners progressively formulate hypotheses, generate data, analyze system behavior, and interpret physical phenomena. Artificial Intelligence is therefore presented not as a substitute for scientific reasoning but as a cognitive partner that supports conceptual exploration and model construction. This interpretation is consistent with current perspectives in Artificial Intelligence in Education, which emphasize augmentation rather than replacement of human learning (Luckin, 2016).

Nevertheless, the present study has several limitations. The proposed framework constitutes a proof of concept and has not yet been validated through classroom implementation. Consequently, its educational effectiveness remains to be demonstrated using rigorous experimental protocols involving pre-test/post-test assessments, cognitive load measurements, and statistical analyses. Furthermore, the present work focuses exclusively on the nonlinear damped pendulum. Future investigations should determine whether similar educational benefits can be achieved in other areas of undergraduate physics, including electromagnetism, thermodynamics, fluid mechanics, and quantum mechanics.

Conclusion and Future Perspectives

This paper presented a proof-of-concept pedagogical framework integrating computational modeling, Python programming, and Machine Learning to support conceptual learning in introductory physics. By combining Cognitive Load Theory, Epistemological Obstacles, Didactic Transposition, and Constructionism, the proposed approach provides a coherent theoretical foundation for introducing Artificial Intelligence into physics education.

Rather than replacing analytical reasoning, the proposed framework complements traditional instruction by enabling students to explore realistic nonlinear physical systems through numerical simulation and data-driven modeling. In doing so, it shifts the educational focus from procedural mathematical calculations toward conceptual understanding, scientific reasoning, and computational thinking. Such an approach contributes to reducing the gap between university physics education and the computational practices that characterize modern engineering and scientific research.

Although the framework has been developed with particular attention to the multilingual challenges encountered in Moroccan higher education, its underlying pedagogical principles are broadly applicable to other multilingual and international STEM learning environments. The proposed methodology therefore offers a transferable model for modernizing introductory physics instruction while preserving rigorous scientific reasoning.

Future work will focus on the experimental implementation of the proposed framework in undergraduate physics courses to evaluate its educational effectiveness using quantitative and qualitative assessment methods. Particular attention will be devoted to measuring conceptual understanding, cognitive load, computational thinking skills, and student engagement through controlled classroom studies.

Beyond mechanics, the methodology may be extended to other branches of physics, including electromagnetism, thermodynamics, fluid mechanics, and quantum physics, in order to evaluate its generalizability across different scientific domains. Finally, future developments will investigate the integration of emerging Artificial Intelligence technologies including Large Language Models (LLMs), intelligent tutoring systems, Physics-Informed Neural Networks (PINNs), and adaptive learning environments to further enrich computational physics education and foster personalized, inquiry-based learning experiences.

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