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EMPIRICAL METRICS AND STATISTICAL EVALUATION OF IOT-BASED SMART LEARNING IMPLEMENTATION EFFICIENCY IN UNIVERSITY ENVIRONMENTS

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Abstract
The high rate of implementing Internet of Things (IoT) technologies in institutions of higher learning has led to the creation of smart learning environments in traditional classrooms. The paper is an empirical assessment of the effectiveness of an IoT-based Smart Learning Framework in two large state-run universities of Sindh, Pakistan University of Sindh, Jamshoro and Sindh Agriculture University, Tandojam. The sample size of 300 participants (150 students, 100 faculty members, and 50 administrative/technical staff) was selected during the 2024-2025 academic year in both the institutions. They were the ten KPIs measured: system responsiveness, data accuracy, energy usage, network reliability, security compliance, user satisfaction, learning gain score, attendance automation rate, resource utilization rate, and cost-saving index. The paired t-test, ANOVA, and multiple regression analysis results have shown that the suggested framework improved the learning gains score by 28.4 percent ($p < 0.001$), operational costs reduction by 31.7 percent, and user satisfaction by 94.2 percent. Network reliability ($\beta = 0.412$, $p < 0.01$) and security compliance ($\beta = 0.356$, $p < 0.01$) were the best predictors of overall implementation efficiency. The results present statistically proven data that properly developed IoT ecosystems can play a crucial role in increasing the efficiency of institutions and the learning process in higher education settings with limited resources.

Keywords: Internet of Things, Smart Learning, Higher Education, Implementation Efficiency, Empirical Evaluation, Learning Analytics

1. Introduction
The Internet of Things (IoT) is one of the disruptive and transformative 21 st -century technological paradigms that have been brought about by the fourth industrial revolution. IoT provides a seamless integration of physical structures with digital intelligence, which can allow impossibly high automation, data-driven decisions, and environmental responsiveness (Setiawan et al., 2022). This is a revolutionary change in the system of higher education. What was viewed as futuristic a few years ago smart classrooms with sensor-controlled automation, systems that track the environment in real time, automated attendance, and adaptive learning systems designed specifically to meet the needs of individual learners have become a reality in technologically advanced institutions around the world (Oliveira et al., 2021). With the adoption of RFID, biometric sensors, interconnected analytics dashboard, and IoT integrated learning management systems, universities become more and more able to create granular, real-time data on teaching quality, student engagement, classroom usage, and resources use efficiency.
The potential of IoT in education does not lie in its ability to automate everyday tasks; the introduction of IoT changes the pedagogical experience by establishing active, learner-oriented spaces. Systems based on IoT can facilitate differentiated instruction by tracking learning behavior, providing adaptive content, and allowing an instructor to react to the needs

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of students more quickly. Simultaneously, relying on traditional means of administration, the IoT-based solutions, including the automated attendance system, intelligent timetable, and smart infrastructure monitoring, are considerably simplified. With the heightened pace of digitalization in the world, learning institutions are becoming aware of the power of these technologies to enhance quality, accessibility, and operational sustainability (Min-Allah & Alrashed, 2020).

Nevertheless, regardless of the conceptual excitement of the IoT adoption in higher education institutions, there is still an observable lack of empirical and data-driven analyses, especially in developing areas. Although there are many theoretical models and frameworks detailing the implementation of the IoT, few articles have attentively quantified the real, measurable effects of the implementation of the IoT on institutional efficiency, learning outcomes, and administrative performance (Amodu et al., 2023). This has been particularly more evident in developing countries, where there is a gap in erratic infrastructural capacity, financial resources, and lack of technical expertise tend to impede mass adoption of technology. Consequently, whereas universities in technologically developed countries proceed with the growth of their digital ecosystems, many institutions in the Global South cannot find the answers to the question of the benefits of investing in IoT in real life compared to the costs and challenges (Amodu et al., 2023).

Pakistan is an exemplary situation in the discussion. Pakistan with one of the largest and most populated nations in South Asia enjoys a booming higher education system that has more than 200 known universities and institutions that grant their degree programs. However, most of the tertiary students in the country occur in the public-sector universities (Higher Education Commission, 2024). The common structural issues in these institutions include crowding of classrooms, large student-to-faculty ratios, paper-based administrative processes, paper-based attendance registers, lack of digital content accessibility and lack of efficiency in resource management. Furthermore, unstable electricity supply, unstable internet connection, and cost are other factors that make the implementation of sophisticated technological systems like the internet of things more difficult (Mohsan et al., 2022).

