

Design of an AI-IoT-ML Framework for Intelligent Physics Education and Evidence-Based Educational Administration in Smart Learning Environments

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Abstract

The increasing integration of Artificial Intelligence (AI), Internet of Things (IoT), and Machine Learning (ML) is creating new opportunities for intelligent and data-informed educational environments. However, applications of these technologies in physics education are often fragmented across instructional support, assessment, learning analytics, laboratory activities and institutional management, limiting their integration into a unified educational decision-support system. This study therefore designed an AI-IoT-ML framework for intelligent physics education and evidence-based educational administration in smart learning environments. The study adopted a Design Science Research (DSR) approach involving problem identification, objective definition, framework design and development, demonstration, conceptual evaluation, and communication. The proposed framework integrates a smart physics environment, IoT-based data acquisition, data processing and storage, ML analytics and prediction, AI decision support, and physics education and educational administration into a layered architecture with a continuous feedback mechanism. The framework provides potential applications in physics teaching and learning, student support, laboratory monitoring, equipment utilisation, resource management, scheduling, maintenance planning and evidence-based administrative decision-making. A key feature of the framework is its human-centred orientation, in which AI and ML provide analytical insights and recommendations while educators and administrators retain responsibility for professional judgement and final decisions. The study contributes a conceptual and architectural artefact that addresses the fragmentation between smart learning technologies, physics education and educational administration. The framework provides a foundation for subsequent prototype development, simulation and empirical evaluation of intelligent physics learning environments.

Keywords: Artificial Intelligence, Internet of Things, Machine Learning, Physics Education, Educational Administration, Smart Learning Environment, Design Science Research.

I. INTRODUCTION

a. Background to the Study

Physics education plays an important role in developing scientific reasoning, quantitative thinking, problem-solving abilities and technological competence. However, contemporary physics education increasingly requires learning environments that can connect classroom instruction, practical laboratory activities, digital resources and evidence about students' learning processes. The growth of smart educational technologies has created opportunities to move beyond conventional instructional and administrative practices toward learning environments in which educational activities can generate exchange and utilise data. Reviews of smart educational technologies indicate that digital systems are increasingly being applied to teaching, learning, assessment, classroom management and institutional resource optimisation (Badshah et al., 2024; Meylani, 2024). In this context, the development of intelligent physics learning environments provides an opportunity to integrate technological infrastructure with pedagogical and administrative processes.

The **Internet of Things (IoT)** provides an important technological foundation for such environments because connected sensors and devices can capture information from physical learning spaces and transmit it for processing and analysis. Within physics education, IoT can support smart laboratories by monitoring environmental conditions, equipment utilisation, laboratory occupancy and experimental activities. At the institutional level, IoT-enabled infrastructure can also contribute to campus and

resource management by providing administrators with timely information about the utilisation and condition of educational facilities. Recent reviews have identified IoT as an enabling technology for smart educational environments, with applications extending beyond classroom interaction to campus management, resource optimisation and learning support (Badshah et al., 2024; Chamorro-Atalaya et al., 2023; Meylani, 2024). Thus, IoT can provide the data-acquisition layer required for more responsive physics education and educational administration.

The availability of educational data, however, does not automatically produce useful educational decisions. **Machine learning (ML)** can provide the analytical layer required to identify patterns and generate predictions from data collected within smart learning environments. In a physics education context, ML may be applied to analyse learning activities, predict student performance, identify unusual patterns in laboratory utilisation, forecast equipment requirements and support resource planning. This creates a transition from simply collecting educational data to extracting actionable information from it. At the same time, the growing literature on artificial intelligence in education indicates that AI applications are increasingly being used to support students and teachers through personalised learning, assessment, intelligent tutoring and learning analytics (Mustafa et al., 2024). However, the same review evidence indicates that comparatively less attention has been directed toward other educational stakeholders, including institutional leaders and administrators (Mustafa et al., 2024).

Artificial intelligence (AI) can therefore provide a higher-level decision-support component within an intelligent physics education environment. Rather than replacing teachers or educational administrators, AI can interpret analytical outputs and present recommendations that support human decision-making. For example, ML may predict increased demand for a physics laboratory, while an AI decision-support component could use that prediction together with timetable, equipment and occupancy information to recommend alternative practical-session arrangements. Similarly, learning analytics could identify students requiring additional support, while an AI-enabled system could assist teachers in selecting appropriate instructional or remedial interventions. This human-centred approach is consistent with current discussions of responsible AI in education, which emphasise appropriate human oversight, transparency, privacy and responsible use of educational data (Mustafa et al., 2024).

The relevance of these technologies is particularly evident in physics education. Recent reviews report increasing applications of AI in physics teaching and learning, including personalised instruction, intelligent tutoring, assessment, virtual laboratories and support for conceptual learning (Mahligawati et al., 2023; Yeadon & Hardy, 2024). More recent systematic evidence from secondary-school physics similarly identifies adaptive learning, virtual laboratories and intelligent tutoring among important applications, while highlighting challenges related to teacher readiness, privacy and responsible use (Al-Kamzari & Alias, 2025). These developments demonstrate the potential of intelligent technologies for physics education, but they also reveal an important opportunity: much of the existing emphasis is directed toward the teaching and learning function, while the integration of intelligent technologies with educational administration and institutional decision-making remains less developed.

