IJSRIS journal

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH AND INNOVATIVE STUDIES

ISSN: 2820-7157

www.ijsrisjournal.com

December 2024 | Volume 3 | Number 6 | 192-201

Received Date: 05 November 2024 | Accepted Date: 26 November 2024 | Published Date: 01 December 2024

An Arduino and Machine Learning Framework for Experimental Physics Education: A Proof-of-Concept Study

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Abstract

Experimental laboratory activities are essential for developing scientific reasoning and practical skills in physics education. However, in many higher education institutions, particularly in developing countries, laboratory instruction remains constrained by limited financial resources and the widespread use of expensive proprietary equipment that conceals the underlying data acquisition process. This paper proposes an interdisciplinary framework that combines low-cost Arduino-based instrumentation with Python-based Machine Learning techniques to redesign experimental physics laboratories. As a proof-of-concept, a kinematics experiment is developed in which students assemble a measurement system using an Arduino microcontroller and an ultrasonic sensor, acquire real-time experimental data, and apply polynomial regression to analyze noisy measurements and estimate the underlying physical relationships. The proposed framework integrates hardware implementation, computational modeling, and data analysis within a unified pedagogical workflow while maintaining a significantly lower implementation cost than conventional commercial laboratory systems. Beyond providing an affordable experimental platform, the approach aims to promote active learning by engaging students simultaneously in physics experimentation, programming, electronics, and data science. This interdisciplinary framework offers a scalable strategy for modernizing undergraduate experimental physics laboratories and supports the integration of computational thinking and Artificial Intelligence into science education.

Keywords: Physics Education; Experimental Physics; Arduino; Machine Learning; Data Acquisition; Open-Source Hardware; STEM Education; Inquiry-Based Learning.

Introduction

- **The Decline of Experimental Physics Education**

Experimental activities constitute a cornerstone of physics education, enabling students to bridge the gap between theoretical concepts and observable physical phenomena while developing scientific reasoning, measurement skills, and critical thinking. Laboratory instruction plays a fundamental role in helping learners understand how physical models are constructed, validated, and refined through experimentation (Séré, 2002). Consequently, practical work should not merely confirm established theories but should actively engage students in the processes of scientific inquiry, hypothesis testing, data acquisition, uncertainty analysis, and interpretation of experimental results.

Despite this central educational role, numerous studies in Physics Education Research (PER) have reported persistent limitations in the design and implementation of traditional laboratory instruction. In many undergraduate physics laboratories, practical sessions continue to follow a highly structured "cookbook" approach, where students simply execute predefined procedures to reproduce expected outcomes rather than designing experiments, solving authentic problems, or developing scientific reasoning skills (Holmes & Wieman, 2018). Such activities often emphasize procedural compliance instead of conceptual understanding, thereby limiting students' autonomy, creativity, and critical engagement with the experimental process.

These pedagogical limitations have been further reinforced by the widespread adoption of commercial laboratory systems equipped with proprietary sensors and automated acquisition software. Although these systems provide highly accurate measurements and facilitate laboratory management, they typically operate as "black-box" technologies that conceal the underlying processes of sensing, signal conditioning, analog-to-digital conversion, and data processing. As a result, students interact primarily with processed numerical outputs while remaining largely disconnected from the mechanisms through which physical quantities are measured and transformed into digital information (Crompton & Burke, 2023). This lack of transparency reduces opportunities for learners to develop a comprehensive understanding of experimental instrumentation and measurement principles.

At the same time, the rapid digital transformation of science and engineering has profoundly changed the nature of experimental practice. Modern engineers increasingly rely on embedded systems, intelligent sensors, real-time data acquisition, computational modeling, and Artificial Intelligence (AI) to analyze complex experimental data. Consequently, physics laboratories should evolve beyond traditional verification experiments and provide learning environments that integrate experimental physics with programming, electronics, and data science. Such interdisciplinary competencies have become essential for preparing graduates to address the technological challenges of Industry 4.0 and contemporary scientific research.

