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INTERNET OF EDUCATIONAL THINGS AND MACHINE LEARNING

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Abstract The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) is reflected in the Internet of Educational Things (IoEd), in which connected devices and digital platforms are used to support learning environments. Research on Machine Learning (ML) in IoEd is fragmented, and comprehensive evaluation is limited. A systematic and bibliometric review of ML-based IoEd studies from 2015 to 2025 is presented, and a structured screening procedure is applied for study selection. A taxonomy that includes supervised, unsupervised, deep, and reinforcement learning is introduced, and applications in adaptive learning, personalized feedback, engagement monitoring, and resource management are examined. Key challenges are identified, i.e., data scarcity, class imbalance, device heterogeneity, limited interpretability, privacy concerns, and constraints in edge and fog computing environments. Future research directions are identified through the integration of generative AI and Large Language Models (LLMs), Explainable Artificial Intelligence (XAI), Federated Learning (FL), Multimodal Learning Analytics (MMLA), digital twins, and energy efficient ML methods. The findings indicate that the integration of ML and IoEd supports the development of intelligent educational systems and requires interdisciplinary collaboration to ensure transparent, ethical, and scalable solutions.

Keywords: Explainable Artificial Intelligence, Machine Learning, big data, Data Science, Federated Learning, Internet of Educational Things (IoEd), Learning Analytics, Education.

AMS Mathematics Subject Classification: 68T05, 68T07, 68M11, 62H30.

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1 Introduction

The rapid digital transformation of education is driven by advances in the Internet of Things (IoT) and Artificial Intelligence (AI), which lead to the emergence of the Internet of Educational Things (IoEd). IoEd is defined as a system in which connected devices, sensors, learning platforms, and analytical tools are integrated to support adaptive and data driven learning environments [1]. Real time data from educational activities are collected and analyzed to evaluate student engagement, academic performance, and resource use in educational institutions [2, 3]. This integration of physical and digital learning environments is used to support context aware educational strategies and informed decision making, which improve educational outcomes [4]. A major challenge in IoEd is the extraction of meaningful insights from the large and heterogeneous data produced by interconnected devices and platforms [1]. Machine Learning (ML) is applied to transform raw data into analytical results that support adaptive and personalized learning systems [5, 6]. Techniques such as supervised learning, unsupervised learning, Deep Learning (DL), and Reinforcement Learning (RL) are used to predict student performance, analyze multimodal data, support emotion recognition, and optimize learning processes [7, 10]. However, previous studies on ML in IoEd remain fragmented and limited in scope, which indicates the need for a systematic review that consolidates current research and identifies future directions.

Table 1: Critical evaluation of key studies related to ML in IoEd.

Authors and Year	Objective	Advantages	Disadvantages
Korkmaz & Correia (2019) [11]	Chart trends of ML in educational media up to 2017.	Provides historical mapping of ML use in education; identifies adoption areas.	Outdated: predates deep multimodal sensing, FL, and on-device inference central to IoEd.
Zeeshan et al. (2022) [12]	Survey IoT for sustainable smart education, focusing on devices, use cases, and stakeholders.	Offers a broad overview of IoT in education; emphasizes sustainability and practical applications.	ML is treated peripherally; lacks taxonomy, evaluation, synthesis, and detailed methodological depth.
Li & Wang (2023) [13]	Link IoT/educational platforms with the adoption of ML.	Integrates IoT and ML in education; highlights potential pathways for adoption.	Conceptual/structural; weak on datasets, model classes, and strict comparative results.
Abuhassna et al. (2024) [14]	Present a bibliometric map of AI/ML in education.	Provides large-scale scientometric insights; shows research trends.	Focuses on AI/ML in general education, not IoEd; does not address sensor/edge-driven pipelines, FL, or benchmarks.
Spaho et al. (2025) [15]	Review IoT–personalized online learning integrations.	Discusses architectures for personalized learning with IoT support; offers design insights.	Emphasis on architectures rather than ML methods; lacks comparison of models, metrics, and reproducible datasets.
Le et al. (2024) [16]	Synthesize distributed ML methods for IoT.	Strong coverage of distributed learning relevant to resource-constrained IoT.	No focus on education-specific data, ethics, or pedagogy; limited application to IoEd.

A detailed examination of prior studies indicates that no ML focused systematic review of IoEd is currently available. Existing literature does not provide a unified taxonomy that links supervised learning, unsupervised learning, DL, and RL tasks with classroom platforms. Comparative evaluation of models and performance metrics on public datasets is also limited. In addition, the integration of distributed and privacy preserving approaches, such as FL and split learning, is rarely examined in educational environments. Requirements related to XAI, fairness, and governance are also insufficiently addressed. These limitations indicate the absence of an integrated ML oriented review of IoEd. To address this gap, a method focused synthesis, benchmark inventory, and research roadmap for ML in IoEd are presented.