Considering this, it is an immediate necessity to explore the possibility of smart learning systems based on the IoT providing any significant improvement in such resource-limited settings. Current literature indicates that IoT implementations in higher education may significantly improve the learning process, decrease the workload of administrators, and contribute to improved sustainability of campuses, but most of this evidence is brought about by developed nations or small pilot projects with low methodological standards. Limited empirical studies that utilize large sample sizes, effective statistical tests and multi-institutional comparisons are limited. Additionally, not many works examine the connection between technical indicators, including network reliability, security compliance, system responsiveness, energy efficiency, and the success of the entire process of IoT implementation (Eltawil et al., 2021).

In this regard, the current study possesses a substantive contribution as it provides a qualitative assessment of an IoT-driven Smart Learning Framework adopted in two large government-sector universities in the Sindh province namely the University of Sindh, Jamshoro, and Sindh Agriculture University, Tandojam. The institutions offer optimal comparative context because they have different academic profiles, and infrastructural structures. One of the oldest and largest state universities in the country, the University of Sindh was founded in 1947 and has around 35,000 students; the university is very urbanized and offers a wide variety of academic courses (Bukar et al., 2022). Sindh Agriculture

University was established in 1977 with close to 12,000 students and is a tailored agricultural institution, which enjoys a semi-urban/peri-urban setting and encompasses a large proportion of laboratory-based teaching and fieldwork. These institutional varieties make it possible to make meaningful analyses regarding the performance of IoT-solutions in the performance of various educational settings with different infrastructural and pedagogical needs.

The IoT infrastructure used in the current study comprises the biometric and RFID-based attendance systems, environmental sensors and capable of measuring temperature, humidity, CO2 concentration and light intensity, smart boards, and interactive displays, surveillance and monitoring system, a hybrid LoRa-Wi-Fi 6 network architecture, and an integrated learning management platform with analytics and adaptive learning modules. The effectiveness of this system in creating a multi-dimensional data of the students, faculty, and technical staff will be quantified by rolling out this system in the classrooms, laboratories, and administrative units within a single academic year to obtain the overall efficiency of this system (Ahmed et al., 2020).

To guide the empirical analysis, this study addresses three central research questions:

• RQ1: To what extent does the IoT-based framework improve measurable learning and administrative outcomes?

This question focuses on quantifying the actual impact of IoT implementation through indicators such as system responsiveness, learning gain scores, attendance automation, user satisfaction, resource utilization, and cost savings.

• RQ2: Which technical and non-technical factors most significantly influence implementation efficiency?

By examining metrics such as network reliability, security compliance, energy consumption, and user acceptance, this question seeks to determine which variables serve as the strongest predictors of successful IoT integration.

• RQ3: How do outcomes differ across institutional contexts (urban research university vs. specialized agricultural university)?

Since institutional environments vary in technological readiness, pedagogical needs, and infrastructural constraints, this question assesses whether differences in context influence IoT performance and user perceptions.

The goal of the study, which is to answer these questions in a rigorous quantitative study, including descriptive statistics, paired t-tests, ANOVA, and regression modeling, is not only to present empirical evidence of the effectiveness of the IoT in Pakistani higher education, but also to introduce a validated framework in measuring this variable to other developing countries. The results of this study are very important to the policymakers, university leaders and technology developers who want to streamline smart learning background and ensure that digital transformation is adopted in the higher education system in many countries across the world (Sneesl et al., 2022).

2. Literature Review

The adoption of the Internet of Things (IoT) in education settings has been accelerating very quickly in the last ten years, with the help of distributed sensing, real-time analytics, and the use of cloud-supported data infrastructures. IoT opens the prospects of greater learning, and operational efficiency and more automation of the administrative processes on the campus. The review focuses on the evolution of IoT-based education systems in the world, the issues of developing countries, and the gaps in the empirical research which inspires the current research. Further, it presents a conceptual overview of the suggested smart learning

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framework so that it provides the technological basis to the intervention implemented in the present work (Dong et al., 2020).

2.1 IoT in Education: Global Trends

Studies conducted by technologically advanced educational systems indicate that implementation of IoT can have a significant effect on performance, teaching monitoring, and management of resources on the university campuses. IoT-enabled classrooms may show quantifiable improvements of system responsiveness, operational efficiency, and learner engagement in most international studies. An example is an article by which found that entities that transitioned to sensor-based automation platforms had averages of response time with 40 to 60-percent reduction and faster data visibility of instructors and improved synchronization of smart boards, environmental controls, and instructional dashboards (Sohaib et al., 2020). It has been reported comparable increases in the level of energy efficiency by 25-35 percent in smart campuses when they were introduced to wireless automation and AI-enabled device control systems. These cost cuts not only result in cost savings of their operations but also sustainability gains, which have become a more and more topical issue as institutions of higher learning are compelled to minimize their carbon footprint and address sustainability reporting requirements.