- **The specific challenges in Developing Educational Systems -The Moroccan Context**

In emerging educational systems, such as in Morocco, the didactic issues of the laboratory are compounded by severe economic constraints. University laboratories serving massive cohorts of first-year students (L1) are chronically under-equipped. Commercial educational hardware is prohibitively expensive to maintain and scale. Consequently, students often work in large groups around a single apparatus, drastically reducing active hands-on engagement. When practical work is marginalized due to a lack of resources, physics is reduced to a purely theoretical and mathematical discipline (Ouyang & Jiao, 2021).

- **Arduino and Artificial Intelligence for Next Generation Physics Laboratories**

Recent advances in open-source hardware and Artificial Intelligence (AI) have created new opportunities for transforming experimental physics education. Low-cost microcontroller platforms such as Arduino have become increasingly popular in science and engineering education due to their affordability, flexibility, and ease of programming. Unlike proprietary commercial laboratory systems, Arduino enables students to design, assemble, and program their own experimental devices, thereby promoting active learning, problem-solving, and computational thinking. This open-hardware philosophy is closely aligned with constructivist learning theories and the Maker Education movement, which encourage students to actively construct knowledge through the design and implementation of tangible technological artifacts (Blikstein, 2013; Halverson & Sheridan, 2022).

In parallel, Artificial Intelligence and more specifically Machine Learning (ML) has emerged as a powerful tool for processing experimental data. Modern engineering increasingly relies on intelligent algorithms to analyze noisy measurements, identify patterns, estimate physical parameters, and support data-driven decision-making. Introducing Machine Learning into undergraduate physics laboratories therefore provides students with valuable exposure to computational techniques that are now widely used in scientific research and industrial practice (Chen et al., 2020; Holmes et al., 2021).

The combination of Arduino-based instrumentation and Machine Learning presents a particularly promising framework for modern physics education. Low-cost sensors inevitably produce measurements affected by noise, limited resolution, and environmental disturbances. Rather than considering these imperfections as disadvantages, they can be transformed into authentic learning opportunities in which students investigate measurement uncertainty, apply computational models, and compare experimental observations with theoretical predictions. In this context, Machine Learning becomes not only a data analysis tool but also a pedagogical instrument that helps students understand how physical information can be extracted from imperfect experimental data **Figure 1**.

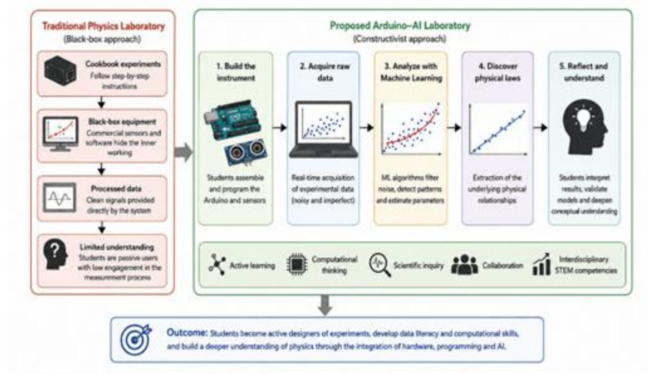

Figure 1. Conceptual framework of the proposed Arduino–Machine Learning approach for experimental physics education.

Despite the growing body of research on Arduino-based laboratories and the increasing adoption of Artificial Intelligence in education, these two research directions have largely evolved independently. Few studies have proposed an integrated educational framework that combines low-cost experimental hardware, real-time data acquisition, and Machine Learning-based analysis within a single undergraduate physics laboratory. Addressing this gap constitutes the primary motivation of the present study, which proposes a scalable and affordable interdisciplinary framework designed to modernize experimental physics education, particularly in resource-constrained educational environments.