The main objective of this paper is to consolidate and advance knowledge on the integration of ML within IoEd through a systematic and critical review. Previous studies examine IoT applications in education or ML use in e learning, yet a systematic review that focuses on the convergence of ML and IoEd is not provided. In this study, the current state of ML driven IoEd research is analyzed, a structured taxonomy of applications and methods is presented, and persistent limitations and research gaps are identified. Bibliometric mapping and qualitative synthesis are combined to present an overview of the field and to highlight future research directions. Four main contributions are provided. First, a taxonomy of ML applications in IoEd is proposed based on learning paradigms and educational domains. Second, a bibliometric and scientometric analysis of publication trends, major contributors, and research clusters is presented. Third, the strengths and limitations of existing studies are evaluated to identify methodological, technical, and pedagogical gaps. Fourth, future research directions are outlined, with attention to XAI, FL, multimodal analytics, and ethical considerations. The remainder of the paper presents the review methodology, an overview of IoEd, a taxonomy of ML applications, bibliometric analysis, comparative evaluation of ML methods, discussion of research challenges, identification of future directions, presentation of a conceptual IoEd architecture, and final conclusions.

2 Methodology

A Systematic Literature Review (SLR) protocol aligned with PRISMA guidelines is adopted to ensure transparency, reproducibility, and academic rigor. Qualitative synthesis and bibliometric analysis are combined to evaluate ML applications in IoEd. The literature search is conducted across five databases, i.e., Scopus, WoS, IEEE Xplore, SpringerLink, and ScienceDirect, to ensure broad coverage and reduce publication bias. A keyword-based Boolean search strategy is applied, and search terms are organized into four categories related to IoEd, ML, education and analytics, and IoTвЂ“AI integration. An initial set of 278 articles from 2000 to 2025 is retrieved. Inclusion criteria are applied to select peer reviewed journal articles and full conference papers in English from 2015 to 2025, while irrelevant studies are excluded. After filtering, 123 articles are retained, and screening is conducted in three stages according to PRISMA. First, title and abstract screening is used to remove studies from irrelevant domains. Second, full text evaluation is applied to assess methodological rigor and relevance. Third, quality assessment is conducted to confirm peer review status, dataset credibility, and the presence of ML based methods. After this multi stage evaluation, 16 studies are retained. These studies represent key ML based IoEd applications, including student performance prediction, adaptive learning, anomaly detection, and distributed learning methods. The complete screening process is illustrated in Figure 1. To complement the qualitative synthesis, bibliometric analysis is conducted to examine ML driven IoEd research. VOSviewer is used for co authorship analysis, keyword co occurrence mapping, and co citation analysis. Biblioshiny is applied to analyze publication trends over time, country level research contributions, and thematic development. CiteSpace is used to identify emerging keywords and influential authors. This combined approach enables quantitative mapping of the research landscape and supports qualitative identification of methodological and pedagogical gaps in ML based IoEd research.

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3 Overview of Internet of Educational Things (IoEd)

IoEd is defined as an evolution of the IoT paradigm that is adapted to digital education needs [1, 18]. IoT enables the interconnection of physical devices, sensors, and cloud infrastructures for data exchange and automation. Early educational implementations are represented by e learning systems, where digital platforms are used for content delivery and assessment but limited personalization is provided. With the integration of IoT technologies, smart learning environments are introduced, where devices such as wearables, interactive boards, and

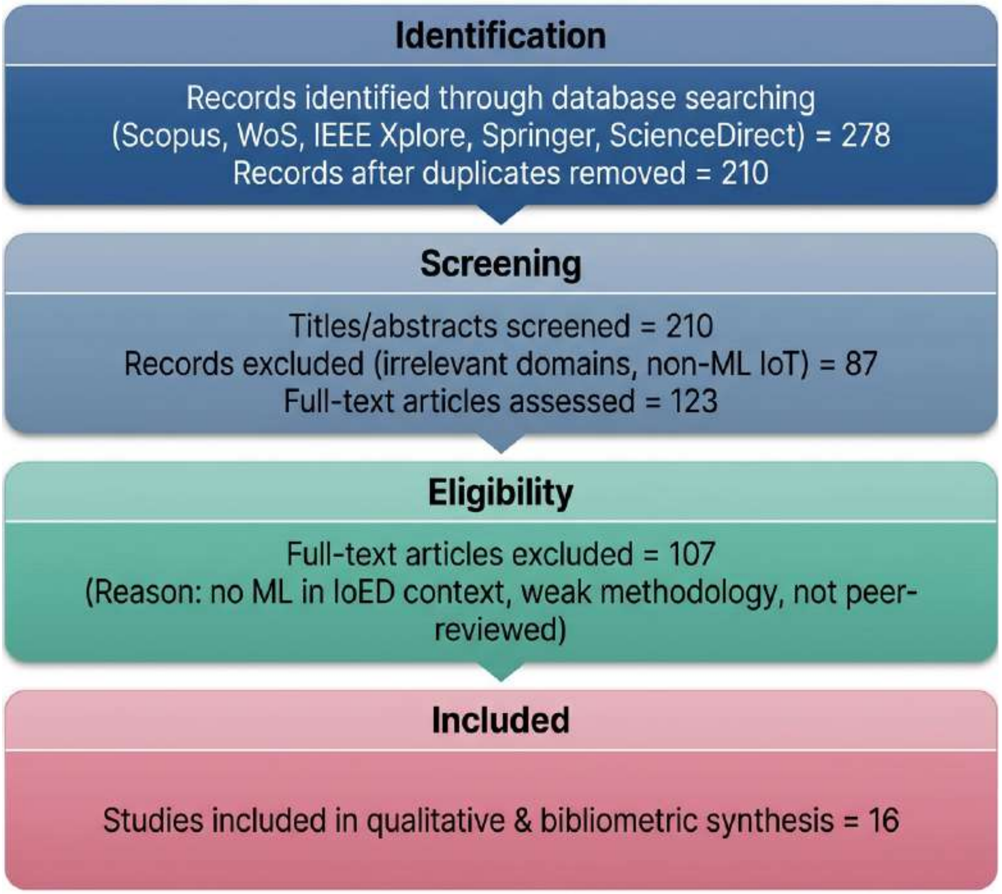

Figure 1: Multi-stage screening process of the reviewed literature based on the PRISMA protocol.