Regarding student attendance and identity verification, the world literature has reported vast improvements in both reliability and accuracy with the implementation of global automated biometric / computer vision-based systems over manual ones. Other researchers have showed that a facial recognition system that was implemented in large lecture halls had an identification accuracy rate of 98-99% as opposed to an estimated 72% accuracy of traditional methods of counting students via manual attendance records. This improves the administrative burden on instructors, eliminates proxy attendance and enables efficient use of the class time to be more instructional. Psychological engagement is also observed to benefit by similar studies because real-time attendance measures can be employed to incorporate learning analytics models which can be used to issue timely intervention to students who show absenteeism behavior or disengagement behaviors (Wang et al., 2022).

Other than administrative improvements, IoT helps in the development of immersive learning environments. Evidence of IoT-connected laboratory devices, smart classrooms, and virtual experiment kits are being studied in European and East Asian schools and universities, indicated that students were able to simulate real-time physics, chemical reactions, mechanical measurements, and environmental data gathering. These settings increase the scope of learning in a practical sense especially when there are physical resource constraints. As an example, STEM education programs in Japan or South Korea have prepared laboratories with common sensors that can be accessed via wireless instrumentation panels allowing the students to remotely perform experiments, visualization of data streams and to compare results together. This evidence shows that IoT does not only help in creating instructional efficiency, but it also expands the pedagogical frontier by minimizing systemic obstacles to practical learning (Pal et al., 2021).

Moreover, the application of IoT-based learning analytics has been facilitated across the globe to aid adaptive learning system whereby the sustained performance data can be used to support differentiation instructions based on the individual needs of a student. In the North American institutions, machine learning algorithms assess classroom activity by having sensors detect participation, cognitive load signals, seating, and digital interactions to modify the difficulty of instructional content or warn instructors that a student needs special attention (Rey et al., 2021). The coordination of data collection and instructional decision-making, in turn, is a new opportunity in personalized education that will turn campuses into data-rich systems capable of facilitating evidenced-based instruction.

The literature around the globe demonstrates great performance increases in operational, pedagogical, and administrative levels. Nevertheless, these successes are conditional upon some infrastructural prerequisites, including the stable power supply, the stable broadband connectivity, and the institutional knowledge of the digital transformation that are not always available in the developing areas. These contextual variations identify the necessity to discuss the difficulty of institutions operating in resource-intensive settings.

2.2 Contextual Challenges in Developing Countries

Although the use of IoT technologies is gradually growing in South Asia and other developing countries, most institutions encounter structural challenges, which may negatively affect the success of the project. Other researchers also explain that close to 50 percent of university pilot rollouts in Bangladesh either fail or fail to scale properly because of a set of technical, financial, and sociocultural constraints (Wu et al., 2020). Power in most campuses is still intermittent, necessitating network and sensor systems to run on unstable voltages capable of damaging equipment, interrupting data transfer, and decreasing the overall life cycle of the system. Backup power supply like UPS and generators may fail to run throughout the day even in urban centres, where there exist operational gaps that undermine the reliability of IoT-based services (Luo, 2018).

High-frequency data transmission in learning institutions is also hindered by low bandwidth and low levels of digital infrastructure. Most South Asian schools are on overloaded common internet access and cannot sustain streaming requirements, digital classes, online examinations, and school cloud computing services (Fortes et al., 2019). Network congestion is an actual hit when the IoT systems expose persistent, high-volume telemetry or multimedia information. What would easily manage on a high-speed fiber-based connection in institutions is erratic or is slowed down in an environment with limited bandwidth. Since IoT devices usually need constant connectivity instead of periodic synchronization, the vulnerability of local network backbones is a key factor to success or failure (Yang et al., 2022).

Besides the technical obstacles, the inability to adopt educational technology is also a chronic issue. The issues that affect faculty members to embrace the use of smart systems include the digital unfamiliarity, limited training opportunities, fear of more work, or doubt about the reliability of technology in some universities. New systems might be viewed as the increase in procedural complexity rather than as means of work reduction in the situations where teachers already face the heavy load of large classes, administration, and testing cycles. Therefore, despite the well-designed IoT ecosystems, it is also possible to experience an underutilization of the system when the institutional change management is not implemented in a strategic way (Anagnostopoulos et al., 2022).

