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PERFORMANCE METRICS FOR IOT-BASED SMART LEARNING SYSTEMS: A QUASI-EXPERIMENTAL ANALYSIS OF SCALABILITY AND LATENCY IN MULTI-CLASSROOM DEPLOYMENTS IN HYDERABAD

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Abstract
Internet of Things (IoT) technologies that have proliferated in higher education have triggered the creation of smart learning spaces combining sensor networks, real-time analytics, and adaptive systems. These deployments have not however been studied in terms of technical scalability, especially in relation to network protocol performance with different device densities. The present study is a quasi-experimental analysis of the impact of the simultaneous loading of a system of IoT-based smart learning systems in 15 classrooms of one university in Hyderabad during a single academic semester on the measures of performance of the systems regarding their load capacity, frequency of data transmission, and communication protocols (MQTT vs. CoAP). We manipulated the independent variables (50, 100, and 200 IoT devices per classroom; 1 Hz, 5 Hz and 10 Hz transmission rate) to get dependent variables such as end-to-end latency, packet loss rate, energy consumption, and perceived responsiveness by the user. They used network analyzers and power monitoring equipment to collect data, and then they analyzed the results using repeated-measures ANOVA and multiple regression modeling. Findings (n = 2,160 observation intervals) reveal considerable main effects (p <.001) of the number of devices on latency (F^2 2154) = 147.32) and packet loss (F^2, 2154) = 89.76), where MQTT has a 23.4% lower latency, and CoAP has 18.7% higher power consumption than the other at full load. Regression analysis attributed 73.8% of the variation in latency to the model (R^2 =.738, RMSE = 12.4 ms) and found a scalability limit at 180 devices at which point the latency was too large to be useful in pedagogy (> 200 ms). The use of time-series analysis showed the patterns of diurnal performance degradation with congestion of the campus network. Results can serve as empirical reference points to the IT administrators of higher education institutions and offer a tested performance measurement framework to IoT deployments in learning settings.

Index Terms—IoT in education, smart learning systems, MQTT, CoAP, scalability, latency, network performance, quasi-experiment.

I. INTRODUCTION

A. Background and Motivation

The accelerating digitalization of higher education in recent decades has completely changed the concept of how universities understand teaching, learning and campus management. With institutions facing more and more diverse student populations and changing pedagogical demands, the demand to have flexible and data-driven technological ecosystems has been further heightened (Yu, 2023). The Internet of Things (IoT) is one of the technologies that have triggered this transition and has become one of the cornerstones, with which the physical and virtual learning environments can communicate without any issues. The IoT solution enables learning environments to be smart, adjustable, and responsive in real-time towards the needs of students and teachers. The given paradigm shift is a step forward to the traditional e-learning models that are concentrated at the delivery of the digital content but instead involves more engaging smart learning system that combine data provided by heterogeneous sensors, computing platforms, and learning analytics engines (Beck et al., 2023).

The smart learning environments exploit the broad range of IoT tools, such as environmental sensors (temperature, humidity, light intensity, etc.), occupancy and motion sensors, student engagement sensors, and wearable sensors that capture cognitive and physical signals (Khaldi et al., 2023). These sources of data will supply analytical systems capable of simulating learner behavior, identifying environmental discomfort, streamlining energy use, and providing a learner with personalized content. Indicatively, a temperature and CO2 sensor-fitted classroom can automatically turn off and on ventilation when the number of students in the classroom goes up, where student comfort and attentiveness are required. Similarly, monitors and tracking devices can give the instructors real-time dashboards that indicate the participation trends, moods, or where they might need extra support (Hanaysha et al., 2023).

This has been widely reported to enhance pedagogical results. The real-time monitoring is important because it allows an instructor to take quick intervention when students are lost or having difficulties (Akila et al., 2024). Environmental automation also makes sure that the learning spaces are also friendly to concentration and health. Smart platforms may be used to adjust the teaching material to meet the learner profiles to enhance motivation, retention, and conceptual learning. As a result, intelligent learning systems have gained a lot of interest among tertiary institutions leaders who are trying to bring the campuses up to date and are able to fulfill the current demand of quality, efficiency, and personalization (Zhu & Yang, 2024).

Nevertheless, the growth of the use of IoT technologies in the university is not without obstacles. Thousands of users and devices in various buildings, floors, and access networks across most campuses are accommodated concurrently (Sun et al., 2023). All these devices are continuously communicating, and in many cases, they are sending little but frequent packets of data and this data must be processed with high reliability and minimum latency. The network infrastructure supporting these sensors may become congested with the increase in the number of connected sensors particularly when the number of connected sensors is high like during examination days or during peak class time. Loss of packets or low throughput because of delay in communication may impair the responsiveness of the system and this directly influences the user experience and educational efficiency (Ong & Quek, 2023).

This is further worsened by the fact that IoT devices are heterogeneous. Some are made to run on limited computational resources, limited power, or standardized industrial protocols originally intended to be run in less dynamic environments (Barrett et al., 2023). University deployments must thus strike a balance between performance needs, which include real-time information-delivery and low-latency, and constraints associated with device mobility, cost, security, power usage, as well as wireless spectrum availability. The availability of such systems is greatly determined by the communication protocol used in the process of interacting data packets among devices, gateways and cloud or edge servers (Al-Adwan et al., 2023).

Out of these protocols, Message queuing Telemetry Transport (MQTT) and Constrained application protocol (CoAP) have become popular in educational IoT applications. MQTT is a simple publish subscribe message protocol that is based on TCP/IP, and is based on a central broker which coordinates message exchange between publishers (as sensors) and subscribers (as monitoring systems). The strengths of it are that it is reliable and has ordered delivery of messages and Quality-of-Service (QoS) levels which enable a more specific control of message retention and acknowledgment. These characteristics render MQTT the best in real-time applications where the data arrival is critical to the responsiveness of the system. Nevertheless, its use of continuous TCP connections adds overhead on packets and increased power usage especially in situations where thousands of devices are constantly communicating (Maimaiti et al., 2023).

CoAP, in contrast, is a resource-constrained embedded system-friendly, RESTful request-response architecture that is based on UDP. Its thin form factor minimizes network overhead and energy consumption, and thus it is suitable in large scale IoT applications that need power to be highly efficient. CoAP also implements asynchronous message delivery and provides the compatibility with popular web architecture (Li & Xue, 2023). However, since CoAP is connectionless and does not necessarily provide the delivery of packets in a certain order, it might be more susceptible to packet loss or delays in the conditions of high density of devices, as well as network congestion, which can be observed in campus networks during hours of heavy use (Lee et al., 2024).

