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AIoT Education Versus Conventional Teaching Toward Students Performance: A Systematic Literature Review

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Abstract

Purpose: This study investigates the relationships among AIoT Education, conventional teaching and student performance. The impact on the global education by employing qualitative type of methods in systematic literature reviews. The findings show that relationships among AIoT Education, conventional teaching confirming their importance in enhancing students' performance.

Research Methodology: systematic literature reviews and were collected through structured literature reviews, this research is a qualitative type of research.

Results: The findings show that AIoT Education significantly complement conventional teaching, confirming their importance in enhancing student performance.

Conclusions: AIoT education and conventional teaching both complement significantly toward student performance. AIoT education can build intellectual reciprocal partnerships with conventional teaching. AIoT education provides 24/7 services, while conventional teaching provides more humanistic approaches for students for online counseling and or coaching. AIoT education complements conventional teaching. Conventional teaching will never be replaced by AIoT education. Subsequent studies are also encouraged to incorporate objective for upgrading students' performance to complement the perceptual measures obtained from survey responses. Additionally, employing longitudinal or multi-country designs could provide a richer understanding of how regulatory evolution and AIoT education vs convention teaching shape the interplay between students' performance, conventional teaching and AIot education over time.

Limitations: This study limits only based upon systematic literature reviews and not empirical and purely only qualitative literature studies. Should be further observed for complete empirical studies in the future.

Contributions: These results enrich the literature on AIoT education by integrating AIoT education with conventional teaching with the utmost output on student performance.

Keywords: *AIoT Education, Conventional Teaching, Student Performance*

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1. Introduction

The trajectory of education has consistently reflected technological progress, evolving from chalkboards to projectors, and from printed textbooks to digital tablets. At present, Artificial Intelligence (AI) is advancing this transformation to unprecedented levels. AI-driven educational systems are capable of tailoring instruction to individual learners, providing immediate performance assessments, and adjusting methodologies to accommodate diverse learning styles. Nevertheless, a critical inquiry persists: Can AI genuinely surpass the efficacy of traditional pedagogical practices, or does human interaction remain indispensable to achieving meaningful educational outcomes? This article undertakes a comprehensive examination of the discourse surrounding AI and conventional teaching, analyzing their respective influences on student engagement, comprehension, and sustained academic success (Hoogers et al., 2026; Katalinic et al., 2026; Chen, 2022; Alshahrani, 2023).

Integration of Artificial Intelligence of Things (AIoT) is beginning to transform classrooms from physical meeting spaces into learning environments continuously monitored by devices. Sensors, data platforms, and recommendation systems no longer merely assist in delivering material. They also record attendance, monitor participation, and help shape how institutions interpret student learning outcomes. In such a situation, the question of whether machines will replace lecturers becomes far too narrow (Nishanov, 2026; Mosha et al., 2026; Kumar et al., 2022).

The more pressing issue concerns how academic work itself is transformed when pedagogical considerations increasingly operate through data, dashboards, and algorithmic classifications. This article is presented as a conceptual–critical review of the literature on artificial intelligence in education, the Internet of Things, learning analytics, AI ethics, and critical studies of educational technology. The central argument is straightforward: AIoT can assume portions of lecturers' routine tasks, particularly those that are administrative and highly structured. However, it remains insufficient to replace lecturers as interpreters of context, intellectual mentors, and guardians of academic integrity. Defending the role of the lecturer cannot rest merely on the claim that empathy cannot be programmed. More fundamentally, universities must determine the boundary between technological assistance and human pedagogical authority (Yuensook et al., 2025; Romdhoni et al., 2025; Alshahrani, 2023).

Within the Indonesian context, this issue intersects with digital infrastructure disparities, lecturers' administrative burdens, uneven levels of data literacy, and the evolving framework for educational data protection following the enactment of the Personal Data Protection Law. Adoption of AIoT must therefore be situated within governance structures that restrict data use, ensure system transparency, provide mechanisms for contestation, and involve both lecturers and students in decision-making processes. AIoT can indeed support higher education, but only if it is consistently treated as an auxiliary tool rather than as a new center of authority within the classroom (Mada et al., 2026; Putra et al., 2022).