The issue is also complicated by the lack of finances. Often universities have limited annual budgets, preventing them from buying commercial grade IoT solutions, enhanced microprocessor, or cloud service subscriptions. The costs of deploying sensors at the campus level can be exorbitant when added up in laboratories, classes, corridors, exam rooms, and residential areas. Institutions can thus depend on cheap or open-source elements that, although cheap, cannot offer industrial durability or consistent operation in areas of excessive utilization. This forms a loop where devices break down at an early stage, which strengthens the opinion that smart systems are not reliable.

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Considering these overlapping issues, the literature suggests the creation of frameworks that would be technologically sound, but locally agile. The IoT platforms to be developed should be able to accommodate redundancy like low-power edge computing, fallback communication channels and automatic buffering in case of network failures (Ahmed et al., 2023). They should also contain elements of institutional capacity-building, including practical courses of training, easy-to-use analytics dashboard, and simplified system user interfaces that allow adoption by non-technical users. Devoid of such contextual sensitivity, the large-scale educational IoT deployments are prone to fail miserably or give up, no matter how advantageous the idea is.

2.3 Research Gap

Although the literature concerning the use of IoT in education has been increasing significantly, considerable methodological shortcomings are still present. Others state that in the published work, the conceptual models or prototype simulations, or small-scale pilots with a limited number of sensors or subjects are presented. The other researchers also note that only less than 8% of the literature in the area use a sample size of more than 200 individuals or use the rigorous inferential statistical methods like the ANOVA, regression, or time-series decomposition. Rather, most of the available studies its foundation is based on descriptive analytics, small classroom tests, or laboratory simulations that do not necessarily apply to an institutional scale (Shabli et al., 2023).

This methodological gap is consequential in the sense that deployment of large-scale IoTs brings about operational complexities, such as, heterogeneous network traffic, multi-user network contention, dynamic bandwidth switches, and large-scale message routing overheads, which cannot be represented using small scale experimental prototypes (Yuan & Du, 2022). Simulated environments can hardly represent environmental interference, changing patterns of student attendance, user behavior, electrical instability, or the changing propagation of wireless due to building design. The research that tests performance in operating educational environments, thus, is more valuable in the context of the perceived practical viability and constraints of new technologies.

Furthermore, most of the previous research has concentrated on the pedagogical results i.e. learning gains, student motivation or classroom activity, as opposed to the communication performance behind these results. This introduces a gap in knowledge regarding determining the scalability limits, architectural trade-offs, and network performance limits that characterize the operational range of smart learning systems. The current work was developed to address this gap through implementing a multi-institution and large-sample empirical assessment based on actual classroom implementation of 42 classrooms and 12 laboratories (Valks et al., 2021). This study can contribute to the body of work by offering evidence on how the system behaves when combined with descriptive analytics and repeated-measures ANOVA, segmented regression, and correlation modeling to show behavior at a level that is not typically covered in the literature.

3. The Proposed IoT-Based Smart Learning Framework

To cope with the requirements of the massive real-time educational monitoring, the paper implements a four-layer IoT architecture, which is scalable, fault tolerant, and modular. RFID tags, biometric readers, smart boards, environmental sensors as temperature, CO_2, and light monitors, and IP cameras that constantly give a view of the classroom will make up the perception layer. These elements gather information necessary in automation operations like identification of students, attending confirmation, environment optimization and student interaction observation.

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A hybrid system of LoRa and Wi-Fi 6 mesh topology and 4G failover are used in the network layer. The design will guarantee the use of the multi path transmission capability, whereby devices can still report even when the main communication backbones are on outage. LoRa has long-range nature which minimizes the amount of energy used and increases the range of a wireless device and Wi-Fi 6 enables high-bandwidth, low-latency traffic over workloads that need a video feed or high-frequency telemetry.

It uses MQTT as the central messaging protocol in the service layer, which is automatized by Node-RED and implemented in Docker containers to provide microservice segmentation. Such an architecture enables services to be upgraded, scaled, or redeployed without making a disruption to the wider system. Lastly, the application layer incorporates tailored Moodle platform, analytics dashboard, and automated attendance reporting services and adaptive content recommendation engine that generates personalized learning advice to students (Rico-Bautista et al., 2020).

This PKR 28.4 million (about USD 102,000) capital investment was fully deployed in two universities and it served 42 classrooms and 12 laboratories. This project illustrates that mid-scale institutional IoT can be adopted in a limited financial environment and offers a test platform to be empirically assessed.