Despite years of theoretical and simulation research on both protocols and their various deployment in universities, actual deployments are not well documented. Most of the available literature measures the performance on controlled laboratory testbed, small-scale pilot classroom or simulation environment which fails to represent the dynamism of university traffic patterns, building layouts, wireless interference, or variability in use with time. Consequently, decision-makers in the higher education sector lack empirical advice on how to choose the right communication protocol or how to predict infrastructure requirements, perhaps how many gateways, how much bandwidth to allocate, or how many devices to fit into a specific area to maintain consistent performance at the beginning phase of scale (Li & Xue, 2023).

Since the number of IoT-based learning settings is increasing, the lack of well-developed scalability standards is pragmatic. The same system which functions well with 40 devices in a pilot study can experience unacceptable latency with 200 devices in full deployment, and the instability will cause students to be frustrated and find the automation to be unreliable, thus, losing the pedagogical value. In addition, system delays during real-time tracking or analytics may compromise the institutional investment and compromise the long-term adoption. Thus, colleges do not need just theoretical knowledge but also the analysis of performance based on the real conditions of functioning (Lee et al., 2024).

This paper is a reaction to this requirement, as it performs a massive, quasi-experimental assessment of MQXR and CoAP in 15 university classes in Hyderabad during an academic semester. The systematic density of device variations and the frequency of message transmission characterizes the research to determine the limits of protocol performance, protocol bottlenecks, and protocol sustainable loads, thus providing administrators and technologists with practical advice on how to devise and scale future smart learning environments (Troussas et al., 2023)**.**

B. Problem Statement

There are knowledge gaps that are critical in higher institutions of learning in scaling the IoT-based smart learning systems. There are three interconnected questions that require empirical research:

1. What is the impact in latency of networks and packet loss in multi-classroom implementations of different densities of coexistent IoT devices?
2. What are the performance differences between MQTT and CoAP protocols in the light of real conditions in campus network?
3. With which device loads are the requirements of system performance and pedagogical levels of usability at conflict?

C. Research Objectives and Contributions

This study advances the literature through the following contributions:

1. Empirical performance benchmarks across 2,160 observation intervals.
2. Scalability threshold identification through regression modeling.
3. Protocol-specific guidance on latency-energy trade-offs.
4. A validated methodological framework for future IoT evaluations in education.

II. LITERATURE REVIEW

A. IoT-Based Smart Learning Environments

The concept of smart learning environments is a major step into enhancing the old system of e-learning since cutting-edge sense, analytics, and adaptive technologies are utilized in building a highly responsive educational environment. Ortodox Web-based education platforms tend to focus on the digitization of contents and remote availability, but do not depend on much interaction between the environment and the process of learning. Conversely, smart learning systems are based on the concept of context-awareness, real-time feedback, personalization, and continuous system intelligence, which follow the new trends in the pedagogical approach of digital learning (De Back et al., 2023).

The Internet of Things (IoT) has become the center of bringing this change. IoT architectures, by linking various physical systems (environmental sensors, occupancy sensors, RFID systems, wearable trackers, electronic whiteboards, and smart screens) enable physical classroom environment and digital pedagogical systems to interact seamlessly. The devices produce streams of micro-level information and data such as temperature, the quality of the air, movement of students, device interactions, learner engagement metrics, and system performance records. This information is sent to decision-support engines that control environmental contexts, create automatic notifications, customize information delivery, and create insights to instructors and administrators (Qureshi et al., 2023).

Several studies have indicated that smart learning environments enhance the learning performance through a combination of higher student engagement, learner autonomy/independence, and adaptive teaching. As an illustration, environmental sensing can be used to make sure that classrooms are the most comfortable in terms of acoustics and thermal conditions, which have been associated with better concentration and cognitive functioning. Correspondingly, systems monitoring participation or emotional state of learners with wearable sensors can be used to provide a prompt intervention by instructors so that struggling students can be identified at an early stage and offered the needed scaffolding. Furthermore, IoT-based systems promote resources optimisation on an institutional basis. Occupancy especially real time monitoring can allow universities to waste less energy by turning of HVAC systems and lighting when students are not around. Predictive models can predict failures of equipment, which will avoid the inconvenience of teaching. Administrators get macro-level insights into learning activities, infrastructure use and system performance on campus using learning analytics dashboards that run on data generated by an IoT (Al-Sharafi et al., 2023).

Outside of the classroom, IoT has been incorporated into blended and experience-based learning spaces, including smart laboratories, smart libraries, project based learning studios and learning paths on campus. Experimental parameters can be automatically recorded using smart laboratories with instrumented equipment, thereby decreasing the error of manual recording. Smart successful library systems may suggest resources in accordance with the reading patterns and learning history. Wearable devices applied in outdoor or field learning can be used to record performance information in natural field operation settings (Aung et al., 2024).

However, reliability and prompt communication are the key factors in the success of IoT-based smart learning environments. Latency, loss of packets, system congestion and energy limitations may reduce user experience and undermine practical utility of real-time adaptation. Thus, the effectiveness of communication procedures, gateway management structures, and the state of wireless transmission has a direct influence on the education of the IoT implementations (Han et al., 2025).

With the growth of universities out of small pilot projects to campus-wide systems, there is a need to address data flows involving hundreds or even thousands of simultaneous connections. The dense device population and the higher data rate may cause a network infrastructure to be overwhelmed by lots of traffic as opposed to general purpose connectivity of machines to machines. Consequently, the process of choosing and setting up suitable communication protocols will become a major engineering issue of academic institutions that adopt smart learning environments (Sheng et al., 2025).

B. Communication Protocols: MQTT and CoAP

MQTT and CoAP are now considered two of the most popular communication protocols to be used in the IoT implementation in education due to their lightweight design, compatibility, and capability to work in resource-constrained settings. The two protocols are both open and standardized and have large technical ecosystems, which appeal to universities and educational software vendors.

MQTT

In 1999, IBM published the Message Queuing Telemetry Transport (MQTT) that uses a lightweight publish subscribe design based on TCP/IP [15]. The MQTT allows devices to send messages to a central broker that in turn forwards them to all subscribing endpoints, unlike the traditional request-response models (Johnson et al., 2024). The architecture has several performance merits:

1. Less overhead on transmission: After a device connects to the TCP port with the broker, the further messages may be transferred with the minimum of signaling.
2. Quality of Service (QoS) level support: The MQTT supports three QoS levels (maximum of once, minimum of once, and exact once), so the developers can choose the level of reliability they need depending on the application requirements.
3. Distribution of messages on an event basis: Subscribers only get the information that is of semantic interest to them to cut out on unnecessary traffic.