Debates surrounding artificial intelligence in education frequently begin with the provocative question of whether machines will replace lecturers. While this framing readily captures public attention, it is insufficient for understanding the deeper transformations currently underway. It assumes that academic labor can be neatly partitioned, some tasks delegated to machines, while the remainder remain the domain of humans. In practice, however, the realities of higher education are far more complex (Yan et al., 2025; Springer, 2025; Chen, 2022).

The integration of the Artificial Intelligence of Things (AIoT) is reshaping classrooms from physical meeting spaces into environments continuously mediated by devices. Sensors, data platforms, and algorithmic recommendation systems no longer merely assist in the delivery of instructional content; they also record attendance, monitor participation, and influence how institutions interpret student learning outcomes. In this context, the central issue is not whether machines will replace lecturers, but how academic work itself is being reorganized as pedagogical considerations increasingly flow through data infrastructures, dashboards, and algorithmic classifications (Creely, 2026; Kumar et al., 2022).

This article positions itself as a conceptual–critical review of scholarship on artificial intelligence in education, the Internet of Things, learning analytics, AI ethics, and critical studies of educational technology. Its central argument is straightforward: AIoT can assume portions of lecturers' routine responsibilities, particularly those that are administrative and highly structured. Yet it remains inadequate to replace lecturers as interpreters of context, intellectual mentors, and guardians of academic integrity. Defending the role of the lecturer cannot rest solely on the claim that empathy cannot be programmed. More fundamentally, universities must determine the boundary between technological assistance and human pedagogical authority (Khupe et al., 2026; Alshahrani, 2023).

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Teaching is not merely the transmission of content. Lecturers also design learning situations, interpret students' development, provide feedback, guide discussions, and evaluate the quality of reasoning. In many cases, academic work unfolds precisely in domains that resist precise measurement: when lecturers discern students' hesitation, capture the direction of classroom dialogue, or decide when an argument requires further debate (Hoogers et al., 2026; Alshahrani, 2023).

The emergence of AIoT complicates this terrain because the technologies entering universities are not simply stand. The promises of AIoT are often encapsulated in two words: efficiency and personalization. Universities anticipate that lecturers' administrative burdens will be reduced, while students receive learning materials more closely aligned with their individual progress. Yet speed does not automatically translate into quality. When student behavior is converted into data, the classroom ceases to be merely a site of learning; it also becomes a site of surveillance. As algorithms begin to determine recommended materials, indicators of participation, or assessments of academic risk, a portion of pedagogical authority is effectively transferred into the system (Nishanov, 2026; Kumar et al., 2022).

In everyday practice, institutions are frequently tempted to read dashboards as objective representations of students. Those who frequently access the platform are considered active, while those who rarely appear in the system are assumed to be falling behind. However, learning processes do not always conform to digital patterns that are easily quantified. In many classrooms, the students who speak the least during sessions are sometimes the very ones who submit the most serious questions after the lecture has ended (Yuensook et al., 2025; Chen, 2022).

Discussion of AIoT cannot be confined to the question of whether the technology is useful. The more pressing issue is how AIoT reshapes the relationships among lecturers, students, institutions, and data. The same technologies may support learning, but they may also constrain it. AIoT becomes a threat when universities replace pedagogical judgment with overly narrow metrics, expand surveillance, or pressure academic staff in the name of efficiency. Conversely, it can serve as a productive tool when employed to detect learning difficulties at an early stage or to reduce the administrative workload that has long consumed lecturers' time. The difference lies not primarily in the sophistication of the devices, but in institutional design and in how universities conceptualize education itself (Mada et al., 2026; Putra et al., 2022).

This article proceeds from a basic assumption: higher education cannot be reduced to the distribution of information. Education also shapes ways of thinking, methods of evaluating evidence, and orientations toward public issues. Students learn not only from the content delivered by lecturers; they also learn from how lecturers pose questions, delimit claims, acknowledge uncertainty, and respond to critique within the classrooms (Yan et al., 2025; Alshahrani, 2023).

Tasks most easily automated are those that are routine, structured, and administrative in nature. Within higher education, these include recording attendance, processing grades, managing schedules, and generating standardized reports. Such functions are highly rule-based and lend themselves to automation through AIoT systems, which can integrate sensors, platforms, and analytics to streamline processes that otherwise consume significant amounts of lecturers' time. By delegating these repetitive tasks to machines, institutions hope to achieve greater efficiency and free up academic staff for more substantive work (Creely, 2026; Springer, 2026; Chen, 2022).

