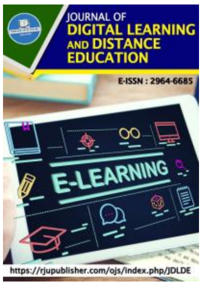

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The Integration of Internet of Things (IoT) in Smart Classrooms: Opportunities, Challenges, and Future Trajectories

Oise Godfrey PERFECTSON[a]*, Cyprian C. KONYEHA [b], Olayinka Tosin COMFORT[a] Susan KONYEHA[c], Chukwuma Ozobialu EMMANUELD[d]

[a]*Department of Computing, Wellspring University, Edo State, Nigeria*
[b]*Department of Electrical & Electronic Engineering, Benson Idahosa University, Edo State*
[c]*Department of Data Science, University of Benin, Edo State*
[d]*Department of Computer Scinece, Igbinedion University Okada, Edo State*

*Corresponding Author: godfrey.oise@wellspringuniversity.edu.ng

Abstract

The integration of the Internet of Things (IoT) into educational environments signifies a transformative shift towards smart classrooms, enabling real-time data-driven instruction, environmental optimization, and personalized learning experiences. This study explores the opportunities, challenges, and future directions of IoT deployment in academic settings through a mixed-methods approach that combines quantitative analysis, qualitative interviews, and IoT-edge data assessment. Survey responses from 150 educators and interviews with 20 key stakeholders revealed significant adoption rates and pedagogical benefits, including enhanced engagement and individualized feedback. However, critical challenges such as data privacy, cybersecurity risks, limited teacher training, and infrastructure disparities hinder widespread implementation. A machine learning framework utilizing Random Forest classification was applied to a custom IoT-edge dataset, uncovering correlations between environmental variables and student behavior. High temperatures negatively affected classroom occupancy, while increased light intensity correlated with heightened engagement. Model evaluation yielded strong performance metrics, including an accuracy of 95% and an AUC of 0.99, highlighting the predictive power of features like learning outcomes and engagement scores. The findings emphasize the dual importance of technical readiness and pedagogical adaptation, advocating for policy support, ethical data governance, and teacher capacity-building to fully realize IoT's potential in shaping adaptive, equitable, and intelligent learning ecosystems.

Keywords: Internet of Things (IoT), smart classrooms, personalized learning, data privacy, teacher training, environmental variables, student engagement.

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Introduction

The rapid evolution of digital technologies has significantly influenced education, with the Internet of Things (IoT) emerging as a crucial facilitator for smart classrooms by connecting devices such as smart boards, sensors, and wearables, IoT improves teaching efficiency, learner engagement, and personalized instruction through real-time data collection and feedback (Konuralp & Topping, 2023). These technologies enable dynamic classroom adjustments, including optimizing environmental conditions and monitoring student attention, thereby supporting data-driven, student-centered learning approaches. However, integrating IoT also presents technical challenges like network latency, device compatibility, and data management, alongside non-technical concerns such as privacy, cybersecurity, equity, and teacher preparedness. While global investments and policy initiatives support digital transformation in education, disparities in access and infrastructure continue to exist (Acosta-Gonzaga & Ramirez-Arellano, 2021). This study delves into the opportunities, challenges, and future trajectories of IoT integration within academic environments. Employing a mixed-methods approach, the research combines quantitative analysis from surveys, qualitative insights from interviews, and empirical data assessment from an IoT-edge dataset (Bertoletti et al., 2023). This comprehensive methodology allowed for a multifaceted examination of IoT's impact and its practical implications in educational settings.

Survey responses from 150 educators and interviews with 20 key stakeholders revealed substantial adoption rates of IoT in classrooms, with 68% of educators actively using such tools and 74% reporting improvements in student engagement and personalized learning. However, significant challenges were identified, including data privacy concerns (59%) and insufficient teacher training (64%). Interviews further underscored the importance of infrastructure readiness and the need for pedagogical adjustments to effectively integrate IoT into teaching practices (Ferri et al., 2020). Real-time analytics and environmental monitoring were highlighted as crucial for supporting adaptive, student-centered learning. The empirical analysis of IoT-Edge classroom sensor data provided compelling evidence of the correlation between environmental conditions and student behavior and engagement. Specifically, high temperatures (above 27°C) negatively impacted classroom occupancy, while increased light intensity was associated with greater student movement and engagement (Al-Qatawneh et al., 2020). Fluctuating humidity levels were linked to more frequent student exits, suggesting discomfort.