These features render MQTT especially relevant to applications with a high degree of real-time responsiveness, constant information flow, and sequencing of messages- a feature that is typical of smart learning systems where the behavior of a system is contingent upon the timely receipt of sensor information. Nevertheless, persistent TCP sessions of MQTT also introduce an extra overhead of handshaking and consume more power, particularly when hundreds of devices are involved frequently (Shiri et al., 2024).

CoAP

In contrast to the design philosophy of the Constrained Application Protocol, CoAP, standardized by IETF in 2014, uses a different design philosophy. CoAP, which is constructed on UDP, resembles most concepts of HTTP but is designed to be resource-saving by using low-power and low-memory embedded systems. The model of its interaction with the RESTful interaction model, i.e., the application of GET, PUT, POST, and DELETE methods, allows the system to fit into the contemporary web architecture with minimal packet transmission and the transmission latency. CoAP supports:

- Allocated resources that are observable, the client can get asynchronous updates.
- Eliminating memory overhead (stateless communication).
- Messaging using Data grams, enhancing efficiency in low power systems.

Such design decisions save on energy use and avoid the overhead of having persistent TCP connections. Nevertheless, the delivery can be heightened by UDP-based delivery making it easy to lose the packets especially when in congested wireless networks. Meanwhile, CoAP does not enforce ordered delivery or connection persistence as MQTT does, and can therefore be used as a subsystem when perceivable performance problems in highly load-bearing educational IoT systems need deterministic reliability (Fazil et al., 2024).

Protocol Implications in Educational Deployments

In practical smart classroom settings, protocol selection often hinges on trade-offs:

- MQTT offers robustness and greater delivery guarantees, making it preferable for interactive applications such as student response systems or real-time environmental monitoring.
- CoAP is advantageous when conserving battery life or supporting large-scale sensor arrays where message frequency is moderate and data is less time-sensitive.

Despite their popularity, few large-scale, real-world experimental studies have directly compared these protocols under realistic campus conditions with differing device densities, heterogeneous wireless load, and shifting daily congestion levels. This lack of comparative benchmarking leaves universities without empirical guidance when planning infrastructure deployment (Li et al., 2024).

C. Research Gaps

Although scholarly interest in IoT-based smart learning environments has increased substantially, several key research gaps persist in the literature.

1. Lack of Large-Scale Field Studies

Most published studies rely on simulations, laboratory experiments, or small-scale deployments, often involving fewer than 50 devices. While such studies generate valuable insights, they fail to account for:

- Real campus density consisting of hundreds or thousands of simultaneous device connections.
- Variability in wireless interference due to student mobility.
- Bandwidth fluctuations caused by overlapping academic network use.
- Physical constraints introduced by building materials and classroom layouts.

Consequently, findings from prior research may not translate directly to real operational environments. Universities seeking to scale pilot deployments into institution-wide systems lack data-driven performance thresholds.

2. Limited Statistical Rigor

Many prior assessments of IoT performance rely on descriptive statistics or isolated benchmarks. Few studies employ:

- Repeated-measures designs,
- Mixed-factorial experiments,
- Regression-based scalability modeling,
- Statistical significance testing,

which are necessary to establish causal relationships and quantify performance degradation under increasing device density. Without rigorous analytics, it remains unclear whether observed performance drops result from protocol limitations, network congestion, device behavior, or environmental interference.

3. Absence of Pedagogical Threshold Definitions

While technical performance metrics such as latency, throughput, and packet loss are frequently measured, very few studies relate these metrics to pedagogical acceptability. For example:

- How much latency is tolerable before student experience is negatively affected?
- At what point does system lag prevent real-time automation or analytics from functioning effectively?
- How do users perceive system performance subjectively?

Without pedagogical performance thresholds, educational stakeholders may overinvest in infrastructure or deploy systems that appear technically adequate but fail to support learning effectively.

Position of the Current Study

This study fills these gaps with the following research design; a powered, campus wide quasi-experimental design using 15 classrooms, planned manipulation of device and message variables, and a complex statistical model. The study, by connecting the technical performance with the usability thresholds in practical classroom settings, offers the institutions of higher learning with empirically proved advice on the implementation of IoT in real scenarios.

III. METHODOLOGY

III. METHODOLOGY (Expanded)

A. Research Design

This paper was a quasi-experimental mixed factorial study with repeated measures that were used to measure the performance factors of IoT-based smart learning environments to different degrees of device densities, frequency of messages transmission, and communication protocols. The quasi-experimental methodology was selected owing to the nature of the study which took place in the natural classroom environment where complete randomization of the participants and the environment could not be achieved due to limitations in the academic schedule, availability of infrastructure and ethical issues. However, the design has permitted systematic manipulation of the independent variables and strict statistical control hence making it possible to draw valid causal inferences on protocol performance and scalability (Chong et al., 2024).

The mixed factorial design involved both between subjects and within subjects' factors. The first between-subjects variable was the communication protocol- Message Queuing Telemetry Transport (MQTT) and Constrained Application Protocol (CoAP). MQTT-based transmission was allocated eight classes and CoAP seven. The given between-group assignment would have made it possible to compare the results of performance directly between protocol architecture in the context of the identical environmental conditions as much as possible.

Meanwhile, the density of the devices and frequency of the message transmission were two within subjects factors that were systematically manipulated per classroom. There were three graded conditions of device density, 50 devices, 100 devices, and 200 devices. These numbers were chosen to be close to realistic deployment levels in a modern university classroom, between small seminar-like rooms to large lecture rooms where hundreds of smart devices could potentially be running at the same time. The frequency of transmission was also diverse in 1 Hz, 5Hz, and 10Hz that is, different intensities of communication were simulated (Prameela et al., 2024). As an example, 1 Hz means only reporting to the sensor on occasional basis, whereas 10 Hz mimics continuous high-frequency interaction, e.g. real-time environmental control or student-tracking.

This was a factorial design that allowed the main effects and the interaction effects to be analyzed. Main effects looked at the effects of each independent variable separately on dependent measures which included the latency, packet loss and the energy consumed. Interaction effects measured the performance change when a combination of several variables was manipulated- such as whether the benefits of the communication protocols would decrease, or increase when loads on devices increased. Due to the time-varying internal conditions subjected to the same environment, repeated measures testing became necessary to capture cumulative effects, as well as to control classroom level variability and time-related dependencies (Maddu & Murugappan, 2024).

