

# A Distributed IoT System for Real-Time Sports Performance Analysis in Physical Education

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**Abstract:** Integrating Internet of Things (IoT) technologies into physical education (PE) presents opportunities for improving the methodologies for collecting, analysing, and managing student performance data. However, it also introduces technical challenges, particularly related to the real-time handling and protection of sensitive data in dynamic training environments. This paper presents a comprehensive solution outline based on a private local network architecture that supports scalable sensor data processing, real-time database integration, and mobile application interfaces. The proposed distributed system ensures data integrity, low-latency communication, and secure access while enabling educators to monitor student performance in real-time and review historical data. The system supports more personalised, data-driven training strategies by providing actionable insights for sports education.

## 1 INTRODUCTION

Integrating software-driven Internet-of-Things (IoT) solutions into sports and education has gained significant attention, providing new ways to process, analyse, and manage student performance data in physical activities (Rajaa et al., 2024). Advances in data system architectures and processing frameworks have enabled the development of scalable, high-performance systems that support educators in delivering more effective training programs. Teachers and coaches can access structured performance data using software infrastructure, offering valuable insights into student training progress, engagement levels, and general well-being.

Despite this potential, effectively incorporating IoT in educational sports settings presents several challenges from the software development perspec-

tive, such as the demands of real-time data processing, ensuring the security and privacy of sensitive information, and providing scalable infrastructure capable of handling high-frequency sensor inputs in dynamic environments. The following research question emerges:

*"How can a software architecture baseline be outlined to process real-time data processing efficiency in IoT-based educational sports monitoring systems?"*

This paper presents a software architecture for an IoT-enabled student training system designed to collect, process, and visualise sports performance data efficiently. The system consists of a private network infrastructure for handling incoming sensor data and a database for structured storage and retrieval of information in real-time with back-end and front-end mobile applications that provide educators with actionable insights.

The proposed solution aims to optimise data integrity, improve system scalability, ensure privacy, and enhance the accessibility of training analytics and performance metrics, allowing teachers and coaches to make informed decisions based on real-time and historical data analysis.

In experimental trials, the system captured and processed real-time data from low latency IoT sen-

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sors, demonstrating its ability to handle sensitive data in practical scenarios.

## 2 RELATED WORK

### 2.1 IoT in Activity Monitoring

IoT technologies have transformed activity monitoring across diverse domains, including healthcare, sports, fitness, and industrial safety. IoT systems enable continuous real-time tracking of physiological and movement-related data by utilising wearable sensors, smart devices, and interconnected networks. These capabilities support a wide range of applications, such as motion analysis, fatigue detection, injury prevention, and performance optimization. IoT enhances education by collecting real-time data from small wearable devices, enabling personalized and adaptive learning. In addition, it supports educators in monitoring student engagement, stress, and cognitive states, leading to more effective and responsive teaching strategies (Hernández-Mustieles et al., 2024).

Nevertheless, significant challenges remain in integrating these technologies into existing infrastructures, mainly concerning economic accessibility, privacy, and data security (Rahmani et al., 2022). IoT improves physical activity by providing real-time feedback, enabling self-monitoring, promoting goal setting, and supporting data-driven improvements in performance. Yang et al. (Yang et al., 2024) grouped the application of IoT in sports into the following sections: activity recognition and motion tracking, injury prevention via fatigue/stress monitoring, performance analytics and physiological variable prediction. However, the study executed by Rajšp and Fister (Rajšp and Fister, 2020) point out that the use cases missing real-world validations and the scarcity of open, publicly available datasets limit reproducibility and cross-validation. Fresta et al. (Fresta et al., 2024) developed a low-cost, end-to-end system architecture for human activity data collection using an edge-cloud model. The system captures data from sensors via Bluetooth and utilizes a cloud-based, open-source framework to collect, process, and distribute the information to end users through stand-alone applications. Also, supports dynamic adjustment of key parameters like sensor sensitivity and sampling rate, enabling adaptability for various activity-tracking use cases.

### 2.2 IoT in Physical Education

In educational contexts, IoT technologies have been shown to enhance student engagement, improve

learning outcomes, and enable instructors to design more effective and personalized training programs based on objective performance metrics (Verma and and, 2018). Also, the study performed by Kassab et al. (Kassab et al., 2019) highlights that the use of IoT technologies enhances collaboration among students, instructors, and staff. IoT supports various learning principles and can provide diverse delivery modes, including face-to-face, online, and hybrid education. The common devices include smartphones, sensors, RFID tags, wearables, and remote lab equipment. These are applied to attendance tracking, remote experimentation, personalized feedback, and support for students with special needs. Despite these benefits, significant challenges include security risks, data scalability, and concerns over the dehumanisation of education.