sensor enabled classrooms are used to monitor student engagement and resource use [19]. IoEd extends this concept through the integration of ML, real time analytics, and edge or fog computing, which transform heterogeneous educational data into actionable insights [7]. A transition from technology-assisted instruction to intelligent IoEd environments is observed, in which personalized learning and institutional efficiency are supported. The architecture of IoEd is designed to manage large-scale educational data, and two models, i.e., centralized and decentralized architectures, are identified [20]. In centralized architectures, data from connected devices, such as smartboards, wearables, and IoT-enabled platforms, is transmitted to cloud-based servers for processing [19]. This approach supports large-scale storage and advanced ML analysis, but latency, network dependency, and privacy concerns are introduced. In contrast, decentralized architectures process data near the source through edge and fog computing, in which local and intermediate processing is applied [6]. These approaches support real-time analytics, context-aware personalization, and improved data privacy.

The integration of edge and fog computing in IoEd creates opportunities that extend beyond conventional e learning systems. Personalized learning is supported through localized data processing and ML methods, where instructional content is adapted to individual learner needs [21]. Exercise difficulty is adjusted, supplementary materials are recommended, and immediate corrective feedback is provided. Learning efficiency is improved and inclusive education is supported through accommodation of diverse learning styles and abilities.

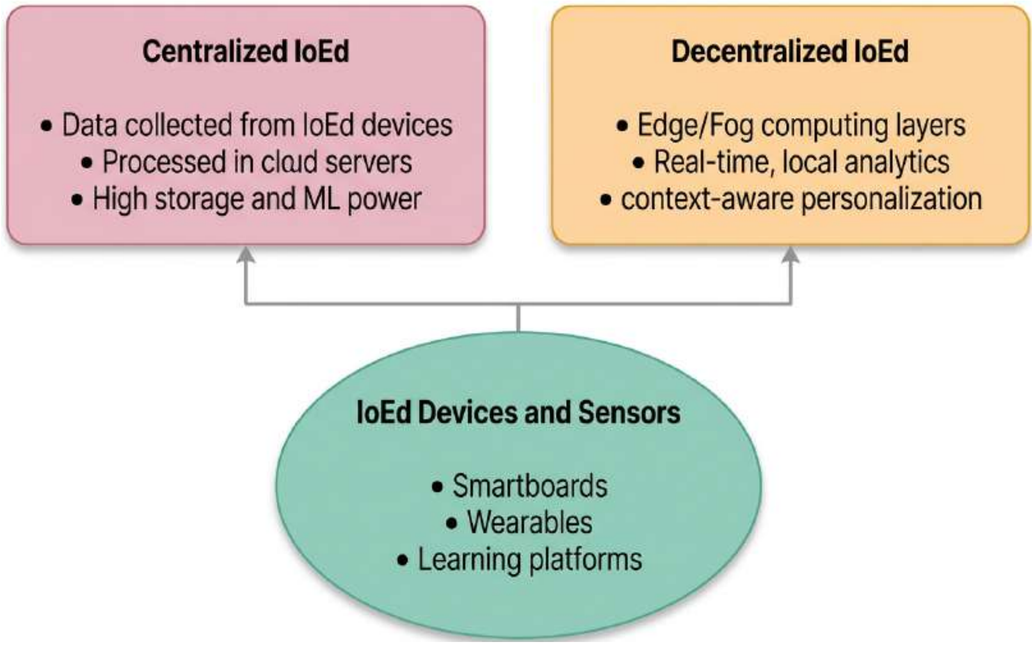

Figure 2: Architectural models of IoEd, highlighting centralized versus decentralized approaches.

Engagement monitoring is also enabled through IoEd architectures that collect indicators of student attention and motivation from multimodal sensors, including eye tracking devices, physiological monitors, and digital interaction data. Real time analysis of these signals is applied to identify disengagement and to support timely pedagogical intervention [22]. At the institutional level, aggregated engagement information is used for data informed curriculum design and resource management. In addition, Intelligent Tutoring Systems (ITS) are identified as a key application of ML in IoEd. Adaptive instructional support is delivered through decentralized architectures that integrate sensing technologies with ML models. Student misconceptions are diagnosed, learning pathways are personalized, and targeted explanations are provided in real time [23]. Access to educational support is expanded, especially in resource-constrained environments. The shift from centralized to decentralized architectures, supported by edge and fog computing, enhances IoEd capabilities. Personalized learning, engagement monitoring, and ITS deployment are supported. However, challenges related to interoperability, scalability, and ethical data management are identified and require further investigation. Intelligent Tutoring Systems (ITS) are identified as a key application of ML in IoEd. Adaptive instructional support is delivered through decentralized architectures that integrate sensing technologies with ML models. Student misconceptions are diagnosed, learning pathways are personalized, and targeted explanations are provided in real time [23]. Access to educational support is expanded, especially in resource-constrained environments. The shift from centralized to decentralized architectures, supported by edge and fog computing, enhances IoEd capabilities. Personalized learning, engagement monitoring, and ITS deployment are supported. However, challenges related to interoperability, scalability, and ethical data management are identified and require further investigation.