1. Constructionism, Maker Education, and Experimental Learning

The proposed framework is grounded in Papert's theory of Constructionism, which extends Piaget's constructivist perspective by arguing that learning is most effective when learners actively construct meaningful artifacts that can be shared, tested, discussed, and continuously refined (Papert, 1980). Within this theoretical framework, knowledge is not passively transmitted by the teacher but actively developed through experimentation, design, reflection, and collaborative problem-solving. Consequently, learning is viewed as a dynamic process in which students progressively build conceptual understanding through authentic interactions with physical and technological systems.

Constructionism has significantly influenced contemporary STEM education through the emergence of the Maker Movement, an educational philosophy that emphasizes learning-by-making, creativity, and interdisciplinary project-based activities (Blikstein, 2013; Halverson & Sheridan, 2022). Rather than reproducing predefined experimental procedures, students are encouraged to design, prototype, test, and iteratively improve technological artifacts while integrating scientific knowledge with engineering design and computational thinking. Previous studies have shown that maker-centered learning environments enhance student motivation, creativity, collaboration, autonomy, and problem-solving abilities while fostering a deeper conceptual understanding of scientific phenomena.

Within experimental physics education, Arduino-based laboratories naturally embody the principles of Constructionism and Maker Education. Instead of relying on proprietary commercial laboratory systems, students design and assemble their own measurement devices, program the data acquisition process, and critically evaluate the quality and reliability of the collected experimental data. Such activities transform laboratory sessions from simple verification exercises into authentic inquiry-based learning experiences in which experimentation, programming, electronics, and scientific reasoning are integrated within a single educational framework. This interdisciplinary approach not only strengthens students' understanding of physical concepts but also develops the computational and engineering competencies increasingly required in contemporary scientific and industrial environments.

Furthermore, the open-source nature of Arduino platforms considerably lowers the economic barriers associated with experimental laboratory instruction, making hands-on experimentation accessible to institutions with limited financial resources. This characteristic is particularly relevant for developing educational systems, where affordable technologies can facilitate the democratization of practical science education without compromising educational quality.

2. Artificial Intelligence in Science Education and Experimental Physics

Artificial Intelligence (AI) has emerged as one of the most influential technological developments in higher education, particularly within science, technology, engineering, and mathematics (STEM) disciplines. Recent studies have highlighted its growing applications in intelligent tutoring systems, personalized learning environments, automated assessment, learning analytics, and scientific data interpretation (Zawacki-Richter et al., 2019; Holmes et al., 2021; Fadel et al., 2023). Rather than replacing traditional teaching methods or scientific reasoning, AI is increasingly recognized as a cognitive support technology that enhances learners' ability to analyze complex datasets, identify meaningful patterns, and solve multidisciplinary problems.

Among AI techniques, Machine Learning (ML) has gained particular importance in scientific and engineering applications because of its ability to model complex relationships from experimental observations. In modern scientific research, ML algorithms are routinely employed to process noisy measurements, estimate physical parameters, classify experimental data, and improve measurement accuracy. Consequently, introducing these techniques into undergraduate laboratory activities provides students with early exposure to computational methodologies that have become fundamental components of contemporary scientific investigation and engineering practice.

Experimental physics offers an especially relevant context for integrating Machine Learning into education because experimental measurements are inherently affected by measurement uncertainty, sensor limitations, environmental disturbances, and random noise. Unlike idealized textbook examples, authentic experimental datasets require preprocessing, filtering, statistical analysis, and computational modeling before reliable physical interpretations can be obtained. Learning to analyze imperfect experimental data therefore constitutes an essential scientific competency rather than a purely computational exercise.

Within the proposed framework, Machine Learning is not viewed merely as a numerical analysis tool but as a pedagogical instrument that supports scientific inquiry. By combining Arduino-based experimental data acquisition with Python-based Machine Learning algorithms, students progressively learn how computational models can assist in identifying physical relationships hidden within noisy experimental measurements. This process simultaneously reinforces conceptual understanding of physics, measurement uncertainty, data analysis, and computational thinking.