In the context of sports-related education, Xu et al. (Xu et al., 2024) report that the implementation of IoT technologies contributes positively to the enhancement of physical education (PE) performance among college students. However, their effectiveness depends on students' acceptance of the technology. The study highlights that students are more inclined to adopt and engage with IoT-enabled systems when they perceive the devices as practical, user-friendly, and conducive to an interactive learning experience.

Software solutions such as the IoT-IPSF framework (Yang et al., 2021) integrate sensor-based monitoring, web interfaces, and mathematical analysis - it offers a scalable and accurate solution for modernizing PE through IoT. Li et al. (Li et al., 2022) used artificial intelligence allied with IoT to enhance PE by analysing real-time data from wearable devices. The system monitors, classifies, and predicts students' physical activities, enabling personalized training and performance optimization. Wu et al. (Wu et al., 2024) integrated gesture recognition using wearable sensors and multi-source data fusion supported by machine learning algorithms. Basketball was the chosen activity for the trials, and the students strongly preferred video-based learning content. The study from Tierney et al. (Tierney et al., 2024) applies wearable devices to football training to collect sensor data about speed, walking distance, and heart rate. Also, the authors notice the lack of intuitive, educationally focused software limits how wearable tech is applied in learning, reclaiming better software tools to support students' performance monitoring and evaluate the learning outcomes. Wang (Wang, 2023) combines IoT with mobile edge computing to help to improve physical education by processing data locally at the network edge, the system reduces latency, improves responsiveness, and allows for real-time monitoring

of students' physical activities. The developed solution supports scientific management through accurate monitoring, performance evaluation, and defining training plans. Also, it helps overcome infrastructure and resource limitations in schools by decentralizing computing and optimizing task distribution.

The integration of artificial intelligence with data from wearable IoT devices and institutional learning management systems has enabled the development of systems capable of automatically generating personalized sports training recommendations for individual students (Rajaa et al., 2024). The system was built to protect sensitive personal health data. Privacy is an important topic when sharing students' health and fitness data collected via wearable biosensors during public sports activities.

These privacy considerations underscore the need for responsible data handling in IoT-enabled educational environments. Data-driven analysis of students' exercise habits and health metrics (Xu and Liu, 2023) enables tailored, personalized training to boost teaching effectiveness, though ensuring data security, managing equipment costs, and protecting user privacy is essential for ethical, scalable implementation. Liu et al. (Liu et al., 2024) propose an edge-cloud computing for IoT wearable devices that scramble the sensitivity of data to securely embed private information within visual data formats (e.g. ECG graphs or movement visualizations) before sharing them over networks.

Collecting data for statistical analysis in PE presents several technical challenges. Capturing limited data may be insufficient to accurately reflect student performance, while delays in real-time data collection can interfere with teachers' decision-making. In response to these limitations, Ding et al. (Ding et al., 2023) propose a publish/subscribe model using the Message Queuing Telemetry Protocol (MQTT) in a client-server architecture. This architecture design overcomes data collection and transmission challenges by sending data to a cloud platform in JSON format. The results demonstrate controlled performance with low latency (averaging 65 milliseconds), enabling teachers to monitor student performance during exercises and make better real-time decisions.

Future directions recommended by the study performed by Deng et al. (Deng et al., 2023), indicate the IoT integration with AI for improving the personalised learning and ensuring data privacy and accessibility. Also, emphasis focuses on developing cost-effective, scalable solutions for massive adoption in schools.

### 3 METHODS

A fundamental requirement of the proposed solution is the capability to transmit substantial volumes of data in near real-time, resulting from the simultaneous participation of multiple students wearing sensor-equipped devices during physical activities. This dynamic environment introduces challenges that differ from those encountered in static data collection scenarios. In addition to performance-related demands, the designed solution needs to preserve the security of sensitive data, adding another layer of complexity to the system, which makes the task of specifying the distributed components and their integration crucial to the solution's successful performance.

#### 3.1 System Architecture

As an architectural inspiration for the solution, we use the Lambda model (Kiran et al., 2015), a software design pattern for big data systems that unifies batch processing and real-time (stream) processing to provide both comprehensive historical insights and low latency updates.

As illustrated in Figure 1, the system architecture is structured into three key layers:

- The first layer is composed of IoT devices, sported by garments equipped with sensors, which collect data on physical activity in real-time.
- The second layer is responsible for processing information, acting as the core infrastructure, hosting and executing various software components, including the central database, *WebSocket*-based data communication, post-session metrics processing services, and the management Application Programming Interface (API).
- The third layer, the presentation layer, two end-user applications are designed to manage athletes and groups, plan and monitor sports sessions, and facilitate other functions related to managing sports groups.