Consequently, there is a need for an integrated framework that connects the physical learning environment, IoT-based data acquisition, ML-based analytics, AI-based decision support, physics teaching and learning, and educational administration within a coherent architecture. The proposed study addresses this need through the design of an AI-IoT-ML framework for intelligent physics education and evidence-based educational administration in smart learning environments. The framework conceptualises IoT as the sensing and data-acquisition mechanism, ML as the analytical and predictive mechanism, and AI as the intelligent decision-support mechanism, while positioning physics educators and educational administrators as human decision-makers. Such integration provides a basis for connecting pedagogical activities with resource management, laboratory administration and evidence-based institutional decisions.

b. Statement of the Problem

Despite the increasing application of artificial intelligence (AI), Internet of Things (IoT) and machine learning (ML) in education, their applications are often developed as separate solutions for teaching, learning, monitoring or institutional management. In physics education, this fragmentation limits the ability to connect real-time data from classrooms and laboratories with predictive analytics and intelligent administrative decision-making. Consequently, physics educators and educational administrators may lack an integrated mechanism for monitoring learning environments, predicting relevant educational and resource-management patterns, and translating such insights into timely decisions. This study therefore addresses the need for an integrated **AI-IoT-ML framework** that connects smart physics learning environments with evidence-based educational administration.

c. Aim of the Study

The aim of this study is to design an AI-IoT-ML framework for intelligent physics education and evidence-based educational administration in smart learning environments.

d. Objectives of the Study

The study seeks to:

- 1.Examine the application of IoT for data acquisition in smart physics learning environments.
- 2.Examine the application of ML for analysing and predicting physics education and administrative patterns.
- 3.Determine how AI can support intelligent decision-making in physics education administration.

- 4.Design an integrated AI-IoT-ML framework for intelligent physics education and evidence-based educational administration.
- 5.Examine the potential applications of the proposed framework to physics teaching, learning, laboratory management and educational administration.

e. Research Questions

The study is guided by the following research questions:

- 1.How can IoT support data acquisition in smart physics learning environments?
- 2.How can ML support the analysis and prediction of physics education and administrative patterns?
- 3.How can AI support evidence-based decision-making in physics education administration?
- 4.What architecture can integrate AI, IoT and ML for intelligent physics education and educational administration?
- 5.How can the proposed framework support physics teaching, learning, laboratory management and administrative decision-making?

f. Significance of the Study

The proposed framework is expected to provide a conceptual basis for integrating intelligent technologies into physics education and educational administration. It may support **physics educators** through learning and laboratory insights, **administrators** through data-driven resource and management decisions, and **institutions** through improved monitoring and utilisation of educational facilities. It may also provide researchers with a foundation for developing and evaluating intelligent educational systems that combine IoT data acquisition, ML analytics and AI-based decision support.

g. Scope of the Study

The study focuses on the design of an **AI-IoT-ML framework** for physics education and educational administration within smart learning environments. It covers IoT-based data acquisition, ML-based analysis and prediction, AI-enabled decision support, physics teaching and learning, laboratory management, resource utilisation and administrative decision-making. The study is limited to **framework design and conceptual validation** and does not involve primary questionnaire-based data collection.

II. CONCEPTUAL REVIEW

a. Physics Education in Smart Learning Environments

Physics education combines theoretical knowledge with practical experimentation, making access to appropriate learning resources, laboratory facilities and meaningful learning experiences important for effective instruction. Smart learning environments extend conventional classrooms and laboratories by integrating digital technologies, connected devices and intelligent systems that can provide contextual information and support adaptive learning. AI applications in physics education have increasingly included intelligent tutoring, personalised learning, assessment and virtual laboratory environments (Al-Kamzari & Alias, 2025; Yeadon & Hardy, 2024). However, the educational value of these technologies depends on their integration with pedagogical practices and the wider management of learning resources.

In the proposed framework, the smart physics environment serves as the **physical and educational foundation** where students, teachers, laboratories, equipment and digital resources interact. Data generated from these activities can subsequently be captured through IoT devices, analysed using ML techniques and transformed into actionable insights through AI. This creates a connection between physics teaching and learning and the administrative processes required to manage the learning environment effectively.

b. Educational Administration in Smart Learning Environments

Educational administration involves planning, organising, monitoring and managing human, physical, technological and educational resources to achieve educational objectives. The emergence of data-driven technologies provides opportunities for administrators to move from predominantly retrospective reporting toward more timely and evidence-based decision-making. AI and learning analytics can support institutional monitoring, resource management and decision support, although recent research indicates that AI applications in education have focused substantially on students and teachers rather than educational leaders and administrators (Mustafa et al., 2024).

Within this study, educational administration is therefore conceptualised as a **decision-making layer** that uses information generated from physics learning environments. Relevant administrative functions include laboratory scheduling, equipment utilisation, resource allocation, maintenance monitoring and analysis of learning-related trends. Integrating these functions with IoT, ML and AI provides the basis for a more responsive and evidence-informed educational management system.

c. Internet of Things in Physics Education

IoT connects physical objects, sensors and computing systems to enable the collection and exchange of data. In educational environments, IoT can support smart classrooms, laboratories, environmental monitoring, equipment tracking and resource management (Badshah et al., 2024). For physics education, sensors can capture experimental measurements and contextual information such as temperature, humidity, occupancy, equipment status and energy consumption.