4 Machine Learning in IoEd

The integration of ML into the Internet of Educational Things (IoEd) is associated with applications such as student performance prediction, adaptive tutoring, engagement monitoring, and system optimization [2]. Due to the breadth of these applications, a taxonomy is required to organize the research domain and to identify methodological patterns and research gaps. A classification is presented in Figure 3, in which ML applications in IoEd are grouped into four directions, i.e., supervised learning, unsupervised learning, DL, and RL. Each category is associated with distinct capabilities and specific educational challenges.

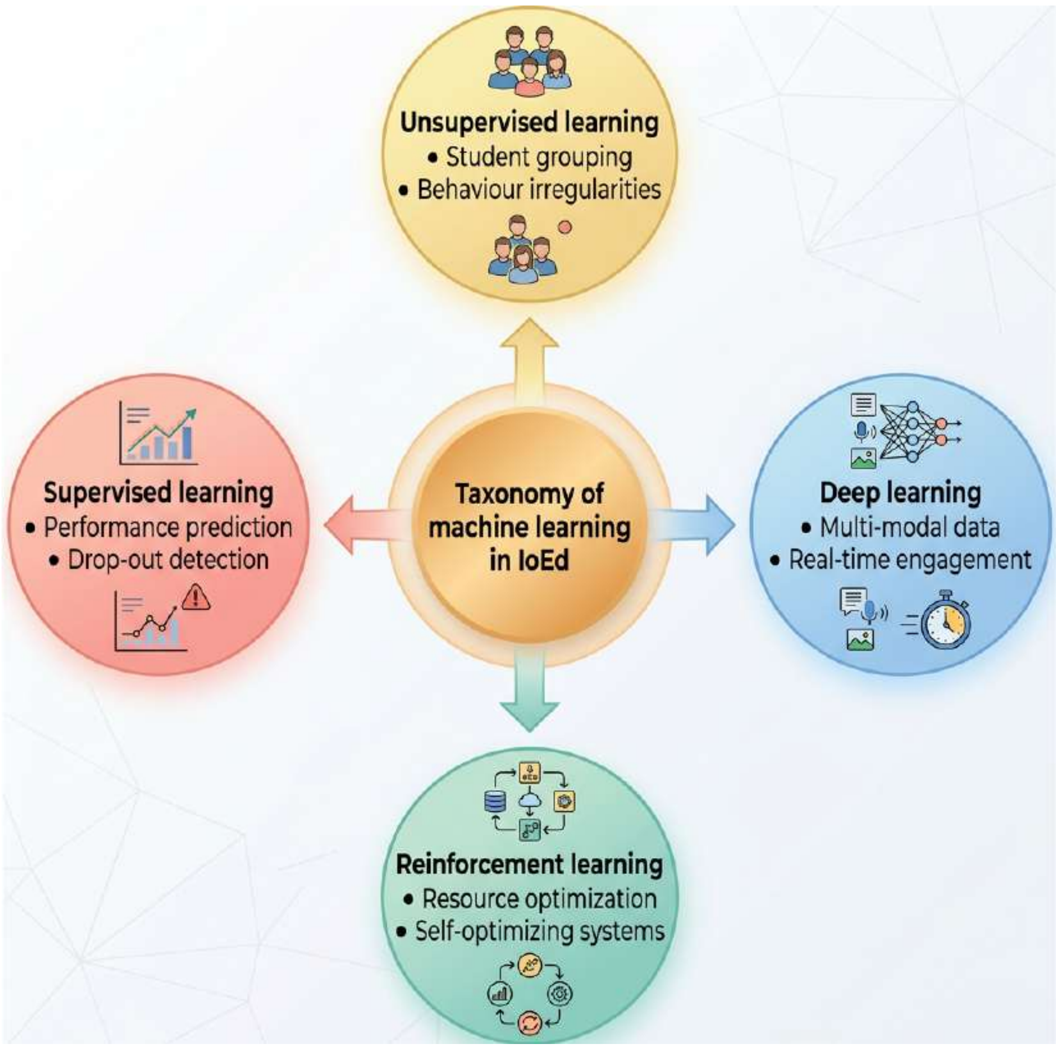

Figure 3: Taxonomy of ML in IoEd with representative use cases.