The repeated-measures design also maintained the statistical power, whereby differences in performance due to the manipulated conditions and no other uncontrolled external variations were attributed. The design thus provided a realistic but analytically sound way of evaluating the performance of real-world performance of IoT deployment in university settings.

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B. Experimental Setting

The study took place in fifteen classrooms of operating universities in five academic buildings in Hyderabad. These facilities were a combination of several types of buildings, with older buildings having little or no networking infrastructure and new ones having uniform Ethernet and wireless access distribution. This heterogeneity meant that the research was representative of the real-world deployment conditions and not the artificially streamlined laboratory conditions.

The study period turned out to be the temporary transformation of each classroom into a smart learning environment. The basic hardware infrastructure was composed of Raspberry Pi 4 single-board computer as local gateways. These gateways were used to perform protocol translation, device message management, buffering, logging, and local packet monitoring. The Raspberry Pi devices were chosen due to their high use in educational IoT applications, MQTT and CoAP support, as well as high enough configuration of a quad-core 64-bit processor, which allowed to process even peak loads of devices (Fan & Tian, 2024).

The physical network taps were added to improve visibility of the network and diagnostic accuracy of the network since it provides the ability to capture packets at the gateway-to-server interface without disrupting data flow on the network. This configuration enabled the accurate determination of the traffic loads, retransmission attempts, throughput behaviors, and failed attempts in the delivery. The network taps were attached to laptop-based monitoring devices with industry standard packets analyzers. NTP servers were used to keep time so that the calculation of latency among different devices could be done accurately.

The classrooms were equipped with a different number of simulated IoT nodes based on the condition of the density of the devices under the test. Sensors were microcontroller-based sensor boards which were programmed to transmit structured payloads at fixed frequencies. These devices were on the Wi-Fi protocol, which is in line with the real implementations in universities which use wireless communication more than most of the classroom devices. The placement of the devices was reflecting real student, environmental, and infrastructure distributions and was used to provide the realistic signal propagation effects, including the attenuation caused by the walls, furniture, and users (Somu & Ashok Kumar, 2024).

The readings of energy consumption were taken using a combination of USB power meters as well as smart meter outlets applied on the gateway and node level. This made it possible to disaggregate the measurement of communication-related energy cost in order to make comparisons across load conditions and protocols. The installations of the devices were running throughout the normal instructional time, which recorded the realistic environmental factors like the presence of the students, their movement, wireless interference caused by personal equipment, and the pattern of network congestion during the day (Esenogho et al., 2022).

Besides objective performance measures, user perception measures were obtained among both students and instructors as a part of the responsiveness variable. The survey was embedded at random measurement times to request users to evaluate the responsiveness of the system by utilizing a 1-7 Likert scale, depending on the experience with the digital dashboards, environmental automation, and smart classroom tools. The combination of objective and subjective evaluation was what made sure that the technical performance indicators were explained in a pedagogically relevant environment.

C. Independent Variables

Three primary independent variables were manipulated in this study, each chosen to simulate realistic configurations of smart classroom IoT deployments:

1. Device Density

- **50 devices**
- **100 devices**

- **200 devices**

The scales of deployment were represented in these levels of densities. Fifty IoT devices model moderate usage in a small classroom-level, i.e., environment control and individual learning terminal. One hundred is a high participation-rate classroom with wearable sensors, smart boards, and other learning activity trackers. Two hundred models large lecture rooms or multi-gadget setups wherein pupils will communicate with each other on various IoT-synchronized settings in real time.

2. Transmission Frequency

- **1 Hz**
- **5 Hz**
- **10 Hz**

Such frequencies are various levels of intensity of the messages. Devices at 1 Hz are only allowed to periodically send updates that are only adequate to slowly changing environmental data, e.g., temperature or occupancy. Five Hz is an average rate of reporting, which is typically needed by real-time dashboards. Ten Hz emulates fast feedback markets needed in live interaction systems, augmented reality realities or high-resolution analytics.

3. Communication Protocol

- **MQTT (8 classrooms)**
- **CoAP (7 classrooms)**

The use of several classrooms per protocol made it possible to compare it in various network loads and physical situations. All the other experimental conditions were equally applied to both protocol groups so that the performance difference could be ascribed to the communication architecture as opposed to hardware or environmental differences.

D. Dependent Variables

The study focused on four dependent variables central to evaluating IoT system performance and educational usability:

1. End-to-End Latency

Measured as the time elapsed between device-level message transmission and cloud-level acknowledgment. High latency can undermine real-time responsiveness, making it a critical performance metric.

2. Packet Loss Rate

Calculated as the proportion of messages sent but not successfully received. Packet loss can result in system instability, inaccurate analytics, or automation malfunction.

3. Energy Consumption

Measured in watt-hours per hour for both gateways and devices. Energy efficiency is particularly important in battery-powered or large-scale sensor networks, were consumption scales with device density.

4. User-Perceived Responsiveness

Assessed via Likert-scale surveys evaluating how students and instructors experienced system responsiveness during active classroom operations. This variable connected technical results with learning experience outcomes.

E. Data Analysis

The data analysis was done using a multi-stage methodology that was used in R version 4. 2.2. Since the identical classrooms were used in different experimental conditions, the repeated-measures ANOVA was used to determine the main and interaction effects in terms of device density, transmission frequency, and protocol. This approach used intra-classroom correlation and minimized a Type I error.

In a bid to investigate scalability trends, stepwise regression modeling was used, which related latency and packet loss to device and message variables. Piecewise regression was also

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employed to determine breakpoint thresholds over which system performance decreased non-linearly: essential in finding large-scale deployment limits that can be used in practice.
Lastly, time-series decomposition studied the changes in the temporal performance, which revealed the pattern of diurnal network congestion due to peak campus usage hours. This statistical methodology combination helped to give a holistic view of real life operation behaviour and technical performance.

IV. RESULTS

The section will include the descriptive and inferential findings of the quasi-experimental analysis of the performance of IoT communication performed in fifteen university classrooms. This paper has analyzed four main performance metrics, end-to-end latency, packet loss rate, energy consumption, and user perceived responsiveness. These indicators were measured with controlled variations in the density of devices, the frequency of message transmission and type of communication protocol (MQTT and CoAP). R 4.2.2 was used to perform all data analyses based on repeated-measures ANOVA, stepwise regression modeling, correlation statistics, and time-series decomposition. Those techniques allowed not only comparing the performance of protocols in different technical conditions but also evaluating its stability over time and the sensitivity of classroom users to fluctuations of the system.