The proposed framework positions IoT as the data-acquisition layer, connecting the physical physics environment with the computational intelligence layers. This allows relevant data to be collected continuously or periodically and subsequently processed for educational and administrative purposes.

d. Machine Learning in Physics Education

Machine learning provides computational techniques for identifying patterns and making predictions from data. In education, ML has been applied to areas such as student-performance prediction, learning analytics, classification and early identification of students requiring support. Within physics education, ML can also analyse experimental and learning-environment data to support prediction and monitoring.

In the proposed framework, ML functions as the **analytical and predictive layer**, transforming IoT-generated and educational data into useful information. Possible applications include predicting student performance, laboratory utilisation, equipment demand and unusual patterns in the learning environment. The selection of specific algorithms would depend on the type and quality of data available.

e. Artificial Intelligence in Educational Decision Support

AI extends the analytical capabilities of the framework by enabling intelligent interpretation of information and generation of recommendations. Current educational AI research identifies applications including personalised learning, intelligent tutoring, assessment and learning analytics, while also emphasising the importance of human oversight, ethical use and data protection (Mustafa et al., 2024; UNESCO, 2023).

The framework does not mean that AI will replace teachers or administrators. Instead, it interprets relevant analytical outputs and provides recommendations to support human decisions. Thus, the conceptual relationship can be expressed simply as:

IoT→Data Collection

ML→Analysis and Prediction

AI → Interpretation and Decision Support

Teachers/Administrators → Human Decision and Action

III. THEORETICAL FOUNDATION

a. Systems Theory

Systems Theory provides a suitable foundation for the proposed framework because it views an educational environment as an interconnected system in which different components interact to achieve defined objectives. In the proposed AI-IoT-ML framework, the physics learning environment represents the system context, IoT devices function as data-input mechanisms, ML provides analytical and predictive processing, while AI provides intelligent interpretation and decision support. The resulting administrative and instructional actions constitute outputs that can generate new information and create a feedback cycle. This systems perspective is consistent with the increasing recognition that smart education requires interconnected technological, pedagogical and organisational components rather than isolated digital tools (Badshah et al., 2024; Ferreira et al., 2024).

b. Technology Acceptance Perspective

The Technology Acceptance Model (TAM) provides a complementary perspective for considering how teachers and educational administrators may interact with the proposed intelligent system. Davis (1989) established perceived usefulness and perceived ease of use as important determinants of technology acceptance. Although TAM is foundational, subsequent educational-technology research has continued to demonstrate the importance of users' perceptions, contextual factors and institutional conditions in technology adoption. For the proposed framework, this perspective emphasises that technological capability alone is insufficient; the system should provide understandable, useful and accessible information to physics educators and administrators.

c. Application of the Theories to the Proposed Framework

The two perspectives complement each other. **Systems Theory** explains how the technological and educational components interact as an integrated system, while the **Technology Acceptance Model** provides a basis for considering human interaction with the resulting technology. Accordingly, the proposed framework adopts a systems perspective for its architecture and a user-centred perspective for its potential implementation. This approach is also consistent with contemporary recommendations that AI in education should remain human-centred, transparent, responsible and supportive of human decision-making rather than simply automate educational processes (Miao & Holmes, 2023; Alfredo et al., 2024).

IV. RELATED STUDIES AND RESEARCH GAP

Recent scholarship demonstrates substantial growth in AI applications in education. Wang et al. (2024), through a systematic review of 2,223 AI-in-education publications, identified diverse application areas and research directions, indicating that AI has

become an established research area within education. Mustafa et al. (2024) similarly found considerable diversity in AI-in-education research but noted differences in educational level, stakeholder focus and research context.

In science education, Almasri (2024) found that AI is increasingly influencing instructional practices, assessment and other dimensions of science education. Physics-specific research has also expanded. Yeadon and Hardy (2024) reviewed the impact of AI across physics education from secondary to university levels, identifying applications including personalised learning, assessment and intelligent educational technologies. These studies establish the relevance of AI to physics education but largely emphasise the instructional and learning dimensions rather than an integrated administrative architecture.

IoT provides another important dimension of smart education. Ferreira et al. (2024) reviewed IoT applications in smart education and identified sensors, cameras, identification technologies and wearable devices among the technologies used to collect information from educational environments. Badshah et al. (2024) similarly described IoT as an enabling technology for smart educational spaces and noted that traditional educational systems often face challenges involving administration, pedagogy, assessment and classroom supervision. These findings support the use of IoT as the data-acquisition component of the proposed framework.

However, a gap remains in the **integration of these technologies around physics education and educational administration**. Existing literature provides substantial evidence on AI in education, IoT-enabled smart education and AI applications in physics, but these strands are frequently examined independently. The proposed framework addresses this gap by bringing together **IoT-based sensing, ML-based analytics, AI-based decision support, physics teaching and learning, and educational administration** within one conceptual architecture. The contribution is therefore not simply the application of AI or IoT to physics education, but the design of an integrated system connecting educational data generation, predictive analysis and evidence-based human decision-making.