More broadly, the proposed approach reflects the growing convergence between experimental science, computer science, electronics, and Artificial Intelligence. By integrating these complementary disciplines within a single laboratory environment, students develop both disciplinary knowledge and the interdisciplinary competencies increasingly required in modern engineering, scientific research, and Industry 4.0.

The fundamental differences between conventional laboratory instruction and the proposed Arduino–Machine Learning framework are summarized in **Table 1**, highlighting their respective educational, technological, and economic characteristics.

Table 1 highlights the pedagogical transformation introduced by the proposed Arduino–Machine Learning laboratory framework compared with conventional physics laboratories. Rather than limiting students to the execution of predefined experimental procedures, the proposed approach actively engages them in the complete scientific workflow, including experimental design, sensor integration, programming, data acquisition, and computational analysis. This progression encourages the development of higher-order cognitive skills such as computational thinking, scientific reasoning, and interdisciplinary problem solving.

The comparison also demonstrates that the proposed framework extends learning beyond traditional experimental physics by integrating computer science, electronics, and artificial intelligence into laboratory practice. Students therefore acquire both disciplinary knowledge and transferable technical competencies that are increasingly required in modern scientific and engineering professions. Furthermore, the use of open-source hardware and software substantially reduces the financial cost of laboratory implementation while maintaining a rich experimental learning environment. Consequently, the proposed laboratory framework represents a cost-effective and scalable alternative for higher education institutions seeking to modernize experimental physics instruction and promote inquiry-based, student-centered learning.

Table 1. Comparison between conventional commercial physics laboratories and the proposed interdisciplinary Arduino Machine Learning laboratory framework

Educational Dimension	**Conventional Laboratory**	**Proposed Arduino–Machine Learning Laboratory**
Learning approach	Verification-based experiments	Inquiry based and project-based learning
Laboratory equipment	Proprietary commercial systems (e.g., PASCO, Vernier)	Open-source Arduino platform and low-cost sensors
Student role	Passive user of experimental equipment	Active designer, programmer, and experimenter
Experimental setup	Preassembled commercial apparatus	Student designed and assembled measurement system
Data acquisition	Automated and opaque	Student-programmed and fully transparent
Data processing	Conventional graphical analysis	Machine Learning-assisted analysis (Python)
Programming skills	Generally absent	Arduino (C/C++) and Python programming
Measurement uncertainty	Limited discussion	Explicit analysis of noisy experimental data
Computational thinking	Rarely developed	Fully integrated throughout the experiment
Interdisciplinary integration	Physics only	Physics, Computer Science, Electronics, and Artificial Intelligence
Student autonomy	Limited	High
Estimated cost per station	Approximately 14,000 MAD (DH)	Approximately 150 MAD (DH)

3. Methodology: Proof of Concept -The Arduino AI Physics Lab

3.1. Hardware Architecture of the Proposed Experimental Setup

To evaluate the feasibility of the proposed interdisciplinary framework, a proof-of-concept (PoC) laboratory experiment was developed in the field of kinematics. The objective was to design a simple, low-cost, and reproducible experimental platform capable of introducing students to the complete experimental workflow, including sensor integration, real-time data acquisition, programming, and computational data analysis.

The proposed setup is built around an Arduino Uno microcontroller coupled with an HC-SR04 ultrasonic distance sensor for displacement measurements. Additional components, including a breadboard, jumper wires, and a USB communication cable, complete the experimental platform. Unlike conventional commercial laboratory systems, which are delivered as fully assembled proprietary devices, this configuration requires students to assemble the electronic circuit, configure the sensor, and develop the acquisition program. Consequently, every stage of the measurement process becomes explicit, allowing students to understand the physical principles of sensing, electronic interfacing, signal acquisition, and digital communication.