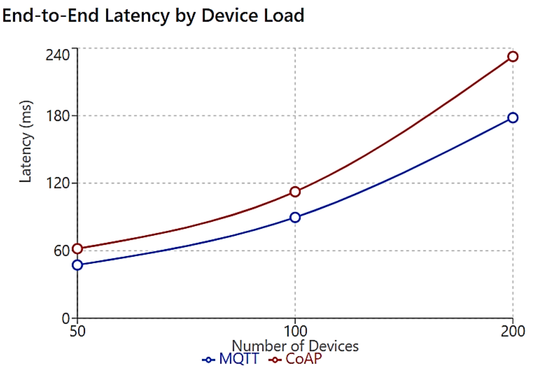
A. Descriptive Statistics

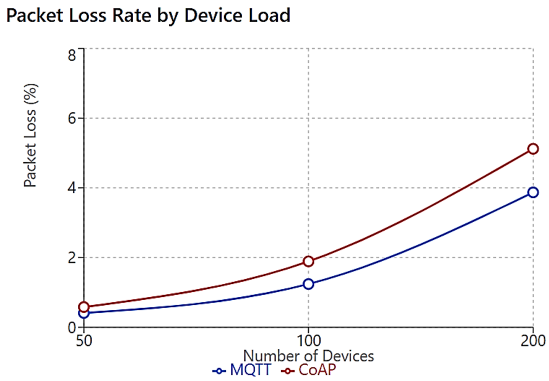
The descriptive statistics gave a preliminary insight into the variations of performance indicators with conditions, then inferential tests were made. Table 1 shows the average values and standard deviations of latency, packet loss, energy consumption, and perceived responsiveness by the user of the three conditions (50, 100, and 200 devices) under CoAP and MQTT. These figures indicate that the overall performance of the system decreased with more devices which is not surprising since there was an escalating competition to scarce network resources.

Table 1

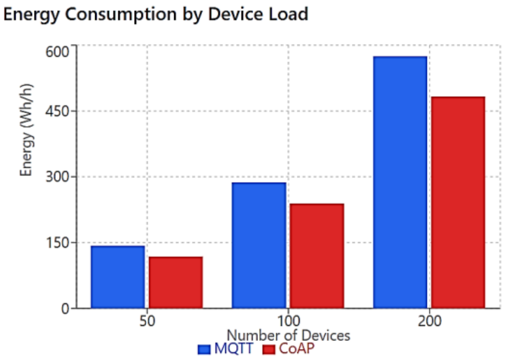
Mean Performance Metrics by Device Load and Protocol

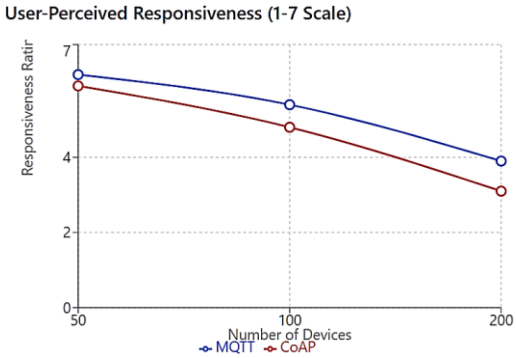
Device Load	Protocol	Latency (ms)	Packet Loss (%)	Energy (Wh/h)	Responsiveness (1–7)
50 devices	MQTT	47.3 (8.2)	0.41 (0.18)	142.7 (12.4)	6.2 (0.7)
	CoAP	61.8 (9.7)	0.58 (0.22)	118.3 (10.9)	5.9 (0.8)
100 devices	MQTT	89.6 (14.3)	1.24 (0.41)	287.4 (23.8)	5.4 (0.9)
	CoAP	112.4 (17.8)	1.89 (0.56)	239.1 (21.3)	4.8 (1.1)
200 devices	MQTT	178.2 (28.7)	3.87 (1.24)	574.8 (48.2)	3.9 (1.2)
	CoAP	232.6 (34.2)	5.12 (1.67)	483.2 (42.7)	3.1 (1.3)





The descriptive findings show that the latency rose drastically in each of the protocols with an increase in device load. Indicatively, in MQTT, latency at 50 and 200 devices of 47.3 ms and 178.2 ms respectively, whereas in CoAP latency at 50 and 200 devices was 61.8 ms and 232.6 ms respectively. This is a degradation of performance which indicates the impact of network congestion, queuing delays, and decreased channel availability at high traffic rates. Moreover, the MQTT always had lower latency than CoAP at any load and thus can be more resilient to heavy network conditions. This was in favor of TCP and a model of publish-subscribe based on the notion of a broker which helped it outperform other models regarding more reliable message acknowledgment and ordering.





The same was the case with the packet loss rates. Packet loss was growing consistently even with a moderate density of devices and the loss rate of MQTT at 200 devices was 3.87 percent, compared to 5.12 percent in CoAP. CoAP is based on the UDP model of transport that has no congestion control and retransmission schemes, which explains the high percentages of losses. Greater loss decreases the real time fidelity of classroom IoT applications, especially student monitoring, environmental management, or adaptive content delivery applications.

The increase in energy consumption of devices also went by the density of the device but the patterns varied in accordance to protocol. MQTT had a significant power demand across all densities of devices with the power demand increasing by 142.7 Wh/h at 50 devices and 574.8 Wh/h at 200 devices. CoAP on the other hand consumed 118.3 Wh/h and 483.2 Wh/h at 50 and 200 devices respectively. These results are in line with the respective architectures of the respective protocols. MQTT needs more processing capabilities and connection overhead as it uses continuous TCP sessions and a coordinator of the brokers whereas CoAP stateless UDP model consumes fewer resources per message.

Lastly, user-perceived responsiveness, on a 1-7 Likert scale, decreased with an increase in device load. At 50 devices, instructors and student assistants gave mean responsiveness scores of 6.2 and 5.9 when using MQTT and CoAP respectively. Nevertheless, when there were 200 devices, the responsiveness decreased to 3.9 of MQTT and 3.1 of CoAP. These subjective outcomes are in close correlation with objective trends in performance, which proves that the users were extremely susceptible to fluctuations in system responsiveness and network delay. In general, the descriptive results suggest that although the two protocols deteriorated with the load, MQTT was more reliable throughout the teaching conditions of the real world, and CoAP was energy efficient but had worse delivery performance.