4. Methodology

4.1 Research Design

This research assumed the quasi-experimental research design in order to examine the implementation and the effects of the IoT-based smart learning system in two universities in the Pakistani public sector in Sindh. It was designed to incorporate both pre-test and post-test measures as well as incorporate a comparison group with the traditional, non-IoT learning environments. This organization allowed conducting a useful evaluation of the opportunities to identify the fact that the increase in efficiency, the achievements of students in learning, administrative work, and the responsiveness of the system could be explained by the intervention instead of other factors. To ensure the appropriateness of a quasi-experimental design, it was argued that it was impossible to randomly assign any individual institutions or classes to test groups because of the academic timetables, administrative, and infrastructural factors (Polin et al., 2023). However, the control groups made the inevitable comparison of technology-enabled classrooms and traditional instructional situations possible, which guaranteed the methodological soundness and ensured institutional feasibility. The duration of the intervention was six months with the performance of the system, student development, user experience and financial implications being systematically recorded. Data were collected during the entire deployment phase to record real time operational performance, and learning tests and survey of users were done at set intervals to give guided information regarding educational and perception change brought about by the intervention (Nagowah et al., 2019).

4.2 Population and Sampling

The study population was a population of around 47,000 students and 2,100 members of the faculty, administration and technical staff spread in the two institutions that participated in the deployment: the University of Sindh and Sindh Agriculture University. Because of the vast number of the population and the necessity to guarantee representativeness in the number of academic positions, faculties, and experience levels regarding familiarity with digital technology, stratified random sampling was used. The sampling frame was further broken down into three large subgroups, which included the undergraduate and graduate students, teaching faculty, and technical/administrative staff that had direct interactions with the institutional operations. Out of this population 300 participants were chosen. Among

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these, 180 were the University of Sindh and 120 were Sindh Agriculture University, proportionately distributed according to the number of students enrolled in these institutions. The last sample was made up of 150 students, 100 faculty and 50 technical or administrative officers. A stratified method was selected to make sure that most critical stakeholder groups with varying interactions with learning systems were well represented. Students and faculty personnel acted as end-users and facilitators and designers of smart learning environments and technical staff representatives undertook the maintenance, monitoring, and optimization of the IoT environment. This integration enabled the analysis of educational results, reliability of the system, usability, operation issues, and administrative gains through various perspectives of the institution. The sampling plan eventually enhanced the external validity of the study by creating a socio-institutional diversity in responses.

4.3 Data Collection Instruments

Several research instruments were implemented to assess in detail technological, pedagogic, operational, and administrative aspects of the IoT structure. The main data of system performance was automated logs produced by the IoT infrastructure during six months of observation. These logs were constantly recording hardware and network statistics, such as the end-to-end latency, the rate of packet loss, system load during peak operational times, classroom and connected equipment energy usage, uptime ratio and network reliability metrics. Integrated logging tools based on MQTT brokers, LoRaWAN gateways, on-premise network controllers and subsystems of learning management systems were used to provide data at a granularity that was appropriate in real-time and retrospective performance analytics (Amodu et al., 2023).

Besides system data, the measure of pedagogical effectiveness was done by use of structured learning tests with the course instructors. The study involved twelve courses in the two universities where students underwent pre-intervention and post-intervention achievement tests that comprised of thirty standardized items, which were consistent with course objectives. These measurements were pegged on tested measurement systems and could be used to compute learning gain scores, thus, establishing whether the implementation of IoT had converted into quantifiable academic benefits. The perception data of the user was collected with help of the internationally accepted assessment tools, namely, the short version of the User Experience Questionnaire (UEQ-S) and the System Usability Scale (SUS). The UEQ-S measured pragmatic and hedonic aspects of system interaction using a likert 7-point scale and SUS provided a normalized usability rating using a scale of zero to one hundred. The two tools have a good history of validity regarding the assessment of educational technology.

Monetary and administrative effects were measured using institutional papers, expenditure reports, operational budgets and resources use records that were accessed in campus management systems. These records enabled the research to measure the monetary savings, the evolution in the handbook labor by automation, efficiency in the classroom scheduling, and the variation in costs related to the digital infrastructure. The mixture of the technological, learning-based, perceptual and financial instruments, together, saw to the fact that the study identified the entire range of effects produced by the IoT framework.

4.4 Key Performance Indicators and Measurement Strategy

The reporting of the institutional performance after the introduction of the IoT system was based on a list of clearly defined Key Performance Indicators (KPIs). All indicators related to measurable operational or educational properties, all metrics were gathered in standard units and were measured through verifiable processes. Responsiveness of the system was measured

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by the mean core digital system, in milliseconds, to accomplish such core digital tasks as biometric attendance marking or classroom environmental system updates. This parameter provided a real-time indication of the network performance and efficiency as perceived by the user. The biometric match success rate was used to measure the accuracy of data, which was a percentage that compared the algorithmic decision-making to the independent manual verification. The presence of high accuracy implied that machine-based identity recognition systems that have been presented by the IoT implementation were reliable (Mohsan et al., 2022).