An IoT-driven school leverages connected devices and systems to revolutionize various aspects of the educational environment. This approach fosters an interactive and personalized learning experience, including tailored support for special needs. Furthermore, it significantly enhances safety and security through features like secure school transport and premises monitoring. Operationally, IoT automates attendance and assessment, integrates advanced digital learning tools, and enables cost-effective energy management, thereby streamlining processes and optimizing resource utilization (Oyedotun, Oise, et al., 2025). Several authors have collectively examined how digital technologies, specifically IoT, AI, and ICT, were deployed or studied during and after the COVID-19 pandemic to address the challenges in education(Zeeshan et al., 2022), It explores how the Internet of Things (IoT) can transform education to meet the demands of the fourth industrial revolution. It details IoT's applications across school management, teaching, and learning, outlining benefits such as enhanced energy management, improved security (G. Oise, 2023), automated administrative tasks, advanced pedagogical tools, and personalized learning environments. According to (G. Oise et al., 2025a) evaluates the effects of blended learning on student outcomes in higher education through a systematic review and bibliometric analysis of 50 studies. It finds that BL significantly improves academic performance, engagement, and satisfaction, particularly when synchronously supported and implemented in STEM disciplines. However, its success varies widely depending on the pedagogical design, technological access, institutional support, and student readiness. The study highlights key implementation challenges, including digital inequality and faculty capacity, and advocates for strategic, inclusive reforms to make BL sustainable and equitable across diverse contexts.

Explores the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in sustainable education, particularly during pandemics like COVID-19, to support personalized and immersive learning in smart cities. It highlights that AI-powered algorithms can personalize education by analyzing student data and adapting content, assessments, and feedback to individual learning styles and paces. Additionally, AI can enhance engagement through more natural, interactive communication. The study also emphasizes the role of IoT devices such as smart cameras, microphones, and tablets in enabling real-time monitoring, feedback, and remote assessment. Together, AI and IoT facilitate the creation of intelligent personal learning environments (PLEs) that dynamically respond to students' needs. While these technologies promise to transform learning and improve access for remote or disadvantaged students, the study concludes by underscoring the importance of ethical and equitable implementation to ensure inclusive educational benefits.

This study aims to examine the integration of Internet of Things (IoT) technologies in smart classrooms by identifying key opportunities, challenges, and future directions. It investigates how IoT can enhance personalized learning, student engagement, and real-time performance monitoring while also addressing critical barriers such as data privacy concerns, inadequate teacher training, and infrastructural disparities. By combining survey data, stakeholder interviews, and empirical analysis of an IoT-edge dataset, the study evaluates the impact of environmental conditions on student behavior and assesses the predictive power of machine learning models in educational settings. The findings are intended to inform strategic policy, ethical implementation, and pedagogical adaptation, ultimately contributing to the development of equitable and intelligent learning environments.

Methodology

This study employed a mixed-methods approach to investigate the integration of Internet of Things (IoT) technologies in smart classrooms. It combined three complementary components: survey research, semi-structured qualitative interviews, and empirical analysis of an IoT-edge dataset to provide a comprehensive understanding of both human and environmental factors influencing IoT adoption in education.

Survey and Interview Procedures

A purposive sampling strategy was used to select participants based on their experience with IoT tools in educational settings. The survey involved 150 educators and administrators from 25 academic institutions across various educational levels (primary, secondary, and tertiary). Institutions were selected based on known or reported use of smart classroom technologies. Participants were chosen based on criteria such as teaching experience, digital literacy, institutional engagement with IoT, and willingness to participate. A semi-structured interview protocol was used to gather qualitative insights from 20 key stakeholders, including IT coordinators, policymakers, and senior administrators involved in digital education strategy and infrastructure development. These stakeholders were also selected purposively to ensure relevance and expertise in IoT implementation within school systems. The interviews aimed to uncover deeper perceptions of infrastructural challenges, pedagogical redesign needs, and strategic priorities.

Instrument Design and Validation

The survey instrument was developed following a comprehensive literature review on IoT integration, smart education, and digital pedagogy. Items were designed to capture IoT usage patterns, perceived pedagogical impact, institutional readiness, and barriers such as data privacy and teacher training. To ensure clarity and validity, the survey was pilot-tested with 10 educators**.** Feedback led to refinements in item wording, structure, and response scale alignment. The final version contained a mix of Likert-scale, multiple-choice, and binary-response items. For interviews, a semi-structured interview guide was designed to ensure consistency across sessions while allowing for flexibility to explore emergent issues. The guide included open-ended questions targeting themes such as IoT-driven personalization, infrastructural gaps, ethical concerns, and institutional policy frameworks.