The use of open-source hardware considerably reduces the cost of laboratory implementation while preserving the essential educational objectives of experimental physics. Such affordability makes the proposed framework particularly suitable for higher education institutions operating under limited financial resources, where access to commercial laboratory equipment often constitutes a major obstacle to practical science instruction.

The hardware components used in the proposed experimental platform and their approximate costs are summarized in **Table 2.**

Table 2. Hardware components of the proposed Arduino-based experimental platform

Component	Specification	Educational Function	Approximate Cost (MAD)
Arduino Uno	ATmega328P microcontroller	Data acquisition, programming, and sensor control	90
HC-SR04 Ultrasonic Sensor	Measuring range: 2–400 cm	Distance measurement	25
Breadboard	830 tie-points	Circuit assembly and prototyping	20
Jumper wires	Male–Male connection wires	Electrical interconnections	10
USB cable	USB-A to USB-B	Communication between Arduino and computer	15
Total Estimated Cost	—	Complete experimental station	**≈160 MAD**

3.2. Phase I: Experimental Data Acquisition

The first phase of the proposed laboratory activity focuses on experimental data acquisition using an Arduino Uno microcontroller and an HC-SR04 ultrasonic sensor. During this stage, students develop a simple acquisition program in the Arduino programming environment (C/C++) to control the ultrasonic sensor, measure the time of flight of the emitted acoustic pulse, and calculate the corresponding distance.

Rather than using pre-programmed commercial laboratory equipment, students actively implement the acquisition algorithm themselves. This activity introduces several fundamental concepts of experimental physics and embedded systems, including sensor operation, digital signal generation, time-of-flight measurement, analog-to-digital acquisition, sampling frequency, and serial communication between the microcontroller and a computer. Through this hands-on programming activity, students gain a deeper understanding of how physical measurements are generated before being processed by computational tools.

The acquisition program periodically triggers the ultrasonic sensor, measures the echo return time, converts this value into distance, and transmits the measurements to a computer through the serial interface. A sampling frequency of 20 Hz was selected to ensure a continuous acquisition of displacement data while maintaining stable communication between the Arduino and the Python processing environment.

A simplified version of the Arduino acquisition program is presented in **Listing 1**.

```
// ------------------------------------------------------------
// Arduino Data Acquisition Script
// HC-SR04 Ultrasonic Sensor
// Sampling frequency: ~20 Hz
// ------------------------------------------------------------

const int trigPin = 9;      // Trigger pin of the HC-SR04
const int echoPin = 10;     // Echo pin of the HC-SR04

void setup() {
  Serial.begin(9600);         // Initialize serial communication at 9600 bps
  pinMode(trigPin, OUTPUT);  // Set trigger pin as output
  pinMode(echoPin, INPUT);   // Set echo pin as input
}

void loop() {
  // Send 10 µs HIGH pulse to trigger the sensor
  digitalWrite(trigPin, HIGH);
  delayMicroseconds(10);
  digitalWrite(trigPin, LOW);

  // Read the duration of the echo pulse
  long duration = pulseIn(echoPin, HIGH);   // Duration in microseconds

  // Convert the time to distance (cm)
  // Speed of sound = 0.0343 cm/µs  →  distance = (duration * 0.0343) / 2 / 100
  float distance = (duration * 0.0343) / 200.0;
  // Send distance to the computer (4 decimal places)
  Serial.println(distance, 4);

  delay(50);   // Sampling frequency ≈ 20 Hz (1000 ms / 50 ms = 20 Hz)
}
```

Listing 1. Arduino program for real-time ultrasonic distance acquisition.

3.3. Python-Based Data Processing and Machine Learning Analysis

Following the data acquisition phase, the experimental measurements are transmitted from the Arduino microcontroller to a computer via the USB serial interface and stored in a structured dataset. Each record contains the acquisition time and the corresponding distance measured by the HC-SR04 ultrasonic sensor. The dataset is subsequently processed in Python using the Pandas and Scikit-Learn libraries for data preprocessing, regression modeling, and parameter estimation.