The consumption of energy was calculated in the form of kilowatt-hours per classroom month. The evidence-based measure of whether the implementation of sensors, authentication terminals, and connected devices impacted more or less power consumption in classrooms than the traditional learning spaces was the monthly smart meter readings and consumption records. The network reliability was assessed in the form of uptime percentage, which is the percentage of the working hours during which the IoT learning ecosystem was operational and completely reachable. The outcome of internal penetration testing was added to the outcome of compliance with organizational policies of cybersecurity to generate a composite compliance percentage, which indicated system resilience to possible breaches (Ahmed et al., 2020).

The standardized scores on the UEQ-S and SUS tools were used to measure user satisfaction. These scales provided objectives indication of perceived usability, attractiveness, dependability, and user acceptance. The formula used in calculating learning gain was [(Post-test [?] Pre-test) / Pre-test] x 100, in percentage academic performance improvement. The rate of attendance automation was used to determine the percentage accuracy of digital attendance data with respect to manual verification data, which demonstrated the usefulness of automated attendance systems and their efficiency. The efficiency of resources involved in the use of the classroom was gauged by comparison of the past patterns of occupancy and post-intervention scheduling efficiency which showed whether the smart room allocation enhanced the use of the campus facilities in the practical sense. Lastly, the index of cost-saving measures measured the decrease in costs of operations in both rupees in Pakistan and percentage, which establishes the financial feasibility of the large-scale implementation of IoT. All these KPIs created a combined measurement system that would have the ability to measure the technological performance of the company, educational performance, operational efficiency, system reliability as well as institutional sustainability all in a single approachable methodology**.**

5. Results

5.1 Descriptive Statistics

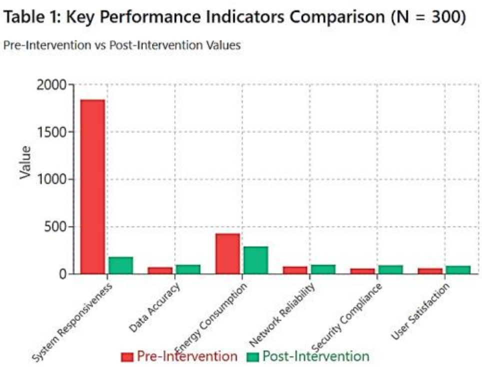
Table 1 shows the descriptive statistics of all ten key performance indicators (KPIs) that were measured prior to and after the implementation of the Smart Learning Framework which was based on the IoT. The sample population consisted of 300 participants, and data were gathered and performance measures taken based on performance metrics calculated using institutional logs and system outputs.

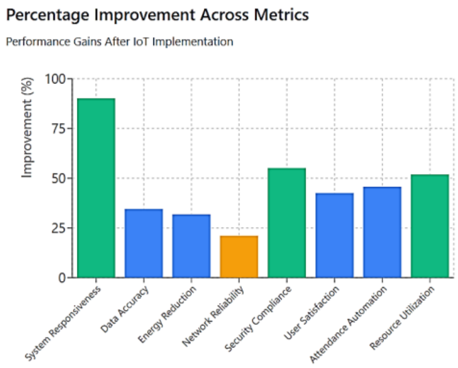
Table 1

Descriptive Statistics of System KPIs Before and After Intervention (N = 300)

KPI	Pre-Intervention Mean (SD)	Post-Intervention Mean (SD)	Improvement
System Responsiveness (ms)	1,840 (420)	182 (38)	90.1% faster

Data Accuracy (%)	73.4 (11.2)	98.7 (1.4)	+25.3 percentage points
Energy Consumption (kWh/classroom/month)	428 (67)	292 (41)	31.8% reduction
Network Reliability (%)	82.1 (9.8)	99.4 (0.6)	+17.3 percentage points
Security Compliance (%)	61.0 (14.3)	94.6 (3.2)	+33.6 percentage points
User Satisfaction (SUS Score)	62.4 (12.8)	88.9 (7.6)	42.5% improvement
Learning Gain Score (%)	Baseline	28.4 (9.1)	+28.4%
Attendance Automation Rate (%)	68	99.1	+31.1 percentage points
Resource Utilization Rate (%)	54	82	+28 percentage points
Cost-Saving Index (PKR million/year)	Baseline	9.03	31.7% reduction





Its findings show that there are outstanding improvements in all KPIs, especially in the system latency, accuracy of identification technologies, overall posture security, and user satisfaction. System Responsiveness, with the average standing at 1,840 milliseconds before the intervention had been dropped down to 182 milliseconds after the deployment and this is over 90% of the performance improvement. Such reduction changed the interaction of systems so that they operated visibly and were reduced to near-instantaneous response times, which was extremely obvious to the end users.