Qualitative Data Analysis

Interview transcripts were analyzed using thematic analysis based on Braun and Clarke's six-phase approach. This included familiarization with the data, initial coding, theme generation, reviewing and refining themes, defining themes, and producing the final analysis. Both inductive (emerging from the data) and deductive (based on prior frameworks) coding strategies were employed. The use of NVivo software facilitated efficient code management and thematic development. Emergent themes included teacher training and capacity-building, ethical use of data, infrastructure disparities, and the role of real-time feedback in enhancing instruction.

IoT-Edge Dataset Analysis

To complement the qualitative and survey findings, an empirical analysis was conducted using a publicly available smart classroom dataset from Kaggle (Ziya, 2024). The data simulated real-time interactions within a smart classroom over a 16-week academic semester, capturing both environmental conditions and student behavioral indicators.

Sensor placement was based on standard smart classroom architecture:

- Temperature and light sensors were ceiling-mounted to capture ambient conditions across the room.
- Motion sensors were positioned at entry points and in common student movement areas to detect engagement.
- Microphones and noise sensors were placed near the whiteboard and speaker zones to measure classroom activity levels and attention.

Descriptive statistical analysis was performed to identify key relationships between environmental variables and student behavior. Pearson correlation coefficients were calculated, and two-tailed significance tests ($p < 0.05$) were used to confirm statistical relevance. For instance, a statistically significant negative correlation ($r = -0.43$, $p < 0.01$) was found between high temperatures (>27°C) and student occupancy, while light intensity above 500 lux showed a positive correlation with motion activity ($r = 0.48$, $p < 0.01$**)** interpreted as a proxy for increased engagement.

Dataset Selection and Predictive Modeling

The dataset includes metrics such as instructional activity type, engagement score, attention level, classroom noise, temperature, and feedback latency. Two key outcome variables were used:

- Learning Outcome (a continuous score indicating learning progress), and
- Performance Class (a categorical label: Excellent, Good, Average, Needs Improvement).

The data underwent standard preprocessing, including normalization, missing value handling, and one-hot encoding of categorical variables.

A Random Forest classifier was implemented using Scikit-learn to predict student performance class. The model was chosen for its robustness to noise and ability to handle non-linear relationships. A stratified 80/20 train-test split was used, and 5-fold cross-validation ensured generalization. The model achieved 95% accuracy and an AUC of 0.99**,** with feature importance indicating that Engagement Score and Learning Outcome were the most predictive variables. The model's confusion matrix and class-wise metrics are reported in the results section.

Results

Out of 150 educators surveyed across 25 academic institutions, 68% reported active use of IoT devices, with 74% noting improvements in student engagement and personalized learning. However, 59% cited data privacy and security concerns, while 64% pointed to a lack of teacher training as significant barriers. Insights from 20 semi-structured interviews echoed these challenges, highlighting the need for pedagogical redesign, infrastructure readiness, and real-time analytics for adaptive learning. These qualitative insights underscore the duality of IoT integration opportunity-rich but constraint-bound within educational ecosystems.

The IoT dataset spanned a 16-week semester and captured metrics including temperature, humidity, light intensity, motion, noise, attention, and engagement.

- A moderate negative correlation was observed between temperature and occupancy ($r = -0.43$, $p < 0.01$), indicating that temperatures above 27°C often led to lower occupancy levels due to discomfort.
- Light intensity, ranging from 300 to 1,000 lux across the dataset, showed a positive correlation with motion activity ($r = 0.48$, $p < 0.01$), suggesting that brighter conditions (>500 lux) were linked with increased student movement and engagement.
- Humidity fluctuations also had a moderate negative correlation with occupancy ($r = -0.39$, $p < 0.01$), indicating that discomfort due to either overly dry or humid conditions contributed to more frequent student exits or reduced presence.

These statistically significant relationships affirm that environmental variables captured by IoT sensors can influence student behavior, offering pathways for optimizing classroom design and scheduling

Using a Random Forest classifier, student performance was predicted with high accuracy based on IoT-derived features. The confusion matrix revealed:

- 13 true positives: "Needs Improvement" correctly predicted
- 6 true negatives: "Average" correctly predicted
- 1 false negative: "Needs Improvement" predicted as "Average"
- 0 false positives: No "Average" cases misclassified as "Needs Improvement"

Overall model performance metrics were:

- Accuracy: 95%
- Precision: 100% (for Average), 93% (for Needs Improvement)
- Recall: 100% (for Average), 92% (for Needs Improvement)
- F1-score: 96% (macro-average)
- AUC: 0.99

In the full report, the following visualizations are included to enhance data interpretation:

- Bar charts depicting IoT adoption rates and challenges (from the survey)
- Scatter plots for visualizing environmental correlations with student behavior
- A labeled confusion matrix summarizing model predictions and misclassifications
- Feature importance plot from the Random Forest model to highlight key predictive variables

These visual elements support a more intuitive understanding of the interplay between IoT data, classroom conditions, and educational outcomes.