For the kinematics proof of concept, a second-degree polynomial regression model is employed to describe the relationship between displacement and time. This choice is motivated by the theoretical equation of uniformly accelerated motion, in which displacement is a quadratic function of time. The regression model can be expressed as:

$$x(t) = \beta_0 + \beta_1 t + \beta_2 t^2$$

where:

- $\beta_0$represents the **initial position**,

- β_1 corresponds to the **initial velocity**, and
- β_2 represents **half of the constant acceleration**.

Accordingly, the experimental acceleration is estimated as:

$$a = 2\beta_2$$

Within the proposed framework, Machine Learning is employed as a **regression and parameter-estimation tool** rather than as an autonomous mechanism for discovering physical laws. Students compare the fitted polynomial model with the theoretical kinematic equation, evaluate the quality of the regression, and interpret the estimated coefficients in terms of their physical meaning. This activity establishes a direct connection between experimental measurements, mathematical modeling, and computational analysis while emphasizing the complementary roles of data-driven estimation and theoretical reasoning.

The overall workflow adopted for data processing and Machine Learning analysis is illustrated in **Figure 2**, which summarizes the complete pipeline from Arduino-based data acquisition to the estimation of the physical parameters.

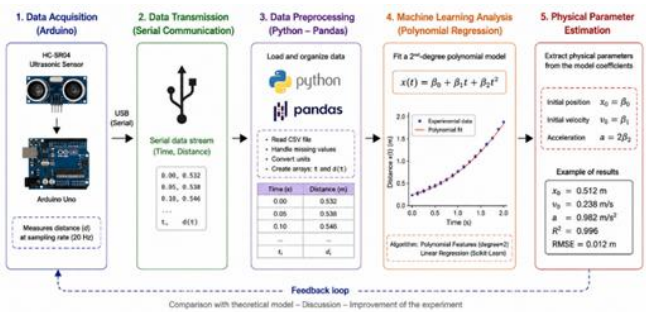

Figure 2. Digital data-processing pipeline integrating Arduino-based acquisition, Python preprocessing, polynomial regression, and physical parameter estimation.

A simplified implementation of the polynomial regression procedure is presented in **Listing 2**.

```python
import pandas as pd
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Loading the raw, noisy Arduino data
data = pd.read_csv('arduino_kinematics.csv')

# Prepare the data
X_time = data['Time'].values.reshape(-1, 1)   # Time (s) as feature
y_dist = data['Distance'].values              # Distance (m) as target

# AI Modeling: Transforming feature space to include t^2
poly_features = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly_features.fit_transform(X_time)

# Training the AI (Polynomial Regression) to fit the data
ai_model = LinearRegression()
ai_model.fit(X_poly, y_dist)

# Extracting the Physics from the AI's weights
initial_position = ai_model.intercept_        # β0
initial_velocity = ai_model.coef_[0]          # β1
acceleration = ai_model.coef_[1] * 2          # a = 2 * β2

# Model evaluation
y_pred = ai_model.predict(X_poly)
r2 = r2_score(y_dist, y_pred)
rmse = mean_squared_error(y_dist, y_pred, squared=False) ** 0.5

print(f"Initial position: {initial_position:.4f} m")
print(f"Initial velocity: {initial_velocity:.4f} m/s")
print(f"Estimated acceleration: {acceleration:.4f} m/s^2")
print(f"R^2: {r2:.4f}")
print(f"RMSE: {rmse:.4f} m")
```

Listing 2. Python implementation of polynomial regression for kinematic data analysis.

The inclusion of the coefficient of determination (R^2) and the Root Mean Square Error (RMSE) provides quantitative indicators of the agreement between the experimental measurements and the fitted polynomial model. Beyond estimating the acceleration, students are encouraged to critically assess the quality of the regression, identify potential sources of uncertainty, and discuss the influence of sensor noise, calibration errors, sampling frequency, and environmental conditions on the experimental results.