Table 1. Summary of the Research Gap

Research area	Major emphasis in existing literature	Gap addressed by this study
AI in education	Teaching, learning, assessment and analytics	Greater integration with administration
AI in physics	Learning, tutoring, assessment and digital laboratories	Integration with institutional administration
IoT in education	Smart classrooms, sensing and connected environments	Integration with ML and AI decision support
ML in education	Prediction, classification and learning analytics	Connection to IoT-generated physics data
Educational administration	Management and institutional decision-making	Integration with intelligent real-time data
Proposed framework	Integrated AI + IoT + ML + physics education + administration	Addresses the integration gap

V. METHODOLOGY

a. Research Design

This study adopts **Design Science Research (DSR)** because the primary outcome is the design of an artefact—a conceptual and technical framework for integrating AI, IoT and ML into physics education and educational administration. DSR is appropriate where research seeks to address a practical problem through the systematic design and evaluation of an innovative artefact (Peppers et al., 2007; Hevner & vom Brocke, 2023). Recent methodological guidance also supports DSR for studies in which an artefact is developed to address a defined real-world problem (Atef et al., 2024).

b. Design Science Research Process

The study follows the DSR process proposed by Peppers et al. (2007), consisting of **problem identification, definition of objectives, design and development, demonstration, evaluation and communication**. These stages are adapted to the educational context of the present study. The problem identification stage establishes the fragmentation of physics education, IoT, ML, AI and educational administration. The objective-definition stage specifies the requirements of the proposed solution. The design and development stage produces the AI-IoT-ML framework, while demonstration explains its operational processes. Evaluation focuses on the logical coherence, completeness and applicability of the proposed architecture, and communication presents the resulting artefact and its potential educational and administrative applications.

Table 2. Adapted DSR Process for the Study

DSR stage	Application in this study	Expected output
Problem identification	Identify limitations of fragmented intelligent educational systems	Defined research problem
Objective definition	Establish requirements for an integrated solution	Framework requirements
Design and development	Integrate IoT, ML, AI, physics education and administration	Proposed framework
Demonstration	Explain framework operation through representative use cases	Operational scenarios
Evaluation	Assess architectural coherence, functionality and applicability	Validated conceptual design
Communication	Present the framework and research contribution	Journal publication

c. Framework Development Procedure

The framework is developed through **literature synthesis, requirement identification, architectural design and conceptual evaluation**. Relevant literature on AI in education, IoT-enabled learning environments, ML-based educational analytics, physics education and educational administration is synthesised to identify functional requirements. These requirements are then translated into architectural components comprising the smart physics environment, IoT data-acquisition layer, data-processing layer, ML analytics layer, AI decision-support layer and educational/administrative application layer.

d. Evaluation Approach

Because the present study is limited to framework design, **no questionnaire or primary human-subject data collection is required**. Evaluation is based on the alignment between the identified problem, framework objectives, system components, information flows and intended educational and administrative functions. The framework is also examined for **functional completeness, logical consistency, interoperability, scalability and human oversight**. This is consistent with the purpose of DSR, in which the designed artefact constitutes a central research contribution (Hevner & vom Brocke, 2023; Peffers et al., 2007).

VI. PROPOSED AI-IoT-ML FRAMEWORK

a. Framework Architecture

The proposed framework integrates Internet of Things (IoT), machine learning (ML) and artificial intelligence (AI) into a unified smart physics learning environment. The architecture follows a layered structure in which IoT devices acquire data from the physical and learning environment, data-processing components prepare and store the collected information, ML models analyse patterns and generate predictions, and AI components transform analytical outputs into actionable recommendations. The final layer connects these intelligent outputs to physics teaching, laboratory management, student support and educational administration. This arrangement reflects the growing movement toward intelligent and connected learning environments while addressing the fragmentation identified in existing physics-AI applications.

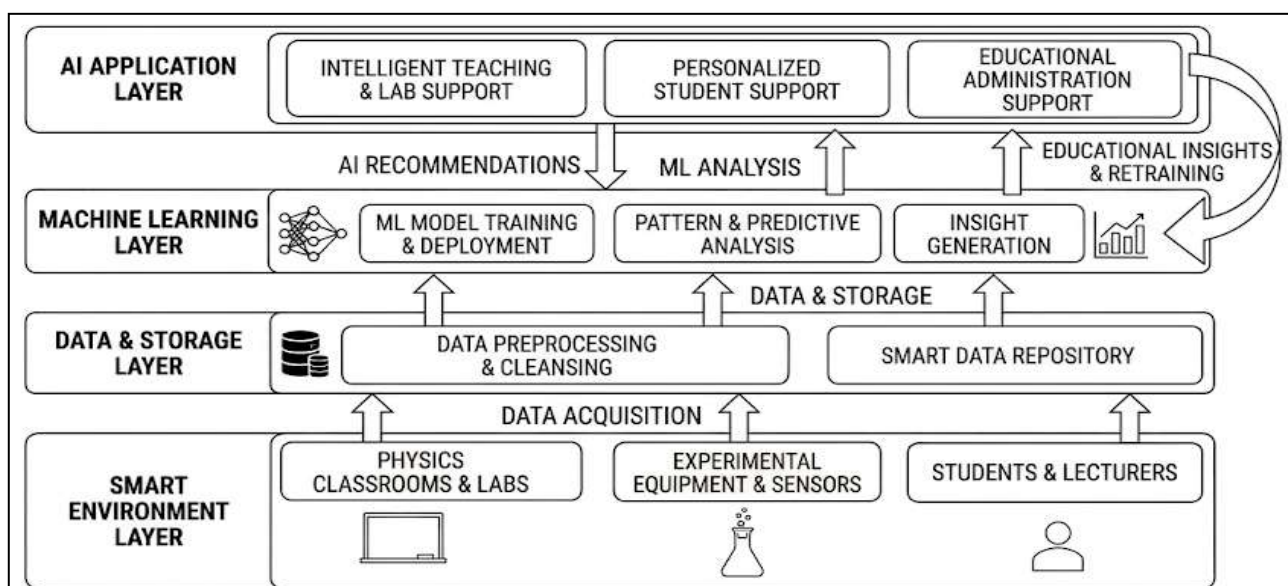


Figure 2: Proposed AI-IoT-ML Framework Architecture for Intelligent Physics Education and Evidence-Based Educational Administration