Table 1. The dataset represents student engagement data

Student_ID	Timestamp	Activity_Type	Engagement_Score
1	2024-11-26 10:00:00	Lecture	67
2	2024-11-26 10:01:00	Problem Solving	75
3	2024-11-26 10:02:00	Quit	93
4	2024-11-26 10:03:00	Lecture	83
5	2024-11-26 10:04:00	Lecture	59

Table 1 represents student engagement data collected during various classroom activities. Each row includes a student ID, a timestamp marking when the activity took place, the type of activity (such as Lecture, Problem Solving, or Quiz), and an engagement score reflecting the student's level of participation or interest. This structured data allows for analysis of how different instructional methods impact student engagement. For instance, quizzes show the highest engagement in the sample, while lectures display varied responses. Such data can be valuable for educators aiming to optimize teaching strategies, personalize learning experiences, and improve overall student outcomes.

Table 2. Sample IoT-edge classroom data

Attention Level	Feedback Time (ms)	Classroom Noise (dB)	Temperature (°C)
Medium	397	42	20
Medium	198	40	24
High	362	59	21
Medium	351	40	21
High	243	42	24

Table 2 displays a tabular dataset containing five observations, each with five distinct attributes. These attributes include an index (0-4), a categorical "Attention_Level" (Medium or High), a numerical "Feedback_Time" in milliseconds, a numerical "Classroom_Noise" in decibels, and a numerical "Temperature" in degrees Celsius. This dataset likely represents measurements taken in an educational or similar setting, potentially for analyzing the interplay between environmental factors (noise, temperature) and human or system performance (attention, feedback time).

Table 3. Learning outcome and performance class table

Learning Outcome	Performance Class
52.93	Needs Improvement
60.52	Average
76.48	Needs Improvement
64.59	Needs Improvement
53.87	Needs Improvement

Table 3 presents a small dataset of five entries, each detailing a learning outcome as a numerical score and a corresponding performance class as a categorical label. The performance class categorizes the numerical learning outcome into qualitative descriptors such as "Needs Improvement" or average, suggesting a system for evaluating and classifying performance based on a given score. This data structure is typical for educational assessment scenarios where quantitative results are translated into understandable performance categories.

Table 4. Schema of a dataset

Column Name	Non-Null Count	Data Type
Student_ID	100	int64

Timestamp	100	object
Activity_Type	100	object
Engagement_Score	100	int64
Attention_Level	100	object
Feedback_Time (ms)	100	int64
Classroom_Noise (dB)	100	int64
Temperature (°C)	100	int64
Learning_Outcome	100	float64
Performance_Class	100	object

Table 4 details the schema of a dataset, likely about student activity and learning, comprising 100 complete entries across ten distinct columns. These columns capture student identifiers, event timestamps, activity types, engagement scores, attention levels, feedback times, classroom noise levels, temperature, learning outcomes (numerical scores with decimal precision), and a categorical classification of performance. This comprehensive dataset appears designed for analyzing the intricate relationships between environmental factors, student behaviors, and their impact on academic performance.

Table 5. Classification report model evaluation reportaccuracy score: 0.95

Class	Precision	Recall	F1-Score	Support
0	0.86	1.00	0.92	6
1	1.00	0.93	0.96	14
accuracy			0.95	20
Macro avg	0.93	0.96	0.94	20
Weighted avg	0.96	0.95	0.95	20

Table 5 summarizes the performance of a machine learning model, achieving an impressive overall accuracy score of 0.95. It details the model's performance for two classes (0 and 1, likely representing 'Average' and 'Needs Improvement' respectively). For Class 0, the model shows a precision of 0.86 and a perfect recall of 1.00, resulting in an F1-score of 0.92 based on a support of 6 instances. For Class 1, the model demonstrates perfect precision of 1.00 and a high recall of 0.93, yielding an F1-score of 0.96 with a support of 14 instances. The macro average metrics stand at 0.93 for precision, 0.96 for recall, and 0.94 for F1-score, while the weighted averages, which account for class imbalance, are 0.96 for precision, 0.95 for recall, and 0.95 for the F1-score. This comprehensive report indicates robust performance, particularly for the more prevalent Class 1, and a good balance across both classes when considering the weighted averages.