IoEd is developed as an educational extension of IoT that integrates connected devices, sensors, and digital platforms to support data driven learning environments [1, 18]. Early digital education systems rely on e learning platforms that deliver content and assessments but provide limited personalization. With the adoption of IoT technologies, smart learning environments are introduced, where devices such as wearables, interactive boards, and sensor enabled classrooms monitor student engagement and resource usage [19]. IoEd further advances this model through the integration of ML, real time analytics, and edge or fog computing, which convert heterogeneous educational data into actionable insights and support personalized and adaptive learning systems [7]. The architecture of IoEd is structured around centralized and decentralized computational models [20]. Centralized architectures rely on cloud infrastructures where data from connected devices is transmitted to remote servers for processing and storage [19]. This model supports large scale data analysis, but latency, network dependency, and privacy concerns are introduced. In contrast, decentralized architectures process data near the data source through edge or fog computing. Edge computing enables local processing on or near IoT devices, while fog computing provides intermediate nodes that aggregate and analyze data before transmission to the cloud [6]. These decentralized approaches support real time analytics, context aware personalization, and improved privacy protection in educational environments.ML applications in IoEd appear across several educational domains. In learning analytics, student data such as grades, interaction logs, and biometric signals are analyzed to predict academic performance and to identify learners who require support. Supervised models such as RF and gradient boosting are applied for prediction, while clustering methods are used to detect knowledge gaps and to support collaborative learning [27]. In smart classrooms, multimodal data are collected through IoT devices to evaluate student engagement and participation. CNN and recurrent models are applied to analyze visual and temporal learning patterns, although privacy concerns remain significant [28]. Adaptive learning systems also apply ML based recommender models to personalize educational content, where RL is used for adaptive sequencing of learning materials [29]. ML is also applied to security and privacy through anomaly detection and intrusion monitoring, while FL enables collaborative model training without the exchange of raw institutional data. Emotion recognition and behavioural analysis are further supported through CNN and transformer models that interpret affective and behavioural signals for adaptive tutoring and engagement monitoring. These applications demonstrate that ML supports predictive analytics, personalized learning, secure infrastructures, and responsive educational environments in IoEd.

5 Bibliometric and Scientometric Analysis

Bibliometric analysis of source titles indicates that ML-based IoEd research is distributed across journals in educational technology, computer science, and applied AI. Major venues include Computers and Education: Artificial Intelligence, Education and Information Technologies, IEEE Access, Sustainability, and Sensors, in which studies on smart educational environments are published. Research contributions are reported from multiple regions, with China, India, and the United States as leading contributors, while European countries such as the UK, Germany, and Spain also contribute through collaborative initiatives. Keyword co-occurrence analysis identifies dominant themes such as Internet of Educational Things, machine learning, deep learning, adaptive learning, student performance prediction, and engagement monitoring, while recent terms such as federated learning, XAI, multimodal analytics, and emotion recognition are also observed. The map in Figure 4 shows three clusters related to learning analytics and performance prediction, smart classrooms and engagement monitoring, and security, privacy, and ethical AI, which indicate a shift toward privacy-aware analytics and adaptive tutoring. Citation analysis identifies the intellectual foundations of ML in IoEd. Highly cited studies include Korkmaz and Correia (2019) [11], in which ML applications in education are examined, and Zeeshan et al. (2022) [12], in which IoT for sustainable smart education is reviewed. Recent influential contributions include Spaho et al. (2025) [15], where IoT integration in personalized learning is analyzed, and Le et al. (2024) [16], where distributed ML for IoT systems is investigated. Frequently cited keywords include learning analytics and adaptive learning, followed by deep learning and emotion recognition. Increasing citation frequency of federated learning and explainable artificial intelligence (XAI) indicates rising attention to ethical, privacy aware, and interpretable ML models in education.

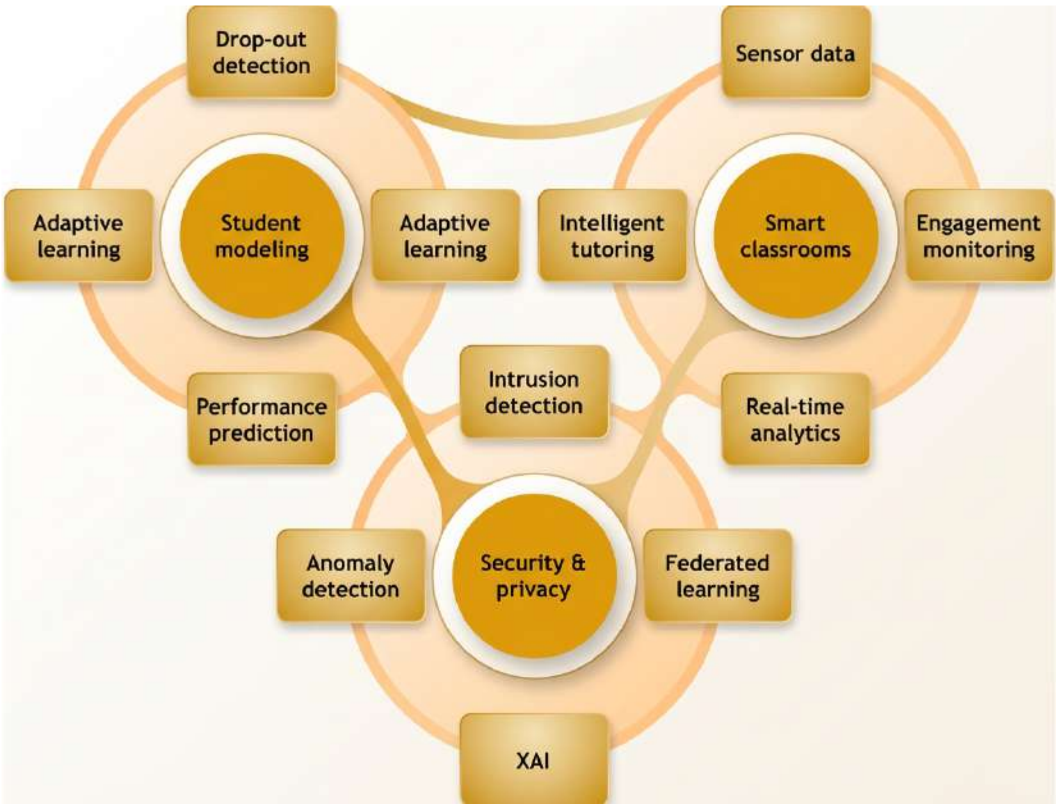

Figure 4: Keyword co-occurrence map of ML in IoEd research (2015–2025), generated using a VOSviewer-style analysis.