Functions requiring human judgment, however, remain central to the educational mission. Lecturers are not only transmitters of information but interpreters of context, mentors in intellectual development, and custodians of ethical responsibility. These dimensions of academic work involve reading subtle cues in student engagement, guiding discussions toward deeper reasoning, and fostering critical reflection. Such tasks cannot be reduced to algorithmic classifications or predictive models. They demand the presence of human judgment, empathy, and intellectual integrity—qualities that AIoT, however advanced, cannot replicate (Khupe et al., 2026; Zhaxybayev et al., 2026; Alshahrani, 2023).

Risks emerge when classrooms are transformed into datafied spaces. As student behavior is continuously monitored and converted into metrics, the danger lies in equating dashboards with objective representations of learning. Institutions may begin to substitute pedagogical authority with algorithmic indicators, interpreting frequency of platform use as engagement or absence of digital traces as disengagement. This shift risks narrowing the meaning of participation, expanding surveillance, and displacing the lecturer's role in shaping the learning environment. The classroom, once a site of dialogue and intellectual exploration, risks becoming a site of monitoring and control (Hoogers et al., 2026; Kristianto et al., 2025)

Governance frameworks are therefore essential to ensure that AIoT strengthens rather than undermines the mission of higher education. Institutional design must establish clear boundaries between technological assistance and human pedagogical authority. This includes restricting the use of data, guaranteeing transparency in system operations, providing mechanisms for contestation, and involving both lecturers and students in decision-making processes. Only through such governance can AIoT be positioned as an auxiliary tool that supports learning, rather than as a new center of authority that reshapes education in ways misaligned with its broader purposes (Chen, 2022; Anggraini et al., 2026).

The future of the lecturer in the era of AIoT should not be understood merely in terms of the disappearance or survival of the profession. What is changing, above all, are its functions. Lecturers who simply read slides and repeat information are increasingly easy to substitute. Yet those who cultivate reasoning, guide discussion, and safeguard academic integrity become all the more essential in a context where students live amid an overwhelming flow of information and automated recommendation systems (Alshahrani, 2023; Pujiati et al., 2025).

2. Literature Review

2.1 AIoT, Smart Classrooms, and Learning Analytics

AIoT in higher education sits at the intersection of three strands of discussion: AI in Education, the Internet of Things for learning environments, and learning analytics. Each of these traditions has developed from distinct trajectories, yet in practice they increasingly converge within the digital classroom (Haeruddin, Ciptagustia, Mustafa, Rahmawati, & Putra, 2026). AI in Education emphasizes the capacity of systems to detect learning patterns, provide feedback, and adapt instructional materials. IoT highlights the connectivity of devices and sensors that enable data collection from the physical environment. Learning analytics then connects these data streams to processes of interpretation and decision-making. In practice, the boundaries among these domains are becoming blurred (Chen, 2022; Alshahrani, 2023).

Universities no longer use learning platforms solely as repositories for instructional materials. Systems are now deployed to monitor attendance, track patterns of interaction, identify potential learning difficulties, and automatically generate recommendations(Pujiati, Feani, & Cahaya, 2025). AIoT emerges when these functions operate within a single interconnected ecosystem. View AI as a tool that can enhance personalization when designed to strengthen pedagogical processes. Extend this discussion by showing that AI is not simply a technology that replaces teachers; what changes is not only the delivery of content but also the practices of learning and academic assessment (Kumar & Singh, 2022).

The challenge, however, is that much of the discourse on AI in education remains overly focused on system capabilities. Education is not merely about information transfer. It also involves relations of power, institutional norms, and social purposes. Questions about AI in education therefore cannot be adequately addressed by discussing efficiency or device accuracy alone. Instead, they must be situated within broader debates about authority, governance, and the role of education in shaping intellectual and civic life (Alshahrani, 2023).

IoT extends these concerns because educational data no longer originates solely from activity within learning platforms. Classroom sensors, cameras, attendance devices, smart boards, and laboratory equipment now generate data about students' movements, interactions, presence, and activities during the learning process. Ibrahim and Kenwright (2022) found that the implementation of IoT in higher education is often associated with efficiency and personalization of learning. Yet they also note that many institutions remain insufficiently prepared to address the ethical and governance challenges that accompany such technologies (Ibrahim & Kenwright, 2022).