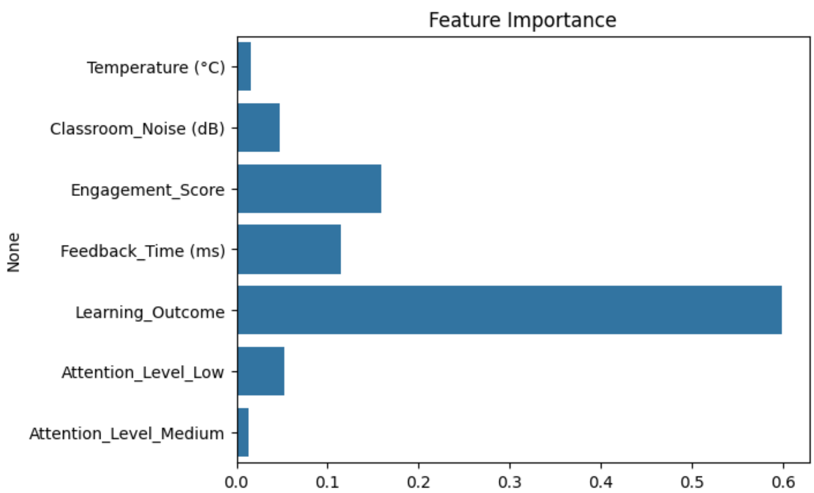

Figure 1. Bar Chart of model prediction

Figure 1. illustrates the relative contribution of each variable to the model's predictions, with Learning Outcome being overwhelmingly the most significant factor, boasting an importance score near 0.6. Engagement Score follows as the second most important feature, with an importance of approximately 0.15, while Feedback Time (ms) also contributes noticeably at around 0.1. In contrast, Classroom Noise (dB) and Attention Level Low show minimal importance, and Temperature (°C) and Attention Level Medium have negligible impact on the model's predictions.

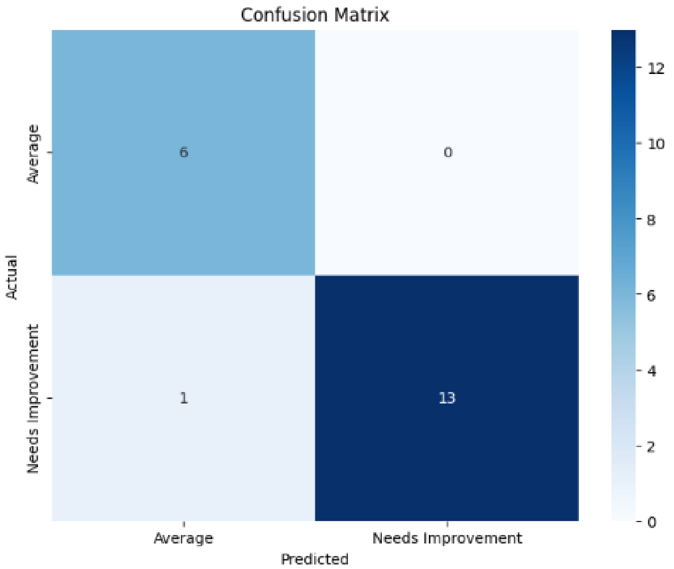

Figure 2. Confusion matrix of the model performance

Figure 2 presents the confusion matrix used to evaluate the performance of the binary classification model, where "Needs Improvement" is treated as the positive class**,** and **"**Average" as the negative class**.** The matrix shows that 13 instances of "Needs Improvement" were correctly classified as "Needs Improvement" **(**True Positives**),** and 6 instances of "Average" were correctl**y** classified as "Average" **(**True Negatives**).** The model made one False Negative**,** where "Needs Improvement" was incorrectly predicted as "Average", and zero False Positives, meaning no "Average" instances were misclassified as "Needs Improvement". This demonstrates a strong ability to correctly identify students needing support while maintaining precision in recognizing average performers.