Bibliometric and scientometric results indicate that ML in IoEd is recognized as a mature research domain. Publication growth, diverse international contributions, and expansion of research themes are observed. Keyword and citation patterns indicate a transition from basic learning analytics to adaptive, intelligent, and privacy aware educational systems. These findings highlight the importance of continuous integration of ML methods with educational practices in order to support technological development and ethical responsibility in future IoEd applications.

6 Comparative Analysis of ML Techniques in IoEd

This section evaluates representative studies on ML applications in IoEd published between 2020 and 2025 through a structured comparative analysis. Each study is examined according to its methodological approach, reported outcomes, and remaining limitations. The analysis highlights recent progress while identifying research gaps that must be addressed to advance ML driven IoEd systems.Several studies demonstrate the potential of ML and IoT integration in educational environments. ML models such as BP networks, GRU based architectures, GAN based recommender systems, RL resource optimization models, and optimized ELM approaches are applied to tasks including student performance prediction, automated grading, course recommendation, sports training monitoring, and educational resource management [31, 32, 33, 34, 35, 36, 40, 43]. DL based approaches show strong predictive accuracy and improved adaptability, particularly when multimodal educational data such as behavioural, physiological, and textual information is used. Some studies also explore distributed or edge based IoT architectures to improve system responsiveness and support real time educational analytics [32, 36]. These developments demonstrate the ability of ML enabled IoEd systems to support personalized learning, adaptive feedback, and intelligent educational management.Despite these advances, important methodological limitations remain. Many studies rely on small scale, simulated, or proprietary datasets, which limits reproducibility and external validity. Several contributions focus on conceptual architectures or system prototypes without comprehensive ML benchmarking or cross dataset validation [32, 38]. In other cases, strong predictive performance is reported but model interpretability, scalability, and privacy considerations are not sufficiently addressed [41, 46]. Traditional ML approaches remain widely used because of their efficiency and interpretability, yet they offer limited adaptability in dynamic educational environments. Conversely, advanced DL and RL methods achieve high accuracy but often lack ablation studies, explainability mechanisms, and standardized evaluation benchmarks. These findings indicate that future research must prioritize large scale datasets, transparent evaluation protocols, and stronger consideration of privacy, fairness, and educational alignment in ML driven IoEd systems.

Table 2: Comparative summary of representative ML–IoEd studies.

Paper	**Objective**	**Method**	**Dataset**	**Evaluation Criteria**	**Advantages**	**Gaps**
Lv (2025) [31]	Optimize talent cultivation & school–enterprise collaboration in tourism education	Back-propagation	Proxy/mapped data	Accuracy, MSE, inference speed	Outperform SVM/RF; lightweight model; fast inference	Use proxy data; lack real education benchmarks; no ablation vs. DL/AutoML
Ma (2025) [32]	Deliver low-latency ideological/political education via IoT & edge computing	Conceptual edge computing–IoT framework	Not specified	Conceptual analysis	Motivate edge offload for responsiveness & privacy	No datasets; no baselines; lack ML comparisons
Zhan (2024) [33]	Develop educational intelligent multimodal optimization system	DL, multimodal pipelines	Coursera video/text/ interaction datasets	Accuracy (feedback 0.98, rec. ≈0.92–0.93), sentiment (0.91)	High performance across tasks; real-time adaptive response	Rely on curated datasets; limited benchmarking; lack validation
Li et al. (2024) [34]	Automated English grading under IoT	Bi-GRU with attention pooling/self-attention	Chinese & English corpora	Accuracy improvements (+19.2% vs. GRU)	Strong accuracy gains; stable convergence	Focus on controlled corpora; limited cross-lingual generalization; lacks XAI
Zhen & Wang (2024) [35]	Personalized PE course recommendation with IoT + GANs	RP-CFGAN (GAN with regularization)	Simulated + IoT sensor data	Top-N recommendation accuracy	Handle cold-start; integrate social + physiological data	Rely on simulated data; scalability/privacy concerns
Han et al. (2024) [36]	Improve educational informatization management & scheduling	Game-theoretic hierarchical Q-learning with fog computing	Simulated management data	Convergence speed; delay; cost	Faster convergence; lower delay; scalable fog architecture	Focus on system metrics, not pedagogy; lack ML benchmarks

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Table 2 (continued).