This diagram illustrates a four-layer hierarchical framework designed for an intelligent physics education system, integrating AI, IoT, and Machine Learning. Here is a short breakdown of the structure and data flow:

Layer 1: Smart Environment (The Foundation)

This layer consists of the physical physics classrooms and labs where data is collected from students, lecturers, and experimental equipment equipped with sensors. The data is acquired and sent upwards.

Layer 2: Data & Storage (The Middleware)

This layer acts as the data management hub. It receives the raw data from the Smart Environment and performs essential functions: data pre-processing (cleaning the data for analysis) and storing it within a Smart Data Repository.

Layer 3: Machine Learning (The Core Analysis)

This is the intellectual engine of the framework. Pre-processed data flows into this layer to train Machine Learning models. The ML algorithms perform pattern analysis and generate insights and predictions based on the incoming environmental data.

Layer 4: AI Application (The Intelligent User Interface)

The analytical outputs from the Machine Learning layer are used here to provide direct intelligent services: personalized mentorship and tutoring for students, real-time lab support for experiments, and decision support for educational administration.

Feedback Loop (The Continuous Improvement)

An essential component of the diagram is the feedback loop labelled "Educational Insights & Retraining." The final outputs and actions generated in the Application Layer are cycled back down to the Machine Learning layer. This continuous feedback is used to retrain and refine the ML models, ensuring the entire system becomes smarter and more effective over time.

b. Smart Physics Environment Layer

The Smart Physics Environment constitutes the physical and instructional foundation of the framework. It includes physics classrooms, laboratories, experimental equipment, students, lecturers, learning resources and connected devices. Sensors may capture environmental and operational variables such as temperature, humidity, illumination, equipment status, laboratory occupancy and energy consumption. Learning-related information, including laboratory participation, experimental measurements and equipment usage, may also be captured where appropriate.

The purpose of this layer is to provide a realistic source of contextual information from the physics learning environment rather than relying exclusively on manually entered records. Such an approach can support more responsive laboratory management and provide contextual data for subsequent analytical processes.

c. IoT Data Acquisition Layer

The IoT Data Acquisition Layer collects information from sensors, smart laboratory equipment, identification devices and other connected educational technologies. Depending on the institutional environment, data may include experimental measurements, equipment usage, environmental conditions, laboratory attendance or occupancy and resource-utilisation information.

The collected data are transmitted through appropriate communication technologies to the processing layer. IoT therefore performs the **sensing and connectivity function** of the proposed framework. Its major contribution is the continuous acquisition of contextual information that can subsequently be analysed for educational and administrative purposes.

d. Data Processing and Storage Layer

The Data Processing and Storage Layer receives raw IoT data and prepares them for analysis. Processing activities may include data cleaning, filtering, transformation, integration and feature extraction. Appropriate databases or cloud/edge storage environments may then be used to maintain structured records.

This layer is important because raw sensor information may contain missing values, duplicated observations, noise or inconsistent formats. Processing the information before machine learning analysis improves the suitability of the data for predictive tasks and provides a common information base for both educational and administrative applications.

e. Machine Learning Analytics and Prediction Layer

The ML Analytics Layer analyses processed data to identify patterns, relationships and predictive indicators. Depending on the application, supervised learning may be used for prediction, while unsupervised learning may support clustering and anomaly detection.

Potential applications include predicting student learning patterns, identifying unusual laboratory conditions, forecasting equipment utilisation, detecting abnormal equipment behaviour and estimating resource requirements. The ML layer therefore transforms collected data into **analytical and predictive information** rather than directly making administrative decisions.

f. AI Decision-Support Layer

The AI Decision-Support Layer interprets analytical outputs and converts them into meaningful recommendations for lecturers and educational administrators. For example, predicted laboratory demand may support scheduling decisions, equipment-use patterns may generate maintenance alerts, and identified learning difficulties may support targeted instructional interventions.

The AI component is therefore positioned as a **decision-support mechanism rather than an autonomous decision-maker**. Human educators and administrators remain responsible for reviewing recommendations, considering institutional circumstances and making final decisions. This human-centred arrangement is particularly important because recent research identifies concerns relating to AI reliability, teacher readiness, privacy and excessive dependence on AI-generated outputs in physics education.

g. Physics Education and Educational Administration Layer

The final layer represents the practical application of the framework. In physics education, the system can support personalized learning, practical-session planning, laboratory monitoring, experimental activities, student support and instructional decision-making. In educational administration, it can support laboratory scheduling, equipment management, resource allocation, maintenance planning, environmental monitoring and evidence-based institutional decisions.