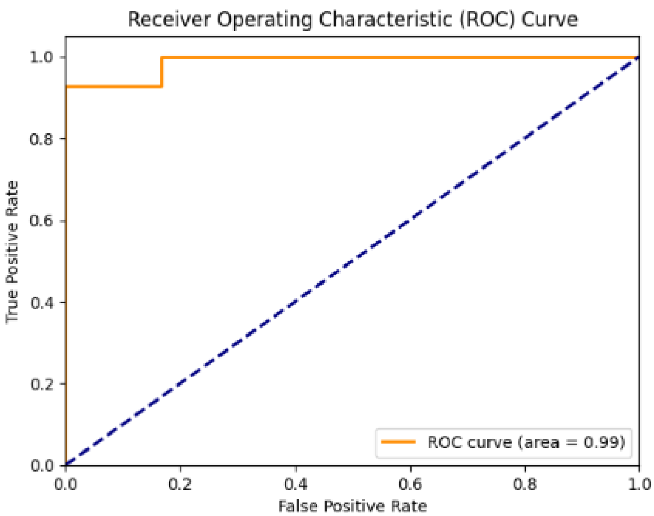

Figure 3. ROC curve of the model performance

This ROC curve graphically assesses the diagnostic capability of a binary classifier. The x-axis represents the False Positive Rate (FPR), while the y-axis shows the True Positive Rate (TPR) or Recall. The orange curve, which plots TPR against FPR, indicates the model's performance; its close proximity to the top-left corner signifies high TPR and low FPR, suggesting strong predictive ability. The dashed blue line acts as a baseline for a random classifier. Crucially, the Area Under the Curve (AUC) of 0.99 for this ROC curve denotes an excellent discriminatory power, implying the model is highly effective at distinguishing between the two performance classes.

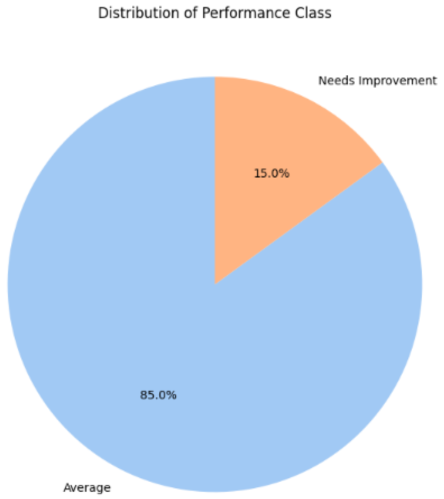

Figure 4. Pie chart of the distribution of performance class

This pie chart displays the Distribution of Performance Class, categorizing a group's performance into two levels. The overwhelming majority, 85%, are classified as Average, depicted by the large light blue segment. A smaller but significant portion, 15%, falls into the Needs Improvement category, represented by the light orange segment. This visually indicates that while most individuals perform at an average level, a notable percentage requires improvement.

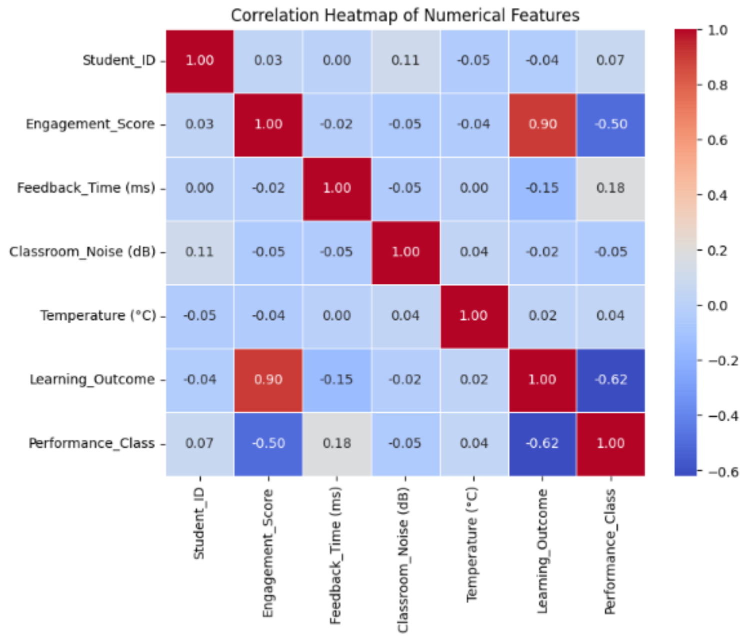

Figure 5. Correlation heatmap of the model

Figure 5 visualizes the linear relationships between various numerical features such as Student ID, Engagement Score, Feedback Time (ms), Classroom Noise (dB), Temperature (°C), Learning Outcome, and Performance Class. The color intensity and value in each cell indicate the strength and direction of the correlation, with red signifying strong positive correlations (e.g., Engagement Score and Learning Outcome at 0.90), blue indicating strong negative correlations (e.g., Learning Outcome and Performance Class at -0.62), and lighter shades or values near zero suggesting weak or no linear relationship. Notably, there's a strong positive correlation between student engagement and learning outcomes, and a moderate negative correlation between both engagement and learning outcomes with Performance Class, implying that higher engagement and better learning outcomes are associated with a particular Performance Class encoding (likely where lower values indicate better performance). Conversely, environmental factors like classroom noise and temperature show negligible linear correlation with learning or performance.