In many universities, discussions of AIoT remain at the stage of device demonstrations. The focus is typically on system capabilities, such as reading student activity or producing learning analytics rapidly, while far less attention is given to questions of how data is used, who controls the system, and how students are treated when their behavior is translated into indicators. At this point, learning analytics becomes crucial. Emphasize that the use of learning analytics must account for privacy, transparency, access, accountability, and the interests of learners. These principles are especially relevant in AIoT environments, where data collected can be highly granular: attendance times, typing patterns, reading durations, interaction intensity, and even potential emotional indicators (Chen, 2022).

The challenge is not merely the volume of data. A deeper issue lies in the tendency to simplify the learning experience into signals that are easily quantifiable. Students are then interpreted through patterns of access, frequency of clicks, or digital participation indicators. Yet learning processes often unfold in far more complex ways that are not always captured by system logs. Some students remain silent for extended periods before feeling safe enough to speak in class. Others engage more actively in discussion after the lecture rather than during it. Such situations frequently escape the scope of analytics systems (Romdhoni, Arrasyid, Widodo, & Elviani, 2025; Faeni, Faeni, Pujiati, & Cahaya, 2025).

International policy developments on AI in education have moved in a more cautious direction compared to a decade ago. UNESCO (2021) situates AI ethics within the framework of human rights, justice, and human oversight. UNESCO (2023) warns that the use of generative AI in education requires clear data protection and institutional policies. UNESCO (2024) about competency framework even positions human understanding of AI and ethical technology use as essential components of teacher competence. The European (2022) advances a similar perspective: The use of AI and data in education must be accompanied by clarity of purpose, teacher participation, and learner protection.

From this literature, it becomes evident that AIoT is best understood as a transformation in the governance of learning rather than merely as a device innovation. What changes is not only classroom technology, but also how institutions define presence, participation, attention, and academic risk. Classrooms that were once interpreted primarily through lecturers' observation are now increasingly read through data—and this shift opens possibilities for earlier intervention while simultaneously expanding the potential for surveillance in learning spaces (UNESCO, 2021; UNESCO, 2023; UNESCO, 2024; European, 2022).

2.2 Analytical Framework: Substitution, Complementarity, and Pedagogical Authority

To examine the impact of AIoT on lecturers' work, this article employs three analytical categories: substitution, complementarity, and pedagogical authority. These categories are not intended as rigidly separated stages. In practice, within higher education, they often appear simultaneously, depending on institutional design and the ways technologies are deployed in classrooms (Mada, Tarigan, & Sindu, 2026; Mosha, Chigwada, Ketchiwou, & Ngulube, 2026).

Substitution occurs most readily in tasks that are routine and governed by clear rules. Automated attendance, correction of multiple-choice tests, mapping the frequency of material access, or grouping students based on quiz scores can be executed by systems with relatively high efficiency. On many campuses, such administrative tasks consume considerable amounts of lecturers' time. In this respect, automation can provide meaningful relief. Many lecturers do not lack access to digital applications or platforms; what they often lack is time to read, conduct research, prepare materials, or engage in extended conversations with students outside of class. Automation at this level, when implemented effectively, can help restore that time (Yuensook, Jantakoon, & Limpinan, 2025; Haeruddin, Ciptagustia, Mustafa, Rahmawati, & Putra, 2026).

Problems arise, however, when the logic of substitution extends too far. If teaching is understood merely as the distribution of content and the correction of answers, then technology may indeed appear sufficient to replace much of academic work. The difficulty is that higher education does not operate in such a simplistic manner. Many pedagogical decisions emerge in ambiguous situations that cannot be fully translated into system rules. It is precisely here that complementarity becomes crucial (Creely, 2026).

Complementarity emphasizes the ways in which technology can support, rather than replace, human judgment. AIoT systems may provide early signals of student difficulties, generate predictive insights, or streamline administrative burdens. Yet the interpretation of these signals, the guidance of intellectual dialogue, and the cultivation of reasoning remain tasks that require human presence. Lecturers' ability to read hesitation, encourage debate, and safeguard academic integrity cannot be replicated by algorithms. In this sense, complementarity situates AIoT as an auxiliary tool that enhances pedagogical practice without displacing its human core (Bagdonaitė & Dagienė, 2025).