The integration of these functions distinguishes the proposed framework from approaches that apply AI only to instructional activities. Existing reviews indicate that AI has already been applied to assessment, personalized learning, feedback and prediction in science education, but the proposed framework extends this technological logic by connecting educational applications with real-time IoT information and administrative decision support.

h. Feedback Mechanism

A feedback mechanism connects the application layer back to the data-acquisition and analytics components. Decisions and interventions implemented by lecturers or administrators may produce new observations that can subsequently be captured, processed and analysed. This creates a continuous cycle of **sensing, analysing, recommending, acting and learning**.

The feedback mechanism enables the framework to evolve with changing learning conditions, laboratory requirements and institutional priorities. It also supports continuous improvement because subsequent data can be used to refine analytical models and improve the relevance of AI-generated recommendations.

i. Summary of Framework Functions

The functional relationship among the major technologies can therefore be summarised as follows:

IoT → Sense and Collect, ML → Analyse and Predict, AI → Interpret and Recommend

Teachers/Administrators → Decide and Act, Feedback → Improve the System

This functional separation establishes a clear technological pathway from real-world physics learning activities to evidence-based educational and administrative decisions. It also ensures that intelligent automation complements, rather than replaces, professional judgement.

VII. FRAMEWORK OPERATION AND APPLICATIONS

a. Framework Operational Process

The proposed framework operates as a continuous intelligent cycle beginning with data acquisition from the physics learning environment and ending with educational or administrative action. IoT devices and connected systems capture relevant environmental, laboratory and learning-related information. The collected data are processed and stored before being analysed by ML models to identify patterns or generate predictions. AI subsequently interprets the analytical outputs and presents recommendations to lecturers or educational administrators. The users review the recommendations and implement appropriate actions, while resulting changes generate new data for subsequent analysis.

The operational sequence can therefore be represented as:

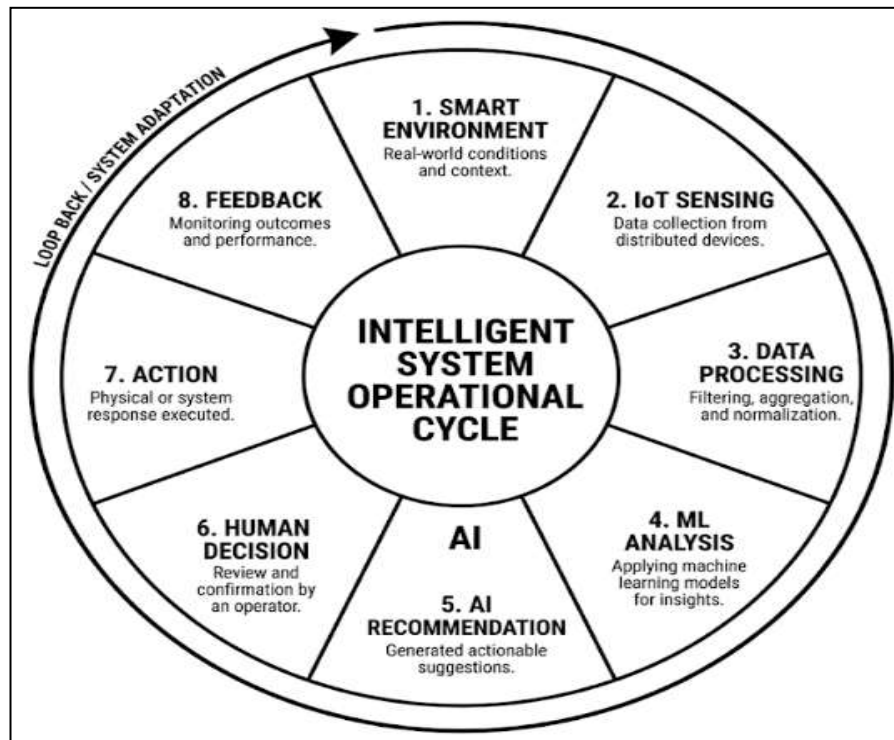


Figure 2: intelligent system operational Cycle

Smart Environment: Real-world physical conditions and context where data originates.

IoT Sensing: Distributed IoT sensors and devices capture raw ambient data.

Data Processing: Collected data undergoes cleaning, filtering, aggregation, and normalization.

ML Analysis: Machine learning algorithms evaluate data to extract patterns and insights.

AI Recommendation: The AI system generates actionable predictions and automated suggestions.

Human Decision: A human operator reviews, validates, or approves the recommendation.

Action: The final control decision is executed physically or digitally.

Feedback: Outcomes and performance metrics are monitored to continuously adapt the system.

This cycle enables the framework to function as an adaptive decision-support environment rather than merely a data-collection system.

b. Application to Physics Teaching and Learning

In physics teaching, the framework can provide contextual information that assists lecturers in understanding learning conditions and identifying areas requiring intervention. For example, learning activity records and experimental performance data can be analysed to identify patterns associated with students' learning difficulties. ML models may then generate predictions that assist the lecturer in determining students or topics that may require additional instructional support.

The AI component can translate these analytical results into recommendations such as targeted revision activities, additional practical exercises, differentiated learning resources or appropriate instructional interventions. Such applications are consistent with recent evidence showing the use of AI in physics education for personalized learning, intelligent tutoring, feedback and problem-solving support.

c. Application to Physics Laboratory Management

The framework can also support intelligent laboratory management. IoT sensors can monitor laboratory occupancy, environmental conditions, equipment status and patterns of equipment utilisation. ML algorithms can analyse these data to identify abnormal conditions, predict resource demand or detect patterns that may indicate possible equipment maintenance requirements.