4. Proposed Experimental Protocol and Evaluation

4.1. Pedagogical Implementation

The proposed interdisciplinary laboratory was designed as a three-hour practical session integrating experimental physics, electronics, programming, and Machine Learning. The sequence follows a progressive learning strategy in which students gradually construct the complete experimental workflow, from hardware assembly to computational analysis and scientific interpretation.

Rather than treating programming and experimentation as separate activities, the proposed protocol encourages students to establish explicit connections between physical measurements, numerical modeling, and theoretical physics. This progressive organization promotes active learning while reinforcing computational thinking, scientific reasoning, and interdisciplinary problem-solving.

The pedagogical organization of the laboratory session is summarized in **Table 3**.

The proposed sequence follows a learning-by-doing philosophy in which each activity builds upon the previous one. Students first construct the experimental apparatus, then acquire real-world measurements, process the collected data using Machine Learning techniques, and finally interpret the estimated physical parameters within the theoretical framework of kinematics.

Table 3. Pedagogical organization of the proposed laboratory session

Time	Learning Activity	Educational Objective	Competencies Developed
00:00–00:30	Hardware assembly (Arduino and HC-SR04)	Understand sensor integration	Electronics, instrumentation
00:30–01:00	Development of the Arduino acquisition program	Understand real-time acquisition	Programming, embedded systems
01:00–01:45	Experimental measurements	Acquire authentic experimental data	Experimental methodology
01:45–02:30	Python preprocessing and Machine Learning	Analyze noisy measurements	Data Science, computational thinking
02:30–03:00	Interpretation and discussion	Compare experimental and theoretical results	Scientific reasoning, critical thinking

This progressive organization encourages interdisciplinary learning by simultaneously developing practical laboratory skills, programming competencies, computational thinking, and scientific reasoning.

4.2. Proposed Evaluation Framework

The educational effectiveness of the proposed laboratory framework may be assessed using the Colorado Learning Attitudes about Science Survey for Experimental Physics (E-CLASS) developed by Zwickl et al. (2014). This validated instrument measures students epistemological beliefs, attitudes toward experimental physics, and perceptions of scientific inquiry.

A future experimental study could compare students participating in the proposed Arduino Machine Learning laboratory with those attending conventional laboratory sessions. The evaluation protocol would include pre- and post-intervention questionnaires together with analyses of laboratory reports, programming assignments, and practical performance.

The evaluation would focus on several complementary dimensions:

- Conceptual understanding of experimental physics;
- Programming and computational thinking;
- Understanding of measurement uncertainty;
- Scientific reasoning;
- Student engagement and autonomy.

Rather than predicting learning gains, the present study establishes the methodological framework that will support future empirical validation.

The overall evaluation methodology proposed for future experimental validation is illustrated in **Figure 3.**

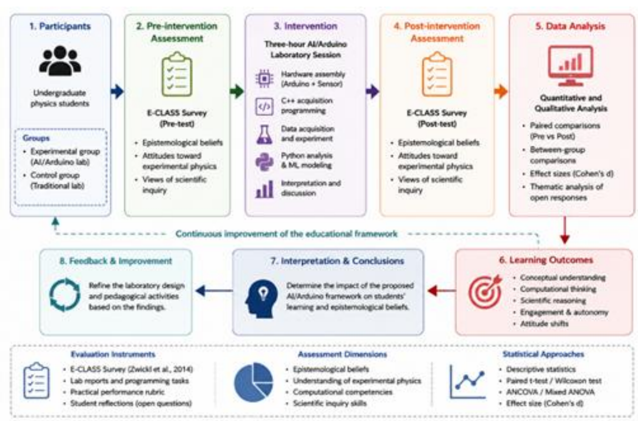

Figure 3. Evaluation methodology of the proposed laboratory framework based on a pre-test/post-test design using the E-CLASS instrument and complementary learning assessments.