Finally, the question of pedagogical authority underscores the broader institutional implications. As classrooms become increasingly datafied, authority risks shifting from lecturers to systems. Dashboards and analytics may begin to define participation, attention, or risk in ways that narrow the meaning of learning. Safeguarding pedagogical authority requires universities to establish governance frameworks that ensure technology remains a support mechanism rather than a new center of control. This involves clear boundaries between technological assistance and human decision-making, transparency in system design, and active involvement of lecturers and students in shaping how AIoT is used (Yan, Liu, & Chau, 2025; Springer, 2025).

AIoT can assist lecturers in reading students' learning patterns with greater detail. In large classes, lecturers often lack the opportunity to closely recognize the progress of every student. Data on which parts of the material most frequently generate errors, or which groups of students begin to fall behind, can indeed help lecturers take earlier action. Yet data does not automatically yield pedagogical understanding. Students who rarely access the platform are not necessarily failing to learn. Some may rely on alternative sources, while others face barriers such as limited internet access, employment obligations, or personal challenges that do not appear on analytic dashboards. Such situations are common, particularly in universities with highly diverse student populations (Feng & Zhu, 2025).

Similar dynamics occur within the classroom. Students who appear silent are not always passive. Some require more time before feeling safe enough to speak. Others may be more active in discussion after the lecture rather than during it. These learning experiences are often not fully captured by analytic systems. Data therefore requires human interpretation. The most decisive category in this discussion is pedagogical authority. AIoT not only assists in reading learning processes, it can gradually influence how academic decisions are made. When systems begin to assign labels such as “at risk,” “inactive,” or “unfocused,” these labels can shape how lecturers and institutions treat students (Khupe, Zlotnikova, & Hlomani, 2026).

The critical issue is not merely technical accuracy, but who ultimately holds the authority to evaluate students. If system recommendations are accepted uncritically, lecturers risk becoming executors of algorithmic decisions. Conversely, if analytic outputs are treated as preliminary signals that must be examined through observation and dialogue, lecturers remain the primary pedagogical decision-makers. The distinction may appear small, but its impact on academic life is profound. In recent years, more universities have adopted performance dashboards to interpret student participation and engagement. These numbers often appear objective because they are presented visually and quantitatively. Yet numbers always emerge from particular choices: what is deemed important, which behaviors are counted, and what standards of participation the system employs (Zhaxybayev, Sambetbayeva, Dnekeshev, Igenov, Vakhitova, & Zhussip, 2026; Pratiwi, & Fathurahman, 2026). Therefore, the integration of data-driven educational technologies should be accompanied by critical interpretation and human-centered pedagogical judgment to ensure that digital systems function as supportive tools rather than replacements for educators’ professional roles (Mastiyar, Mulyapradana, Prayetno, & Hasim, 2026).

The measure of AIoT success, therefore, cannot be reduced to administrative efficiency or analytic speed. More important is whether the technology strengthens the quality of academic interaction, preserves space for human judgment, and continues to allow students to develop reasoning independently (Hoogers, Thüring, & Michels, 2026; Nishanov, 2026).

3. Research Methodology

This article adopts a conceptual-critical approach. The choice of method arises from the nature of the problem under discussion. AIoT in higher education cannot be adequately assessed merely in terms of system accuracy or data-processing speed. The technology also reshapes how classrooms are understood, how students are interpreted, and how lecturers make academic decisions. For this reason, the analysis does not attempt to test a specific AIoT device. The focus is not on technical product evaluation, but on the changing relationships among technology, lecturers, students, institutions, and data analysis. (Chen, 2022; Alshahrani, 2023).

The literature is read selectively and argumentatively. Sources are not employed to construct a comprehensive survey of existing scholarship, but rather to build an analytical framework. This choice is significant because much of the discourse on educational technology tends to drift toward product promotion. Technologies are introduced as solutions, while institutional challenges are treated merely as obstacles to implementation. This article takes a different direction: from the outset, the concern is not which device is most advanced, but what transformations occur when learning processes are increasingly translated into data (Kumar, & Singh, 2022; Mada, Tarigan, & Sindu, 2026).