AI can then provide recommendations to laboratory personnel or administrators. For instance, predicted high demand for particular equipment may support improved practical-session scheduling, while abnormal equipment readings may generate an inspection or maintenance alert. The final decision remains with the responsible laboratory officer or administrator.

d. Application to Student Support and Learning Analytics

The framework can support evidence-based student intervention by analysing learning-related data collected from connected learning environments. ML models may identify patterns associated with low participation, declining performance or difficulty with particular physics topics. Such predictions can provide early indications that a student may require academic support.

AI can transform these analytical outputs into understandable recommendations for lecturers, such as providing additional explanations, assigning targeted learning activities or initiating academic support. This approach is consistent with broader science-education research in which AI has been applied to assessment, personalized learning and prediction of academic performance.

e. Application to Educational Administration

At the administrative level, the framework provides a mechanism for transforming data generated within physics learning environments into information that can support institutional decisions. Administrators may use the system to monitor laboratory utilisation, identify resource requirements, support equipment planning, examine patterns of practical-session demand and coordinate learning-space utilisation.

For example, historical and real-time laboratory-utilisation data may be analysed to predict periods of high demand. The AI component can subsequently recommend alternative scheduling arrangements or resource-allocation options. Administrators can evaluate these recommendations alongside institutional policies, available resources and other contextual factors before making decisions.

f. Application to Evidence-Based Decision-Making

The framework supports evidence-based administration by establishing a connection between observed conditions and institutional decisions. Instead of relying exclusively on manually compiled records or subjective observations, administrators can access continuously generated information and predictive insights.

The framework does not imply that algorithmic recommendations are automatically correct. AI outputs should be treated as decision-support information and reviewed against professional judgement, institutional requirements and relevant contextual factors. This is particularly important because recent physics-education reviews identify concerns relating to AI reliability, teacher readiness, privacy and excessive dependence on automated outputs.

g. Integrated Use-Case Summary

Table 3 The major applications of the proposed framework can be summarized as follows:

Application Area	IoT Contribution	ML Contribution	AI Contribution
Physics teaching	Captures learning/environmental data	Identifies learning patterns	Recommends instructional support
Student support	Captures participation/activity data	Predicts potential learning difficulties	Suggests intervention options
Physics laboratory	Monitors equipment and environment	Detects anomalies and predicts demand	Generates maintenance/scheduling recommendations
Resource management	Captures resource-use information	Forecasts utilisation patterns	Supports allocation decisions
Laboratory scheduling	Provides occupancy and usage data	Predicts demand	Recommends scheduling options
Educational administration	Provides real-time institutional information	Generates analytical evidence	Supports planning and decision-making

h. Human-Centred Operation

An important principle of the framework is that intelligent technologies support rather than replace educators and administrators. IoT provides information about the environment, ML generates analytical and predictive outputs, and AI provides interpretable recommendations. Professional users remain responsible for reviewing the outputs and deciding whether and how to act upon them.

This human-centred approach is important for responsible implementation because current research highlights issues of reliability, privacy, transparency, AI literacy and appropriate human oversight in educational AI.

VIII. DISCUSSION

a. Contribution of the Proposed Framework

The proposed AI-IoT-ML framework addresses the fragmentation identified in the literature by integrating three complementary technological functions within a single smart physics education environment. IoT provides continuous data acquisition from the physical and learning environment, ML transforms collected data into analytical and predictive information, while AI interprets these outputs and supports educational and administrative decisions. This integrated arrangement extends beyond the isolated application of individual technologies and provides a structured pathway from real-world educational data to actionable decision support.

The framework is particularly relevant because existing research on AI in physics education has largely concentrated on applications such as adaptive learning, intelligent tutoring, virtual laboratories, automated feedback and problem-solving. Recent systematic reviews similarly report that AI applications in physics are expanding rapidly but remain fragmented across pedagogical functions and research contexts. The proposed framework therefore contributes an additional perspective by connecting instructional applications with laboratory information, resource management and educational administration.

b. Implications for Physics Education

The framework has implications for both classroom and practical physics education. By connecting IoT-enabled environments with ML analytics and AI decision support, information generated during practical activities can become useful for instructional planning and student support. This creates an opportunity to move from predominantly retrospective assessment toward more continuous and evidence-informed instructional decision-making.

This contribution is consistent with evidence from science-education research showing that AI has been used for assessment, personalized learning, feedback and prediction of academic performance. However, the proposed framework does not assume that AI-generated recommendations automatically improve learning. Instead, it positions such outputs as additional evidence that lecturers can consider alongside professional judgement and pedagogical knowledge.

c. Implications for Educational Administration

A major contribution of the framework is the extension of intelligent technologies from instructional applications to educational administration. IoT-generated information concerning laboratory occupancy, equipment utilisation, environmental conditions and resource usage can provide an additional evidence base for administrative planning. ML can identify patterns and forecast requirements, while AI can present recommendations concerning scheduling, maintenance and resource allocation.