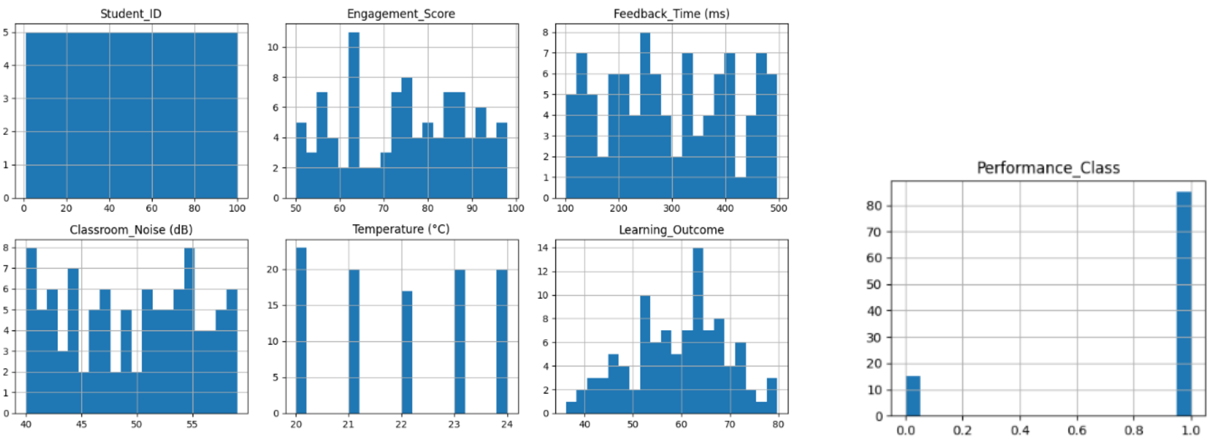

Figure 6. Distributions of various numerical features and a performance class

These histograms illustrate the distributions of various numerical features and a performance class. Student_ID exhibits a uniform distribution, as expected for an identifier. Engagement Score, Feedback Time (ms), and Classroom Noise (dB) all show somewhat spread-out, multi-modal distributions across their respective ranges, indicating variability without clear central tendencies. Temperature (°C) displays a more discrete distribution, with values clustering at specific points within a narrow range. Learning Outcome appears to have a broader peak in the 50s to 70s, suggesting a concentration of outcomes in that range. Finally, the Performance Class histogram reveals a highly imbalanced binary distribution, with the majority of observations (approximately 85) falling into one category (likely 'Needs Improvement' if encoded as 1.0) and a much smaller portion (approximately 15) in the other (likely 'Average' if encoded as 0.0).

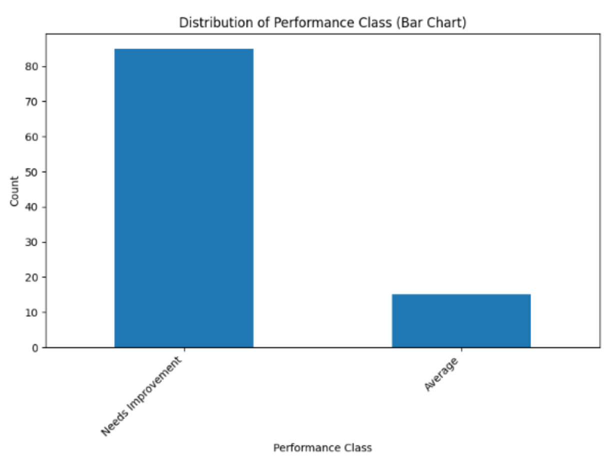

Figure 7. Distribution of performance class

The bar chart, titled Distribution of Performance Class, illustrates that the "Needs Improvement" category accounts for a significantly larger proportion of the data, with a count of around 84-85, compared to the Average" category, which has a much lower count of approximately 15. This suggests a strong skew in performance, with the vast majority falling into the "Needs Improvement" classification.