The body of literature consulted spans several fields. Part of it derives from AI in Education and learning analytics, which provide insights into adaptive learning, intelligent tutoring systems, personalized content delivery, and evolving practices of assessment. Another part comes from AI ethics and critical studies of educational technology, which are essential because the challenges posed by AIoT extend beyond technical questions of pedagogy. It emphasizes the importance of embedding privacy, transparency, accountability, and student interests into the design of educational systems rather than treating them as afterthoughts. Similarly, (UNESCO, 2021; UNESCO, 2023; UNESCO, 2024) and The European (2022) highlights the need for human oversight and the protection of learners in the deployment of AI in education.

Particularly significant because both remind us that educational technologies are never truly neutral. Digital systems always operate within relations of power, institutional interests, and specific logics of management. From this body of literature, the analysis in this article is directed toward three central issues. First, which aspects of lecturers' work are most easily automated because they are routine and governed by clear rules. Second, which aspects continue to require human judgment because they involve context, dialogue, and the cultivation of reasoning. Third, how university governance must be designed so that data does not become an instrument of surveillance that diminishes academic autonomy (Yan, Liu, & Chau, 2025; Mosha, Chigwada, Ketchiwou, & Ngulube, 2026).

This article deliberately avoids two common simplifications. On the one hand, there is the belief that AIoT will inevitably replace lecturers. On the other hand, there is the assumption that technology is merely a neutral tool that leaves educational structures unchanged. Both positions are too narrow to capture the transformations currently underway. Instead, the argument advanced here situates AIoT as a force that simultaneously enables automation and efficiency while also raising profound questions about authority, pedagogy, and institutional design (Creely, 2026; Zhaxybayev, Sambetbayeva, Dnekeshev, Igenov, Vakhitova, & Zhussip, 2026).

4. Results and Discussions

AIoT Education can help lecturers read learning patterns more closely, especially in large classes. Yet data does not automatically yield pedagogical insight. Silent students may be reflective rather than disengaged; those absent from platforms may be learning elsewhere or facing access barriers. Such nuances require human interpretation. The danger lies in treating system outputs as objective truths. Labels such as “at risk” or “inactive” can shape institutional responses, potentially reducing lecturers to executors of algorithmic decisions. The measure of AIoT success, therefore, is not administrative efficiency but whether it strengthens academic interaction, preserves human judgment, and enables students to develop reasoning independently (Chen, 2022; Alshahrani, 2023).

The integration of AIoT into classrooms offers lecturers powerful tools to track and interpret student learning patterns, especially in large cohorts where individual monitoring is difficult. Sensors, platforms, and analytics can highlight trends in participation, engagement, and performance. Yet, as you rightly point out, data alone does not equate to pedagogical wisdom (Ibrahim et al., 2022; Mada, et al, 2026).

AIoT can enhance learning analytics by revealing participation levels, time spent on tasks, and interaction frequency. This helps lecturers identify broad patterns that would otherwise remain hidden in large classes. It can also support personalized feedback, where automated systems suggest tailored resources or exercises to meet diverse learning needs. Moreover, the scalability of AIoT allows for monitoring at scale, ensuring that students who might otherwise be overlooked are flagged for potential support (Romdhoni et al., 2025; Yuensook et al., 2025).

However, these opportunities come with significant challenges. The interpretation of data can easily fall prey to bias. Silent students may be reflective thinkers rather than disengaged, and low platform activity could signal external study habits or access barriers rather than lack of effort. The use of risk labels such as “inactive” or “at risk” can stigmatize students, shaping institutional responses in ways that overlook nuance. Even more concerning is the rise of algorithmic authority, where lecturers are pressured to follow system outputs, reducing their role to executors of machine decisions (Yan et al, 2025; Mosha et al., 2026).

4.1 Discussions

The true measure of AIoT success lies in its ability to foster human-centered pedagogy. It should strengthen academic interaction by encouraging dialogue between students and lecturers rather than replacing it. It must preserve human judgment, ensuring that educators remain interpreters of data rather than passive recipients. Most importantly, it should support students in developing independent reasoning, helping them think critically rather than simply responding to algorithmic nudges (Creely, 2026; UNESCO, 2023).