This orientation is supported by smart-education research identifying smart administration as one of the potential applications of IoT-enabled educational environments. The proposed framework consequently establishes a connection between classroom and laboratory activities and institutional management, allowing educational administration to benefit from information generated directly within the learning environment.

d. Human Oversight and Responsible Use

The framework deliberately retains teachers and administrators within the decision-making loop. This is important because current reviews of AI in physics education identify concerns relating to teacher readiness, data privacy, reliability and excessive dependence on automated outputs. Recent research also highlights epistemic unreliability and overreliance on AI outputs as continuing challenges in physics education.

Accordingly, the proposed framework should be implemented with appropriate privacy protection, access controls, transparency, data-quality procedures and human oversight. AI recommendations should be interpreted in relation to institutional policies and the educational context rather than treated as unquestionable decisions.

e. Theoretical and Practical Implications

The framework demonstrates the usefulness of Systems Theory for representing smart physics education as an interconnected system involving data inputs, technological processes, human decisions, actions and feedback. The inclusion of the Technology Acceptance perspective further emphasizes that successful implementation depends not only on technical capability but also on whether teachers and administrators perceive the system as useful and manageable.

Practically, the framework provides institutions with a conceptual basis for developing smart physics laboratories and data-informed administrative systems. It can also serve as a reference architecture for subsequent prototype development, simulation or empirical evaluation. Their modular structures allows institutions to begin with basic IoT monitoring and progressively introduce ML analytics and AI decision-support functions according to available infrastructure and institutional requirements.

f. Relationship to the Research Gap

The framework responds directly to the research gap established in the earlier sections. Existing studies demonstrate substantial progress in AI-supported physics education and IoT-enabled smart education, but these strands are frequently examined separately. The present study brings them together through an integrated architecture in which sensing, prediction and intelligent decision support are connected to both physics education and educational administration.

The principal contribution is therefore not the invention of a new AI, IoT or ML algorithm. Rather, it is the integration and architectural organisation of these technologies into a coherent framework specifically oriented toward intelligent physics education and evidence-based educational administration. This provides a foundation for future implementation and empirical assessment without claiming that the proposed framework has already been experimentally validated.

IX. CONCLUSION

This study designed an AI-IoT-ML framework for intelligent physics education and evidence-based educational administration in smart learning environments. The framework integrates IoT-based data acquisition, data processing and storage, machine learning analytics, AI-driven decision support, and human-led educational and administrative action within a unified architecture. IoT provides contextual information from physics classrooms and laboratories, ML analyses and predicts relevant patterns, while AI transforms analytical outputs into actionable recommendations.

The proposed framework extends the application of intelligent technologies in physics education by connecting instructional activities with laboratory management, student support, resource utilisation and educational administration. Its layered architecture establishes a continuous pathway from environmental and learning data acquisition through analysis and intelligent recommendation to human decision-making and feedback.

The study contributes a conceptual and architectural artefact that addresses the identified fragmentation between smart learning technologies, physics education and educational administration. By maintaining educators and administrators within the decision-making process, the framework promotes a human-centred approach in which AI and ML provide analytical and decision-support capabilities while professional users retain responsibility for final educational and administrative decisions.

Overall, the proposed framework provides a coherent architecture for integrating AI, IoT and ML within smart physics learning environments and establishes a conceptual foundation for intelligent, data-informed educational practice and administration.

RECOMMENDATIONS

Based on the proposed framework, the following recommendations are made:

1. Institutions should adopt phased implementation of smart physics environments, beginning with IoT-based monitoring and gradually integrating machine learning and AI decision-support capabilities according to available infrastructure.
2. Physics laboratories should be equipped with appropriate IoT devices for monitoring relevant environmental conditions, equipment utilisation, experimental activities and other variables that can support teaching and laboratory management.
3. Educational institutions should establish appropriate data-management and privacy measures to ensure that information collected from students, staff, laboratories and connected devices is securely managed and used only for legitimate educational purposes.
4. Physics educators and educational administrators should receive appropriate AI and data-literacy training to enable them to interpret analytical outputs and critically evaluate AI-generated recommendations.
5. Human oversight should remain an essential component of implementation. AI-generated recommendations should support, rather than replace, the professional judgement of lecturers, laboratory personnel and educational administrators.
6. Institutions should promote collaboration among computer scientists, physics educators, educational administrators and ICT personnel during the implementation of AI-IoT-ML systems to ensure that technological development corresponds with actual educational and administrative requirements.

FUTURE WORK

Future research can extend the proposed framework from conceptual design to practical implementation and empirical evaluation. A prototype can be developed using physical or simulated IoT devices to demonstrate real-time data acquisition, processing, machine learning prediction and AI-based decision support within a physics laboratory environment.

Future studies can also investigate the performance of different machine learning algorithms for predicting student learning patterns, laboratory utilisation, equipment demand and other relevant educational indicators. Comparative evaluation of prediction

accuracy, processing latency, scalability and resource consumption can provide empirical evidence concerning the technical performance of the framework.

In addition, the framework can be implemented in selected physics laboratories and evaluated using authentic educational data. Such studies can examine usability, reliability, decision-support quality, learning outcomes, laboratory efficiency and administrative effectiveness. Future research should also investigate privacy-preserving data management, explainable AI, model fairness, security and human-AI interaction to strengthen the responsible deployment of intelligent educational systems.

Finally, the framework can be extended to other science disciplines and smart educational environments to determine its adaptability beyond physics education and to examine how the architecture can support broader institutional decision-making.

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