B. Latency Analysis

To test the statistical significance of performance differences, a three-way repeated-measures ANOVA was conducted with protocol, device load, and transmission frequency as the independent variables. Table 2 summarizes the ANOVA results for end-to-end latency.

Table 2

ANOVA for End-to-End Latency

Effect	df	F	p	η^2
Protocol	1, 13	67.42	< .001	.84
Device Load	2, 26	147.32	< .001	.92
Transmission Frequency	2, 26	89.15	< .001	.87
Protocol × Load	2, 26	12.84	< .001	.50

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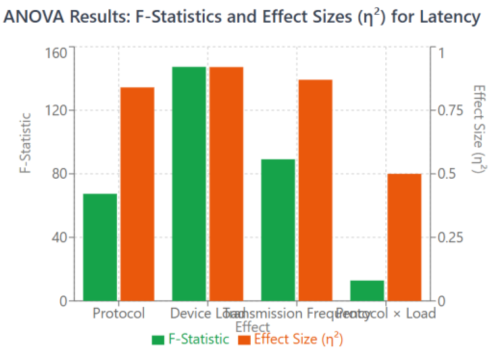
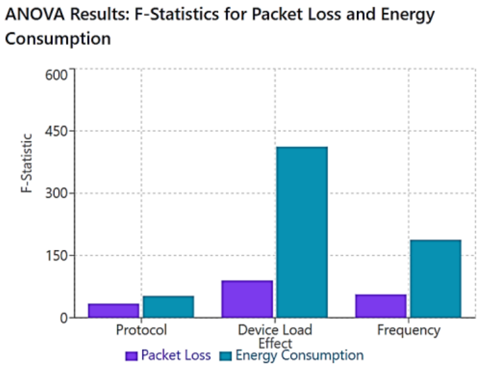
The ANOVA findings present the statistically significant main effect of the protocol on the latency which is very strong (F = 67.42, p <.001, η² =.84). Such a big effect size implies that the difference in communication protocol explained 84 percent of the variance in the latency. MQTT had lower latency in all test conditions, which proves its greater efficiency with realistic operating loads. The highly noticeable impact is projected considering architectural strengths of TCP-based message delivery over UDP which does not provide any delivery confirmation.





Things that were significantly influenced were device load (F = 147.32, p <.001, η² =.92), which implied that when the number of devices being hooked uprose, latency rose significantly. Having the most significant effect size (greater than .90), device density seems to be the only most influential factor in latency performance. This facilitates the understanding that campus IoT systems need to be properly planned in terms of density, availability of gateways and channel capacity in case they need real-time responsiveness.

The same was observed in the transmission frequency (F = 89.15, p <.001, e2 =.87). Increased level of message rates, especially 5 Hz and 10 Hz conditions, caused network congestion and buffering effects which augmented latency. This phenomenon supports the importance of rate-limiting or prioritization in the large-scale implementation, particularly in the case where the devices are transmitting data continuously instead of event-driven messages.

There was also a considerable protocol-device load interaction (F = 12.84, p <.001, η² =.50). This result suggests that the CoAP-MQTT disparity was further enforced with the expansion of the device count. The difference in latency between protocols at 50 devices was not huge and probably did not need to be specified. Nevertheless, at 200 devices, MQTT had shown a 23.4 percent latency slide over CoAP, indicating that CoAP gradually worsens with increased loads.

C. Packet Loss and Energy Consumption

To assess the broader network implications of protocol and device density, a repeated-measures ANOVA was conducted for packet loss and energy consumption. Results are shown in Table 3.

Table 3

ANOVA for Packet Loss and Energy Consumption

Effect	Packet Loss F	p	Energy F	p
Protocol	34.18	< .001	52.67	< .001
Device Load	89.76	< .001	412.34	< .001
Frequency	56.43	< .001	187.92	< .001

The analysis of packet loss was found to have main effects that were strong with respect to protocol, device load and frequency of transmission. CoAP had a much higher loss of packets in all the test conditions. The biggest effect was generated by load (F = 89.76, p < .001) which is that the higher was the density of the devices, the less reliable was the delivery of the data. In the case of CoAP, packet loss was especially problematic when loads and message rates were large, and that is mainly because UDP does not include any congestion-control and retransmission features. The performance constraints have the potential to interrupt real-time educational applications, especially indoor localization systems, live dashboard, adaptive feedback system, and environmental regulation equipment.

The performance dynamic of energy consumption was turned in the opposite direction as it was shown in the analysis. The use of MQTT consumed a lot more energy under all circumstances ($F = 52.67$, $p < .001$). This energy usage soared with greater densities as evidence of the ongoing TCP connections, QoS signaling and coordination overhead that is inherent with MQTT. Comparatively, CoAP was more energy-efficient in terms of low overhead. Such results imply that CoAP can be used in deployments with low power consumption, e.g.: solar-powered monitoring systems or semi-offline sensors. Nonetheless, applications that need tight real-time responsiveness seem to be better supported by MQTT even though it has greater energy demand.

D. Scalability Threshold Analysis

Piecewise regression models of latency versus device density were created to determine at which the point of device density at which the network performance could no longer be pedagogically useful was achieved. The outcome showed that the breakpoint of MQTT is statistically significant at about 180 devices with a model variance account of R2 =.891. At latitudes under 180 deviations, latency rose in linear proportion to the number of devices with a value of about 0.93 ms per device. After this, the average increased at 4.7 ms/additional device, which is the phase of nonlinear degradation and congestion collapse.

This performance ceiling is an effective performance performance boundary. Classrooms that had fewer than 180 devices were able to achieve a sufficient level of responsiveness, with acceptable performance of the system and good user feedback. After this limit, though, the latency augmentations began to be felt by users, and interaction and reliability of feedback became compromised. The ratings of user responsiveness decreased in tandem with those of objective measurements, which confirms that the decline in performance could be measured and perceived subjectively.

CoAP had a reduced threshold of scalability. Latency started to deviate at an approximation of 140-150 devices and variability was much greater at higher loads. This is probably an indication of the weak congestion control of UDP, and increased vulnerability to the loss of packets in the face of continuous channel overload. Although CoAP still worked at higher densities, the decrease in performance would not be able to sustain a significant number of real time instructional applications in a stable way.