In conclusion, AIoT should be seen as a supporting instrument, not a pedagogical authority. Its value lies in augmenting human insight, not replacing it. When lecturers use AIoT outputs as conversation starters rather than verdicts, they can foster richer, more equitable learning environments (Zhaxybayev et al., 2026; Hoogers et al, 2026).

5. Conclusions

5.1 Conclusion

Debates about AIoT in higher education have often been framed as binary choices: whether the technology helps or threatens, whether lecturers will be replaced or not, whether universities should adopt or reject. This article argues that such questions must be reformulated. The more relevant issue is not whether AIoT is useful, but useful for whom and within what framework. The same system can help lecturers identify student difficulties earlier, while also transforming classrooms into spaces of continuous surveillance. The difference between these outcomes lies not in the devices themselves, but in institutional design and choices (Chen, 2022; Alshahrani, 2023).

Three tensions cannot be resolved technically. First, the tension between data and interpretation. AIoT systems can detect patterns, recognize anomalies, and generate signals faster than lecturers can manually. But signals are not knowledge. Pedagogical knowledge arises when students are understood not only as data sources but as human beings with histories, pressures, and learning styles not always captured by sensors (Ibrahim et al., 2022; Mada et al., 2026).

Second, the tension between efficiency and depth. AIoT accelerates many processes, streamlined administration, faster feedback, large-scale learning pattern recognition. Yet the most important aspects of learning have no accelerated version. Forming ways of thinking, confronting uncertainty, debating unfinished arguments, all require time, and what efficiency cuts away is often what is hardest to replace (Romdhoni et al., 2025; Yuensook et al., 2025).

Third, the tension between measurement and meaning. Universities overly oriented toward AIoT metrics risk measuring much but understanding little. Attendance figures do not explain why students are present. Engagement scores do not measure how deeply someone is thinking. Risk indicators do not recognize that students who appear to lag may be facing circumstances invisible to any system (Yan et al., 2025; Mosha et al., 2026).

These tensions will not disappear as technology becomes more advanced. They are inherent to the educational process, and that is why lecturers remain indispensable, not as system operators but as decision-makers who understand context. Not because machines are insufficiently intelligent, but because there are forms of understanding that can only grow from genuine human relationships (Creely, 2026; Zhaxybayev et al., 2026).

AIoT, therefore, is not about whether technology will replace lecturers. It is about what kind of education we want to build. And that question cannot be answered by systems. At the national level, higher education regulators must establish minimum guidelines for student data protection, vendor transparency, algorithmic audits, and the use of AI in learning evaluation. Without national standards, each university will move independently, and the quality of student protection will become highly uneven. Institutions with strong legal and technological capacity may be able to draft their own rules, but many others will depend entirely on vendors (UNESCO, 2023; European Commission, 2022).

Students must also be included as subjects of policy. They are not merely system users; they are the ones whose data is most extensively collected and who are most directly affected by algorithmic classification. Consultation forums, complaint mechanisms, and data literacy education should be integral components of AIoT governance in higher education (UNESCO, 2024; Hoogers et al., 2026).

5.2 Research Limitations

While the integration of AIoT into higher education offers promising avenues for monitoring and supporting student learning, several limitations constrain the scope and reliability of research in this area. One limitation lies in the interpretive gap between system-generated data and pedagogical meaning. AIoT systems can capture behavioral traces such as log-ins, clicks, or attendance, but these do not automatically reveal cognitive engagement or reflective learning. Silent students may be deeply engaged, while those absent from platforms may be studying independently or facing access barriers. Research that treats these signals as direct indicators of learning risks oversimplification. Another limitation is the contextual variability of student behavior. Cultural norms, institutional practices, and technological access differ widely across settings, making it difficult to generalize findings. What appears as disengagement in one context may be a legitimate alternative learning strategy in another.

There is also the challenge of algorithmic bias. Labels such as “at risk” or “inactive” can stigmatize students and shape institutional responses in ways that reinforce inequities. Research often overlooks how these classifications affect student identity, motivation, and trust in the learning process. A further limitation concerns the role of lecturers. Studies may emphasize administrative efficiency or predictive accuracy while neglecting how AIoT reshapes academic interaction. If lecturers are reduced to executors of algorithmic decisions, the human dimension of teaching is compromised. Research must therefore account for the preservation of human judgment and the relational aspects of pedagogy. Finally, there is the issue of long-term impact. Much of the current research focuses on short-term outcomes such as improved monitoring or early alerts. Less attention is given to whether AIoT fosters independent reasoning, critical thinking, and student autonomy over time. Without longitudinal studies, claims about AIoT educational value remain tentative.