Paper	**Objective**	**Method**	**Dataset**	**Evaluation Criteria**	**Advantages**	**Gaps**
Jayachandran et al. (2024) [37]	Integrate IoT, ML, and Big Data into engineering curricula	IoT-Edu-ML-Stream GUI tool	Student surveys + emulated IoT data	Survey responses; learning gains	Significant student skill gains; open-source platform	Tool-focused; no ML benchmarking; privacy/scalability ignored
Hu (2023) [38]	Smart classroom innovation using IoT, fuzzy control, DL	IoT + fuzzy + DL conceptual integration	Surveys/ questionnaires	Conceptual + qualitative analysis	Links IoT, DL, fuzzy control; identify teaching gaps	Conceptual; lack of datasets & evaluation
Mohamed et al. (2023) [39]	Model interprofessional education improvement	IoT-assisted ML (GPR, ANN, etc.)	Questionnaire data (20 vars)	Predictive accuracy (training/validation)	GPR best performance; show ML potential	Questionnaire-based only; limited IoT sensor use; no DL baselines
Li et al. (2022) [40]	IoT-assisted PE training network virtualization & resource mgmt	Deep RL	IoT wearable + simulation	Accuracy (98.3), F-score (92.2), error rate	High accuracy; effective resource optimization	Simulation-heavy; dataset diversity lacking; limited real-world validation
Wang & Yu (2021) [41]	IoT-assisted smart educational learning	IoT-IS with facial recognition + psychometrics	Video classroom data	Performance (98.5%), accuracy (95.3%)	Real-time attention detection; high metrics	Ignore interpretability, scalability, privacy
Qiu & Han (2022) [42]	Intelligent college student management	C-RNN, KNN, BiLSTM, anomaly monitoring (ip2vec)	University (private)	System performance, anomaly detection	Privacy-aware anomaly detection; stable ops	Closed data; lack of benchmarks; simulation focus
Wang & Du (2022) [43]	Optimize PE training system	ELM	IoT PE data streams	Prediction accuracy	Improved accuracy; robust IoT monitoring	Simulation-only; no large-scale dataset; lack of DL comparisons
Shang (2022) [44]	Evaluate college English teaching via ML + IoT	ML-based IoT system (unspecified algorithms)	College English class experiments	Student grammar, structure, and expression	Gains in lower-performing students; improved blended learning	Localized dataset; no ML benchmarks; generalizability issues
Zong et al. (2022) [45]	Integrate psychological education into PE via IoT+DL	DL + IoT evaluation index system	College PE student data	Psychological/ emotional score improvements	Strong improvements in emotional control, critical thinking	No large-scale validation; lack of model comparisons; ignorance of sustainability
Souri et al. (2020) [46]	IoT-based student health monitoring	SVM, RF, DT, MLP	IoT vital signs (wearable sensors)	Accuracy (SVM 99.1%)	Reliable health monitoring	Controlled lab data; no deployment validation; lack of privacy/explainability

7 Challenges in ML-based IoEd

The integration of ML within IoEd presents substantial potential, but several technical, educational, ethical, and infrastructural challenges are identified. Data scarcity and class imbalance remain major technical limitations. Although IoT devices are widely used in classrooms, high quality labeled datasets are limited and many studies rely on small scale or simulated data. Interoperability across heterogeneous devices and platforms is also limited because IoEd systems combine multiple sensors, software platforms, and communication protocols. The absence of standardized data formats complicates the integration of multimodal data such as video, physiological signals, and academic records. Scalability is also constrained when ML models are deployed across large institutional infrastructures.

Limited interpretability of ML predictions is also identified as a major educational concern. Many DL and RL models operate as black box systems, which reduces trust among educators and administrators. XAI is proposed to improve transparency, but its adoption in IoEd remains limited. Bias and fairness issues are also observed because ML models trained on imbalanced datasets may produce unequal outcomes across student populations. Ethical and privacy risks remain significant because IoT based classrooms collect large volumes of personal and behavioral data. Educational institutions are therefore required to ensure compliance with GDPR. Continuous monitoring and long term data storage may also introduce risks related to surveillance and misuse of data. Technical safeguards such as FL and privacy preserving mechanisms, together with strong governance policies, are required to protect student rights.

Infrastructural limitations further restrict large scale deployment of ML based IoEd systems. Many institutions lack digital infrastructures that support edge or fog computing environments, particularly in resource constrained regions. Device heterogeneity and high operational costs also affect system reliability. These challenges indicate that although ML based IoEd improves predictive analysis and personalized learning support, current implementations remain constrained by data limitations, restricted interpretability, privacy risks, and infrastructural barriers. Interdisciplinary collaboration among researchers, educators, policymakers, and system designers is therefore required to support reliable, ethical, and sustainable IoEd systems.

Figure 5: Challenges in ML-based IoEd.

8 Open Issues and Future Research Directions

Existing studies indicate that ML supports intelligent IoEd applications, yet several open issues remain. Future research directions include integration with generative AI and LLMs, XAI, FL, MMLA, digital twins, and sustainable ML. Generative AI and LLMs support adaptive learning materials, conversational tutoring, and automated feedback, but risks such as hallucinations, cultural bias, and weak curriculum alignment remain [48, 49]. Trust in ML predictions is also limited because many DL models operate as opaque systems. XAI is therefore required to provide transparent model explanations through visualization tools and natural language reasoning, which support fairness and informed educational decisions [50]. Privacy concerns are addressed through FL, where decentralized training is performed and only model updates are shared, although heterogeneous devices, non IID data, and communication overhead remain challenges [51]. MMLA is also emphasized because learning behaviour is analyzed through combined video, audio, textual, and physiological data, yet difficulties in data synchronization, fusion, and missing information persist [52]. Digital twins are proposed to simulate students and classrooms for predictive analysis and educational decision support, although accurate behavioural modelling and secure IoT data integration are required [53]. Sustainability issues are also recognized because DL models and IoT infrastructures require high computational resources. Energy efficient ML methods and edge based deployment are therefore required to support sustainable IoEd systems.