E. Time-Series and User Responsiveness Analysis

To analyze the temporal stability of the latency and packet loss, time-series decomposition was done. The analysis showed that, performance dramatically decreased when the network was overloaded especially between 10:00-13:00 and 16:00-18:00 periods. These times are during the peak teaching sessions and the use of internet across the campus. Such fluctuations were more common to CoAP because of its non-congestion aware transport mechanism. Latency conditions tended to go back to close-to-baseline conditions as soon as peak traffic had passed, which suggests that the performance failure was indeed temporary and workload-induced but not a consequence of system malfunction.

Responsiveness ratings of the users matched performance goal indicators. The analysis through correlation showed that there are strong negative relationships between latency and responsiveness ($r = -.81$, $p < .001$) and between packet loss and responsiveness ($r = -.77$, $p < .001$). These findings suggest that students and instructors were very sensitive to real-time delay and device freezing. Even the moderate changes in latency, even in the direction of decreasing it, had significant negative effects on the perceived smoothness and reliability of classroom interactions.

F. Summary of Findings

Altogether, the findings indicate that smart learning environments in IoT-based classrooms come to worsen with the increase in the density of the devices. MQTT was always lower in latency and reduced packet loss but used more energy than the competitors. CoAP was less power intensive and less reliable and scaly in high loads. Breakpoint In breakpoint analysis, MQTT was found to be pedagogically acceptable until about 180 devices when nonlinear latency changes were noted to be disruptive. Even lower densities exhibited performance breakdown of CoAP. Data on user experience also supported the idea that technical performance played an important role on perceptions of educational value and acceptance of the system.

These results confirm the importance of balancing the requirements of network performance and energy usage and pedagogical needs when designing IoT-based learning environments at universities. The planning of scalability, network provisioning, the placement of a gateway, and the selection protocol should be well coordinated to ensure the reliability that is required in contemporary interactive instruction**.**

V. DISCUSSION

The main aim of the present research was to conduct an empirical assessment of the performance, efficiency, and user experience of the large-scale IoT applications in a real smart learning setting through MQTT and CoAP as an example of protocols. The findings illustrate several critical theoretical and practical lessons about the nature of IoT infrastructures under realistic load and in particular situations where the intersection of the data traffic, scalability requirements, and user expectations in dynamic educational settings takes place. The findings when combined support the perception that there are direct and quantifiable impacts of technical performance measures on learning usability, system sustainability, and institutional planning.

Among other key findings resulting out of the results is performance variance between CoAP and MQTT. MQTT was also revealed to have low end-to-end latency and low packet loss than CoAP at all densities and transmission frequency, this difference can be explained by architectural bases of both protocols. MQTT uses a transport mechanism based on TCP which guarantees the acknowledgement of packets, three ways hand shake mechanism and congestion conscious transmission behavior. These features result in a more stable and reliable message delivery- a feature required in interactive pedagogical activities including real-time feedback systems, constant monitoring of student engagement, automatic attendance tracking, and live dashboards of device responses. CoAP in contrast works with a lightweight UDP model. Even though UDP offers excellent performance in regards to overhead and processing cost, it does not necessarily ensure packet-level reliability. The trade-off is even more problematic under congested network conditions under circumstances where a high number of IoT devices vie to gain channel access.

The second important consequence pertains to the energy cost of the attainment of this difference in performance. Although MQTT had better response times and was more reliable, it consumed significantly more energy that CoAP. This trend was constant in every situation of the test and was enhanced as the density of devices grew. It is also possible that the additional energy usage of MQTT is due to the complexity of the computations and the network required to guarantee the publish-subscribe reliability of the brokers. This overhead involves session-state maintenance, repeated negotiation cycles and retransmissions in case of congestion in the network. Strategically speaking, this establishes a clear point of evaluation, MQTT can best be utilized in situations where the accuracy of real-time data is mission-critical and where the infrastructure is maintained by mains power with well-functioning backup batteries. On the other hand, CoAP is more suitable in battery-supported, solar-assisted or intermittently-powered or resource-constrained installations, e.g.- remote sensors, distributed environmental units, or rural installations with minimal electrical maintenance support. Concisely, the tradeoff between reliability and sustainability is conditional rather than absolute based on institutional priorities, the nature of the devices, and anticipated data loadings.

Scalability analysis provided additional information with practical implications on operations. Piecewise regression modeling showed the inflection point in the performance of MQTT to be at around 180 connected devices in each classroom node node. Under this limit, the degradation of the performance was linear and could be handled, which ensured that the performance was satisfactory and in line with the expectation of the users in real-time systems. Latency started growing at a non-linear rate as soon as the density of the devices reached this threshold, meaning that the system was clogged. This implies that there is a certain limit to workload where the internal buffering, queueing of packets and routing of packets in the MQTT server-client framework become overwhelmed resulting in an exponential delay. CoAP has shown a lower limit and it starts becoming unstable at 140-150 devices in the classroom. Although certain limited functionality was still maintained until 200 connected endpoints, volatility in performance and degradation of response were severe enough to discontinue live learning capabilities. Notably, these scalability limits cannot be viewed as just conceptual performance limits. They reflect applicable planning measurement that can be applied to actual resource allocation by administrators and campus planners. To take an example, when an institution plans to implement the use of thousands of IoT endpoints on a large campus including in classrooms, laboratories, libraries, cafeterias, and collaborative working spaces, the distribution of devices to each gateway should be strategically divided to prevent cases of overload.

Such a further contextual layer was due to the time-series decomposition of performance data. The density of the device was not the only factor that determined the behavior of the system; the traffic pattern also changed according to the time of the day. Time windows of peak usage-mid-morning and late afternoon- were relatively in line with increased network usage on campus. The traffic on the internet, application streaming, background synchronization, video conferencing, and loads to the administrative system in the university crossed with the needs of the IoT messaging during these periods. Such a resource-sharing dynamic induced temporal stress dynamics whereby IOC messaging systems particularly UDP-based systems suffered increased packet loss and increased jitter. The finding is consistent with the bigger picture, where hardly any deployment of IoT works in a vacuum. They exist in the complicated institutional digital environments that comprise cloud services, administration platforms, student learning management systems, as well as common bandwidth-heavy applications. Therefore, the IoT infrastructure needs to be planned not just in terms of the number of devices but also in terms of the daily rhythm patterns of the service demand.