The self-contained system runs on a private network, with no internet access to external servers, thus maintaining the confidentiality of the data and preventing its transfer to external storage locations within the institution.

#### 3.2 Data Collection

The process begins by collecting data directly from the source: athletes wearing the embedded sensors in the textiles. The sensors transmit the collected information via *WebSocket*, integrated with *RabbitMQ*

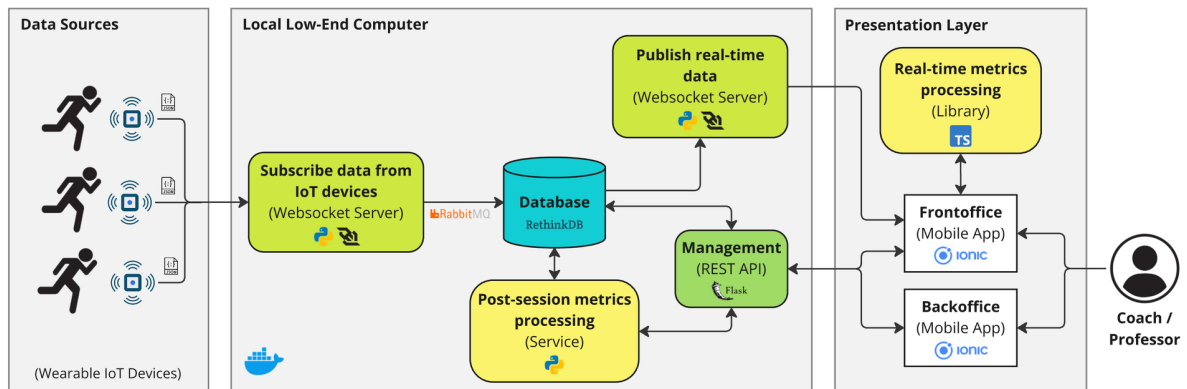


Figure 1: Software architecture diagram.

(RabbitMQ, 2025) queues, to a local low-end computer (LLEC) responsible for communication and managing data input. Embedded in sports apparel, these hardware components continuously capture sensor data from athletes in real time, such as ECG (Electrocardiogram) voltage, acceleration, and orientation.

The data transmission process operates locally and independently of the Internet, utilizing a private network to ensure optimal performance and enhance data security. Communication is facilitated through a local router that is confined to the pre-configured network environment. All messages exchanged within the system are formatted using *JavaScript Object Notation (JSON)*, enabling structured, lightweight, and platform-independent data representation.

### 3.3 Data Processing and Availability

Once the data is received by the dedicated service, it is sent to the server, the component responsible for all the data processing tasks. The server handles processing and service hosting, including receiving sensor data, storing it, processing it, and distributing the data to mobile applications. A low-end computer was used in the system setup. All services operate continuously and are managed using *Docker* (Docker, 2025), which provides containerization for consistent deployment, scalability, and isolation across the system environment.

All incoming data is first stored in the database and subsequently transmitted to the front-end services in real time, enabling educators to access and monitor relevant information as activities unfold. Due to the large amount of data received in real time, it is crucial that the database fulfils criteria that guarantee robustness, reliability, and low streaming latency. For this reason, we chose *RethinkDB* (RethinkDB, 2025) as the database, an open-source solution that can handle massive data ingestion in near real-time

while maintaining system integrity and performance. Following its storage in the database, the information is transmitted to the end-user services using the *Web-Socket* communication protocol, in a similar way as the data collection process from the athlete garment's sensors. This is achieved through a dedicated *Web-Socket* server and the use of the *websocket-ts* library, enabling real-time delivery to the User Interface (UI).

The participant identities are dynamically presented in real-time for educators, while the stored dataset is encoded using anonymous numeric labels.

The mobile application, responsible for visualising the data, listens for incoming messages whenever there is an active sports activity. In this live scenario, the loss of data in real time is not problematic because the metrics calculated are used by the teacher to monitor the course of the session. The crucial aspect is storage in the database, because more complex metrics are calculated after the session, with all the data collected during it, resulting in post-session reports per student.

### 3.4 End-User Services

The end-user interface consists of two distinct mobile applications, developed using the *IONIC Framework* (Ionic, 2025), which enable real-time activity monitoring and post-session data analysis. The two applications share a similar tabs layout, designed to easily navigate and group the main sections of content, which can also be collapsed to increase the size of the content in mobile devices.