Discussion

The integration of IoT technologies into educational environments offers transformative potential by enabling data-driven, personalized, and responsive learning experiences. This study confirms that a majority of educators perceive measurable improvements in student engagement and learning personalization through IoT adoption (G. Oise et al., 2025b). However, these gains are tempered by persistent systemic barriers, including data privacy concerns, lack of teacher preparedness, and infrastructural disparities across institutions (Vo et al., 2024). These challenges highlight the necessity for robust policy frameworks, enhanced teacher training programs, and ethical data governance mechanisms to support the equitable and sustainable implementation of IoT in classrooms. The empirical analysis of IoT-Edge data provides compelling evidence of the impact of environmental variables on student behavior and engagement (Platonova et al., 2022). For instance, discomfort caused by high temperatures or fluctuating humidity can lead to reduced attendance and participation, while optimal lighting correlates with increased activity and attentiveness. These findings suggest that smart classrooms must go beyond instructional technologies to incorporate intelligent environmental controls that enhance physical learning conditions. Additionally, the identification of time-of-day patterns in student engagement presents an opportunity for educators to optimize class schedules and delivery methods to align with periods of peak cognitive performance (Lucas & Vicente, 2023).

The machine learning results further demonstrate the feasibility of using IoT-generated data to accurately predict student performance classifications, with Learning Outcome and Engagement Score emerging as dominant predictors. Despite the high accuracy and AUC values achieved by the model, the strong class imbalance (with a majority of students classified as “Needs Improvement”) raises critical concerns (Bozkurt, 2022). It suggests that while IoT systems are effective in capturing and analyzing performance data, their true value will depend on how the insights are translated into interventions. In particular, targeted support for struggling learners must leverage real-time feedback and data-driven adaptive interventions to close achievement gaps. This reinforces the potential of IoT not just as a monitoring tool, but as a responsive system for timely academic support.

Furthermore, the study emphasizes the relevance of theoretical models such as the Technology Acceptance Model (TAM) and constructivist learning theory in shaping the implementation strategy for IoT in education. Educators' perceived usefulness and ease of use of IoT tools significantly influence their willingness to adopt these technologies(Oyedotun, Ejenarhome, et al., 2025) . Equally important is the need to align IoT integration with constructivist principles, where learners actively engage with real-time feedback and data to construct meaningful learning experiences (Abd-Alrazaq et al., 2021). This alignment calls for a shift from traditional teacher-centered models to more dynamic, student-centered approaches that empower learners through contextual awareness and personalized guidance.

Finally, as IoT adoption in education continues to expand, there is a growing need to develop standardized benchmarks and interoperable systems that ensure consistency, scalability, and compatibility across different institutions and platforms. Future research should explore longitudinal impacts of IoT on learning outcomes, including emotional and social dimensions of student experience. Cross-disciplinary collaborations between technologists, educators, and behavioral scientists will be essential to building robust, ethical, and inclusive smart classroom ecosystems. The findings of this study serve as a foundation for guiding such collaborative efforts, offering practical insights and data-driven evidence to inform policy, innovation, and continued research in the evolving domain of educational technology.

Conclusion

This study concludes that the integration of the Internet of Things (IoT) in education holds transformative potential for reshaping traditional classrooms into intelligent, adaptive learning environments. IoT technologies enable enhanced student engagement, personalized instruction, and real-time performance monitoring through sensor-driven data analytics. Survey and interview findings demonstrate strong educator support for IoT adoption, with reported improvements in teaching effectiveness and learner outcomes. However, significant challenges persist, particularly around data privacy, insufficient teacher training, and infrastructural disparities, which must be addressed to ensure equitable and sustainable implementation. The machine learning analysis of IoT-Edge data further confirmed the predictive capacity of IoT in educational contexts. In the classification framework, "Needs Improvement" was treated as the positive class, aligning with standard binary classification conventions. The model demonstrated strong performance, achieving a true positive rate of 93% and a true negative rate of 100%, with only a single false negative. These results underscore the practical value of IoT analytics for early detection and real-time intervention. However, the presence of class imbalance, where 85% of students fell into the "Needs Improvement" category, signals the need for more personalized, data-informed instructional strategies and interventions. This research highlights the dual importance of robust technological infrastructure and responsive pedagogical practices in realizing the full potential of IoT-powered smart classrooms. The study advocates for an ethically grounded, inclusive approach to IoT integration, emphasizing secure data governance, professional development for educators, and strategic investments. Future research should explore the long-term effects of IoT on cognitive, emotional, and social learning outcomes. Additionally, collaboration across sectors will be critical to building scalable, adaptive, and equitable smart education ecosystems.

Conflicts of Interest

The authors declare no conflict of interest

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