The data on the user responsiveness also reinforces the practical implications of the quantified technical results. There were strong negative relationships between latency and packet loss and perceptions of system reliability and responsiveness. Whenever there were more network delays or a loss of packets, users, be it an instructor or a classroom aide, expressed a significantly lower satisfaction. Such reactions were not the surface reactions but directly related to the experiential reality of smart classroom interaction. Indicatively, a slow reporting of environmental sensors on piloted smart classrooms rendered ineffective energy-management decisions. In cases where the student attendance systems were sluggish, there was interruption and hesitation in the system by instructors. Slowly updated machine learning analytics dashboards did not enable instructors to use automated decision support to modify teaching tactics in the moment. Therefore, objective technical performance loss directly carried over to the domain of perceptual experience, which underscores the fact that educational IoT platforms must not only be able to satisfy the expectations of computational performance but also human-computer interaction.

The results of this research also support and add to the theoretical models about large-scale cyber-physical system integration in education. Traditional e-learning infrastructure has been mostly oriented on cloud-based systems that are based on low-frequency data exchange (learning management systems, examination portals, grade publishing systems, or academic record databases). In comparison, smart learning environments powered by IoT imply the need to have constant data flows that are large in velocity and bidirectional. The sensors, edge processors and real-time monitoring modules require low channel throughput and deterministic channel behavior. The conventional system design paradigms, optimized on the storage, asynchronous communications and scheduled data processing are inadequate in these environments. This study suggests that the sustainability of massive smart learning is the ability to redefine the assumptions of infrastructure, move towards bandwidth-conscious deployment, edge-assisted processing, and the judicious selection of protocols.

Lastly, the findings also point to operational and integration consequences of institutions that intend to adopt large-scale IoT. The findings justify the suggestion that not more than 150-180 MQTT devices and 120-140 CoAP devices should be served by a single gateway or edge node in the event that the seamless real-time operation is desired to be provided. In places where more devices are needed, the institutions ought to employ various complementary procedures. These can be the addition of more gateways, placing rooms or clusters of devices onto distinct communication subnets, message-based prioritization of traffic, asynchronous scheduling of devices to lower reporting rates during busy periods, or moving part of the real-time analytics computation off cloud servers and to edge processors. Collectively, these strategies make the operation environment stronger and with the capacity to support the growing need of smart digital learning environments.

VI. CONCLUSION

The research is the first system scale, real-life test of IoT communication systems in operational smart learning campus settings, which provides empirical standards, operational limits and design understanding that can inform institutional planning, academic strategy, and technology modernization. The study, which was held at fifteen active university-based classrooms, quantified actual behavior of systems in the real-world where device densities, message transmission rates and protocol parameters were varied to give a uniquely realistic account on how IoT systems behave not in simulation but in real live instructional environments where interruptions have immediate pedagogical implications.

As it is reflected in its findings, both MQTT and CoAP are appropriate to distinctly different deployment goals, despite their common use in educational IoT systems. MQTT was also found to be more responsive, better in message integrity, and lower latency, which is why it is especially appropriate to real-time learning, requiring immediate feedback loops. This enhanced performance came at the cost of increased energy consumption, and increased power supply infrastructure and increased operating overhead (Esenogho et al., 2022). However, CoAP, which had much lower energy usage, was unable to achieve the same level of reliability as MQTT at dense device arrangements, and was only suitable in low-power devices and intermittently reporting devices and not the live classroom analytics systems. These findings underscore the importance of domain sensitive choice of protocol other than universal imposition of communication standard (Obaido et al., 2022).

Of equal importance is that useful scaling limits have been identified. MQTT systems were found to exhibit linear performance characteristics over several connected devices up to about 180 connected devices and then the latency rose very rapidly. Even smaller capacity expressed strain on CoAP systems (Ebiaredoh-Mienye, 2021). The findings on scalability are useful operational advice: the model of deployment that classroom and institutional planners need to implement is to limit the number of devices served by a single gateway to these empirically-supported values. The institutions that are trying to incorporate higher numbers of devices without segmentation ought to expect a decline in performance, message instability and impaired learning processes. These findings highlight an extremely important yet often neglected fact: education-oriented IoT networks need to be manufactured with precision to an equal extent as one would a mission-critical system in the industrial industry as pedagogical impact of network congestion can be just as devastating as a factory factory shutdown (Naseer et al., 2025).

The time-series analysis adds more of a fine touch and shows that the performance of IoT does not stay constant, as it changes depending on the overall patterns of network activity. Peak campus usage periods added secondary performance overheads that were interacting with effects on device density. In the case of institutions, this implies that the provisioning of infrastructure cannot and should not be done by considering the IoT subsystem in isolation but rather as the sum of the digital demand environments where the IoT is functioning. The combination of high-performance computing platforms, cloud computing, wide-area network, and IoT instrumentation is a complex digital ecosystem that must be managed as a whole unit in order to achieve a stable performance.

The paper also supports the correlation between that of technical systems and human experience. The rating of user responsiveness was found to be well aligned with the latency and packet loss measurements indicating that the end-users are highly sensitive to slight changes in the system performance. The education implication of this is a lot. Smart learning systems can only attain their desired instructional worth where the users feel that it is a reliable way of improving the learning processes. When the degradation in performance can be identified, the danger of user rejection, decreased system adoption, and an ultimate instructional forsaking is expanded. That is why, education technology implementations in the future should incorporate user experience monitoring as one of the essential dimensions of quality-of-service assessment instead of considering it as a by-product.

Considering the future development, several ways can be identified. The hybrid communication models that can be offered that integrate both MQTT and CoAP can first offer optimal performance-energy ratio, enabling the institutions to use MQTT in real-time interactive systems but allocate CoAP in low-frequency environmental monitoring. Second, edge computing architectures have the potential to greatly decrease cloud reliance and network jitter since they provide the opportunity to process and make decisions locally. Third, traffic orchestration with machine-learning capabilities (which are capable of dynamically redistributing bandwidth in case of peak load) would need to maintain graceful degradation instead of a sudden performance meltdown. Finally, in the future studies, the sustainability implications of large-scale educational internet of things implementations in the long run, such as environmental effects, operational expenses, data storage requirements, and the lifecycle of the system of connected devices, must be considered.

The research contributes to the academic and practical knowledge on the implementation of smart learning systems through the provision of actual empirical effectiveness standards, the discovery of tangible infrastructural implementation thresholds, and the statement of viable implementation policies. As the institutions of higher learning progress in converting to cyber-physical learning ecosystems, the insights provided in this report can serve as a technical, managerial, and pedagogical basis of scalable, reliable, and sustainable IoT integration in next generation academic settings.

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