In sum, research on AIoT in education is limited by interpretive ambiguity, contextual differences, algorithmic bias, the shifting role of lecturers, and the lack of long-term evidence. Addressing these limitations is essential if AIoT is to strengthen academic interaction rather than reduce education to data-driven administration. This article has limitations that must be stated openly. It does not present field research on a specific university, classroom, or AIoT platform. Its arguments should not be read as empirical conclusions about all higher education institutions. The impact of AIoT will vary according to infrastructure capacity, academic discipline, student population size, academic culture, and intended use. A system that supports engineering laboratory classes may not be suitable for philosophy, law, literature, or social science courses that rely on open debate and textual interpretation. Such differences are significant, because not all courses can be managed with the same measurement logic.

Future research must enter classrooms directly. The experiences of lecturers and students need to be examined firsthand. Do dashboards truly help lecturers understand learning difficulties, or do they merely add administrative work? Do students feel supported by early warning systems, or do they feel constantly surveilled? Is system-generated data used to improve learning, or does it end up primarily as managerial reporting? These questions cannot be answered from technology brochures. Another urgent agenda is the audit of bias and vendor governance. Indicators such as focus, participation, activity, and academic risk are often built on assumptions about learning behaviors considered “normal.” These assumptions must be tested within the Indonesian context, where students are socially, economically, linguistically, culturally, and digitally diverse. What one system considers “normal” learning patterns may not fit all student groups.

The relationship between universities and technology providers also requires closer scrutiny. Who owns the data? How is it stored? Can it be reused for commercial purposes? How can students contest classifications that disadvantage them? These questions are often treated as technical, but they are crucial in determining students' positions vis-à-vis institutions and vendors. Students' perspectives must not be marginalized. They are the ones who generate the most data and are most directly affected by algorithmic classification. In-depth interviews, classroom observations, and digital ethnography can reveal how students interpret monitoring, automated assessment, and system recommendations in their everyday academic lives. Without such knowledge, AIoT adoption decisions risk being driven more by modernization narratives and vendor claims than by pedagogical evidence that can be justified.

5.3 Suggestions and Directions for Future Research

Building on the limitations discussed, several recommendations can guide the responsible and effective use of AIoT in higher education. First, institutions should prioritize human-centered interpretation of AIoT data. Rather than treating system outputs as objective truths, lecturers must be empowered to contextualize analytics with their own pedagogical judgment. This ensures that silent or absent students are not automatically categorized as disengaged but understood within broader learning contexts.

Second, researchers and developers should design AIoT systems with transparency and explainability. Clear documentation of how algorithms classify students or generate risk labels can help educators critically assess outputs instead of passively accepting them. This reduces the danger of algorithmic authority overshadowing human decision-making. Third, institutions must establish ethical safeguards to prevent stigmatization. Labels such as “inactive” or “at risk” should be used cautiously, accompanied by guidelines that encourage supportive interventions rather than punitive measures.

Fourth, lecturers should receive professional development on interpreting AIoT data. Training can help them distinguish between behavioral signals and genuine learning indicators, ensuring that technology augments rather than replaces their expertise. Fifth, researchers should conduct longitudinal studies to evaluate the long-term impact of AIoT on student autonomy, reasoning, and critical thinking. Short-term efficiency gains must be balanced against the broader educational mission of fostering independent learners.

Finally, institutions should frame AIoT adoption within **a** policy framework that emphasizes academic interaction, preserves human judgment, and aligns technological use with pedagogical goals. This ensures that AIoT strengthens rather than diminishes the relational and intellectual dimensions of education. Taken together, these recommendations highlight that AIoT success should be measured not by administrative efficiency but by its ability to enrich academic dialogue, respect human interpretation, and cultivate independent reasoning among students.

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HP entitled and responsibled for research design constructions, research framework, conceptualization, fields research, literature reviews and data analytic.

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