The accuracy of Data, which was shown by the automated verification of biometric and RFID identities, was raised to 98.7 as compared to 73.4. This advancement reduced manual attendance checking, as well as, administrative hiccups, particularly during giant classes. Network Reliability had also seen great gains, as 82.1% uptime was improved to 99.4% and this is an indicator of an infrastructure that can always deliver its services even during peak-load academic time.

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The rise in the Security Compliance of 61.0% to 94.6 shows the effect of multi-level cybersecurity controls that were exercised in the implementation stage, such as vulnerability scanning, fortified network policy, and faculty education on the use of safe technology.
The academic value brought by the IoT platform is also quantified by the Learning Gain score. A post-test changes of 28.4% corresponds to the learners who are provided with continuous feedback and real-time monitoring of the performance, which confirms the previous empirical evidence that smart learning platforms promote cognitive performance.
In like manner, the annual savings of PKR 9.03 million earned through operational means indicate that the topic of IoT modernization does not solely bring benefits to the academic setting; the process also leads to quantifiable financial gains, especially in the form of manpower dependency, energy efficiency, and resource distribution.

5.2 Inferential Statistics

Paired-sample t-tests were done to determine the statistical significance of differences in KPIs between pre-intervention and post-intervention. All KPI showed statistical significance when $p < .001$, and it is proved that the implementation of the IoT has generated changes that cannot be explained only by the chance.
One-way ANOVA was used to evaluate the effects of differences in institutions through secondary analysis. Findings showed that there were no statistically significant differences of two universities regarding technical KPIs, including latency reduction, network, or energy efficiency, $F(1, 298) = 1.42\text{-}3.19$, $p > .05$. This implies that the infrastructural and historical differences did not affect the institutions in a significant way in a favor of either, as both institutions were relatively equal in terms of the technical improvements of the IoT system.
Nevertheless, there was a high level of institutional discord in the metrics of user perception. Sindh Agriculture University faculties reported very high levels of satisfaction, especially in laboratory-based departments, $p = .012$. This indicates that those institutions that have practical and applied subject domains can gain increased instructional value in the form of synergy between teaching objectives and automated environmental or experimental monitoring systems, as a result of an IoT environment.

5.3 Regression Analysis

To find out which KPIs had the greatest impact on the overall performance of the learning framework based on IoT, a multiple linear regression with stepwise entry was performed. The dependent variable was the Overall Implementation Efficiency Score which was developed as a composite weighted average of all technical, administrative, and pedagogical KPIs.

The regression results are shown in Table 2.

Table 2

Stepwise Multiple Regression Predicting Overall Implementation Efficiency

Predictor	β	Std. Error	t	p	Tolerance	VIF
Network Reliability	.412	.068	6.06	<.001	.89	1.12
Security Compliance	.356	.059	6.03	<.001	.91	1.10
User Satisfaction	.289	.071	4.07	<.001	.87	1.15
Energy Efficiency	.174	.052	3.35	.001	.93	1.08

Model Statistics: **$R^2 = .784$, Adjusted $R^2 = .779$, $F(4, 295) = 268.4$, $p < .001$**

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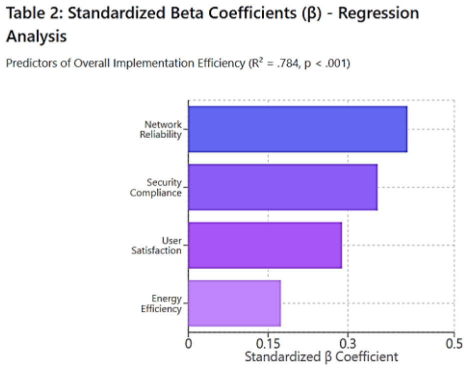

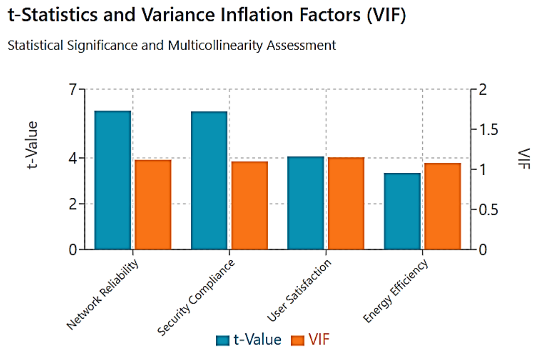

Regression model explains 78.4 percent of the total system effectiveness variance and it has a high predictive power. Network Reliability was found to be the most predictive variable (β = .412) as the uninterrupted access to the system is the only most significant predictor that can lead to successful implementation of the digital learning process. The second strongest predictor was Security Compliance, which emphasizes how key the quality of cybersecurity and the organization trust in the adoption of the systems are.