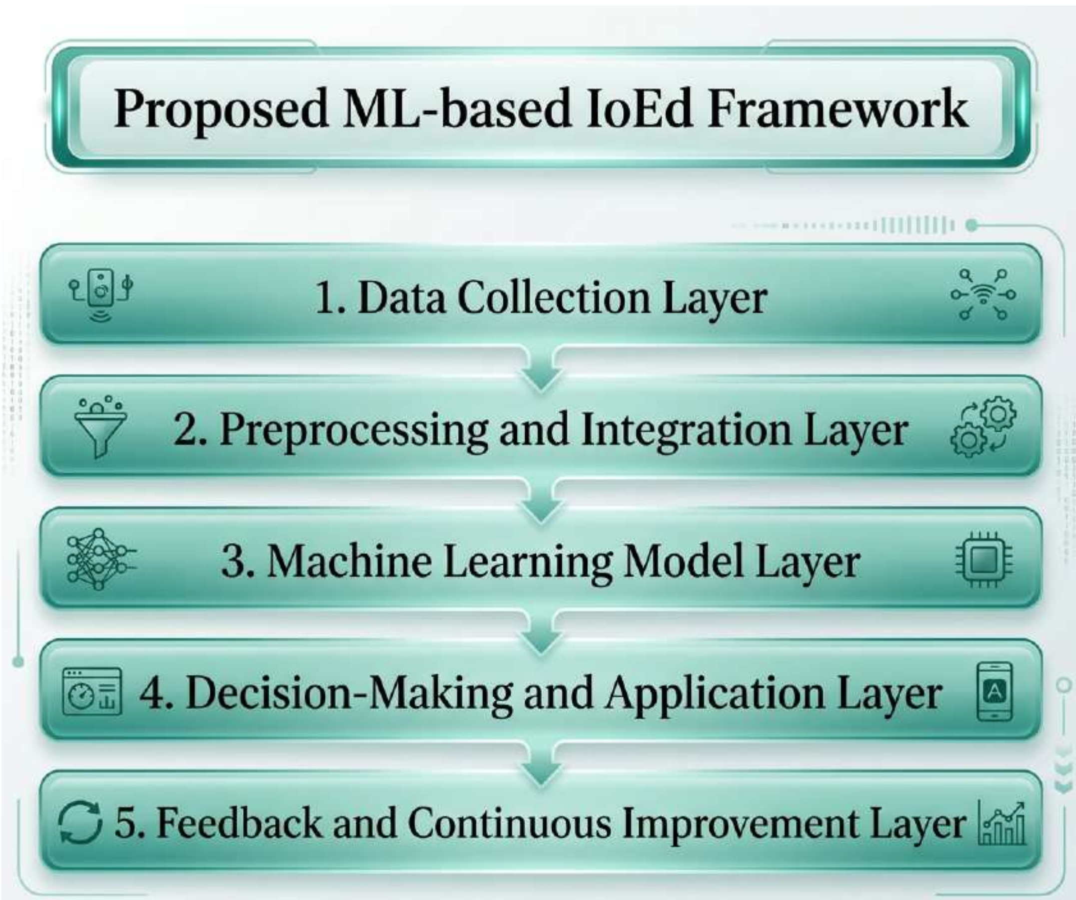

Figure 6: Proposed layered framework for integrating ML into IoEd.

9 Conclusion

This review examines the relationship between ML and IoEd and presents the conceptual development, technical foundations, applications, and research trends reported in recent studies. ML is identified as a key analytical mechanism that supports adaptive learning, personalized feedback, engagement monitoring, and resource optimization in connected educational environments. However, the heterogeneous nature of IoEd systems introduces several challenges. Technical limitations include data scarcity, class imbalance, and interoperability across heterogeneous devices. Concerns related to interpretability reduce trust among educators, while algorithmic bias raises issues of fairness in educational decision making. Student data protection and compliance with privacy regulations such as GDPR remain essential requirements in sensor rich educational environments. Infrastructure limitations are also observed because ML deployment in edge and fog environments introduces challenges related to scalability, latency, and energy consumption. Future research directions include the integration of generative AI and LLMs to support personalized tutoring and automated feedback. XAI is required to improve transparency and trust in ML predictions. FL is proposed to support privacy preserving analytics across distributed institutions, while MMLA is applied to capture complex student interactions through multimodal data sources. Digital twins are also suggested as simulation platforms for testing adaptive educational strategies, and sustainable ML design is required to ensure energy efficient IoEd infrastructures. Overall, the convergence of ML and IoEd is characterized as a socio technical transformation that reshapes the delivery, monitoring, and optimization of education. Progress in this area depends on interdisciplinary collaboration among AI researchers, educators, system designers, and policymakers so that future IoEd systems remain accurate, transparent, ethical, and educationally meaningful.

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