5. Discussion

The proposed interdisciplinary framework demonstrates the potential of combining Arduino-based experimental instrumentation with Machine Learning to address both pedagogical and economic challenges in undergraduate physics laboratories. From an educational perspective, replacing proprietary "black-box" laboratory systems with open-source hardware encourages students to actively participate in every stage of the experimental process, including circuit assembly, programming, data acquisition, computational analysis, and scientific interpretation. This learning-by-doing approach is consistent with the principles of Constructionism and Maker Education, which emphasize knowledge construction through the design and manipulation of tangible artifacts (Papert, 1980; Blikstein, 2013). Furthermore, integrating Machine Learning into the analysis of noisy experimental measurements enables students to perceive uncertainty not as an experimental limitation but as an inherent characteristic of real-world scientific data requiring computational modeling and critical interpretation. This perspective aligns with recent developments in Physics Education Research, which advocate authentic laboratory experiences that promote scientific reasoning, computational thinking, and interdisciplinary problem-solving (Holmes et al., 2021). In addition to its pedagogical value, the proposed framework offers a practical and affordable alternative to commercial laboratory equipment, making experimental physics more accessible to higher education institutions operating under limited financial resources. Nevertheless, the present work constitutes a methodological proof of concept rather than a classroom validation. Future studies should therefore investigate the educational effectiveness of the proposed framework through empirical implementations involving undergraduate students, using validated assessment instruments such as the E-CLASS questionnaire together with analyses of programming performance, laboratory reports, and conceptual learning outcomes. Such investigations will provide quantitative evidence regarding the impact of integrating Arduino and Machine Learning on students' scientific competencies, computational skills, and attitudes toward experimental physics.

Conclusion

This study proposed an interdisciplinary framework that integrates Arduino-based experimental instrumentation with Python-based Machine Learning to modernize undergraduate experimental physics laboratories. By combining low-cost open-source hardware, computational modeling, and data-driven analysis within a unified pedagogical workflow, the proposed approach addresses both educational and economic challenges associated with conventional laboratory instruction. Beyond reducing implementation costs, the framework encourages students to actively participate in every stage of the experimental process, including hardware assembly, programming, data acquisition, computational analysis, and scientific interpretation. In doing so, it promotes inquiry-based learning, computational thinking, and interdisciplinary competencies that are increasingly essential in contemporary engineering and scientific practice.

Nevertheless, the present work has several limitations. First, it constitutes a methodological proof of concept and has not yet been validated through large-scale classroom implementation involving undergraduate students. Second, the proposed framework was demonstrated using a single kinematics experiment; therefore, its applicability to other areas of experimental physics, such as mechanics, electricity, optics, thermodynamics, or modern physics, remains to be investigated. Finally, although the educational potential of integrating Machine Learning into laboratory instruction has been discussed, its impact on students' learning outcomes has not yet been empirically assessed.

Future research will focus on implementing the proposed framework in undergraduate physics courses and evaluating its educational effectiveness using validated assessment instruments such as the Colorado Learning Attitudes about Science Survey for Experimental Physics (E-CLASS), together with analyses of conceptual understanding, programming competencies, scientific reasoning, and computational thinking. Additional studies will also investigate the extension of the proposed approach to other experimental physics topics, the integration of more advanced Machine Learning techniques, and the use of generative Artificial Intelligence to support both laboratory instruction and student learning. Through these developments, the proposed framework has the potential to contribute to the design of affordable, scalable, and interdisciplinary experimental laboratories capable of meeting the evolving needs of higher education in the digital era.

More broadly, this work illustrates how low-cost open-source technologies and Artificial Intelligence can contribute to democratizing experimental physics education while preparing students for the computational challenges of next-generation scientific and engineering practice.

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