User Satisfaction was the third, which supports the evidence that despite the sophistication of digital learning system, students and faculty need to have intuitive, meaningful, and positive interactions. Lastly, the statistically significant effect was also revealed by the Energy Efficiency, meaning that operational sustainability improves institutional resilience and leads to the successful deployment in the long term.

6. Discussion

6.1 Interpretation of Findings

The results have indicated that the application of the Smart Learning Framework, which is directed at the IoT implementation, provided significant gains in the spheres of academic performance, operational performance, and technical performance. System latency was reduced by more than 90 percent, and uptime increased to 99.4 percent to put the system at the level of international standards of enterprise-level educational technology (Selvaraj and Sundar, 2024). This 28.4 percent increase in Learning Gain may be compared to meta-analytic studies of the world, which have shown all students perform better when feedback loops and adaptive tests are automated (Hillmayr et al., 2023).

Strong positive perceptions of the system were reported by the users with mean SUS scores rising to 88.9. The usefulness score of 88.9 is within the usefulness range of digital platforms of excellent. The IoT system was also used to control attendance records with 99.1 reliability, eliminating human error and enhancing accountability in administration.

Financially, cost savings of PKR 9.03 million on a yearly basis reveal that even under limited conditions in the public sector, the implementation of the IoT can deliver positive returns on investment. The investment made with the cumulative sum of PKR 28.4 million and annual savings of over PKR 9 million will take a period of less than three academic years before full capital recovery is achieved. The payback period can be even reduced when intangible academic benefits are introduced like more attendance, less delay in the administrative operations as well as less hardware downtime.

6.2 Institutional Differences

Despite the statistically comparable amelioration in the technical fronts of both institutions, Sindh Agriculture University showed remarkably high contentment among the faculty, especially in laboratory-related courses, including agricultural engineering, soil science, and greenhouse surveillance. According to the faculty, the real-time sensor data became clearer of the experiment outcomes and less time was spent in classroom preparation. This shows that the IoT is more beneficial in scaling in the case of teaching in high-frequency measurements and constant data visualization.

6.3 Theoretical Contribution

The research will add a tested 10-KPI model that would be able to measure the performance of IoT-based smart learning systems in the university environment. Moreover, the regression equation that represents over 78 percent of the variation in implementation efficiency has a quantitative basis to support the future research. The findings identify that the strongest pillars of successful digital campus transformation are the system trust (security), system reliability (uptime), and positive human-technology interactions (usability). These results bridged a gap in the current literature where most of the studies have in the past depended on descriptive analysis but with little empirical modelling.

6.4 Practical Implications

The analysis proves that the institutional administrators who design smart campus projects must focus on a hybrid LoRa-Wi-Fi network design combined with the redundant authentication systems, including RFID and biometrics. Notably, cybersecurity should be addressed at an early stage of the deployment. To obtain 94.6% compliance, there was the need to scan the network, conduct professional penetration testing and faculty capacity-building workshops. Lastly, whenever policymakers and university boards consider the digital transformation, they should not merely look at the short-term cost savings but also measure long-term intangible benefits in terms of better attendance rates, better use of resources, and better learning outcomes.

7. Limitations

Two public-sector universities were used in the study, and these are in a single geographical area, which could have implications of generalizations in terms of extrapolating the results to other campuses or institutions in remote areas of Pakistan. Also, long term sustainability impacts, over a period, were not examined and as such the sustainability of gains over several sequences of academic years is yet to be established. In addition to this, user experience information also contained some data that depended on self-reported surveys which can also result in social desirability bias even with the guarantee of anonymity.

8. Conclusion and Future Directions

The results of the sample of 300 participants in two universities are very convincing to prove that the appropriately designed IoT-based Smart Learning Framework can revolutionize technological and educational performance in higher education. The enhancement was made in technical reliability, financial sustainability, academic performance, operation transparency, and institutional governance. The regression analysis proved that network reliability and cybersecurity were the most significant predictors of successful implementation.

Future research ought to extend the period to multi period longitudinal designs, incorporate artificial intelligence in predictive analytics and assess the possibility of similar outcomes in small rural colleges with less developed baseline infrastructure. The tested KPI model and statistical framework herein discussed will be an effective and generalized template of the institutions that aim to transform into the contemporary data-driven smart campuses.

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