The back-office application, *AURORA Studio*, assists the coach in managing athletes, groups, such as classes or teams, sports sessions, as well as handling other contextual information within the system. Once a set of athletes are assigned to a group, the user can schedule a session for that group in a given date, consisting of a sequence of sports activities, and a set

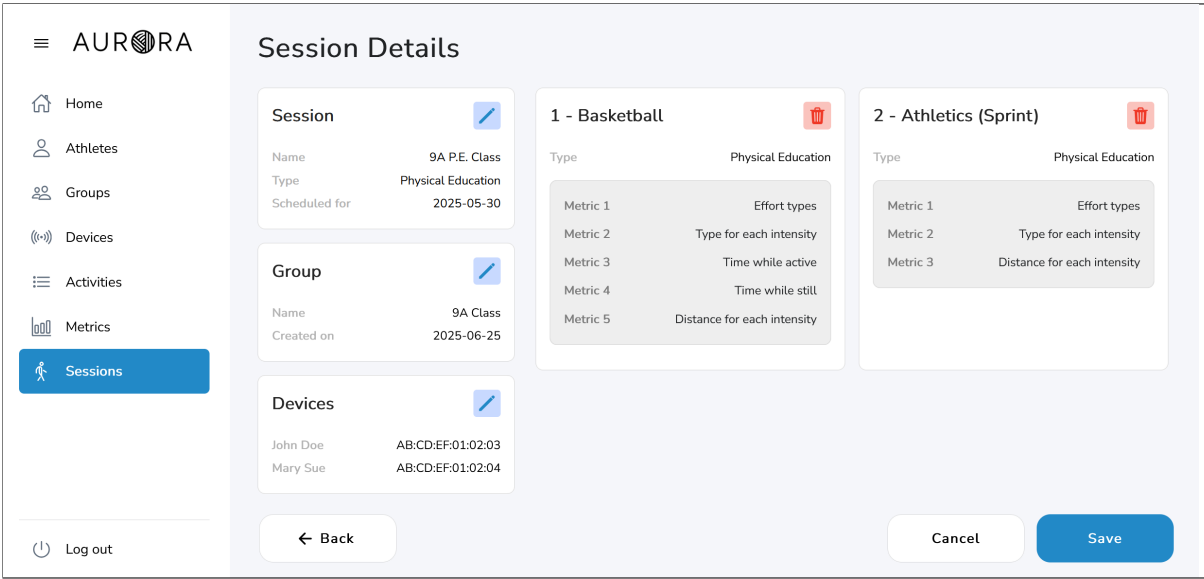


Figure 2: AURORA Studio mobile application.

of metrics to be calculated for each sport, as shown in Figure 2. After a session, the user may also use the app to trigger the processing of the data generated during its time frame. Once the processing of the session data is completed, the user can generate reports and perform analytics over this data.

The front-office application, *AURORA* (Figure 3), processes data in real time, helping to track and monitor training sessions previously planned in the back-office application. In this application, a teacher or coach can check the state of the wearable data sources and assign them to the athletes of a session. After beginning a session with the selected group and devices, the user is able to start, pause, or stop the activities that were planned, as the session is ongoing. During the activity, the teacher/coach monitor the performance of multiple athletes simultaneously, through a set of simple metrics displayed on the screen, both numerical and categorical: Heartbeat Rate, Exercise Intensity, Cadence and Activity State.

By selecting a specific athlete, the user can also visualize this data in different representations, such as charts, to monitor the variation of these values through time. These charts are updated as the data is received through repeated calls of functions that perform the required calculations. In this way, the user can monitor some athletes' physical indices during their sporting activity.

A Representational State Transfer (REST) API was designed to control all system-related configurations and data, including managing athletes, groups, activities, and sessions. It serves as the primary access point for retrieving detailed information across the

data ecosystem, and its implementation is based on the *Flask framework* (Flask, 2025) for minimal web applications. Regarding sports metrics, they are processed in two stages, accounting for the metric type calculated. Real-time metrics, such as the heartbeat rate or velocity of the athlete, are processed as the data is collected, at the front-office application. On the other hand, post-session metrics are calculated after the sports session due to the complexity of these processing algorithms and the data size involved, on the server.

4 RESULTS

The proposed IoT-based monitoring system was evaluated in a controlled physical training environment using a sensor-embedded garment configured to transmit data over a secure private network.

The main objective of the evaluation was to assess the system's ability to reliably capture and process real-time performance data with minimal latency.

Preliminary findings emerged during the trials, involving a small group of students from a sports university. The results demonstrate the system's effectiveness and reliability in capturing and analyzing real-time student performance data. Figure 4 presents quantitative performance metrics focusing on message transmission latency between the IoT device and the mobile application, over a span of 5 minutes.

The IoT device transmitted messages at fixed intervals of 250 milliseconds. Latency measurements were conducted across the system architecture, de-

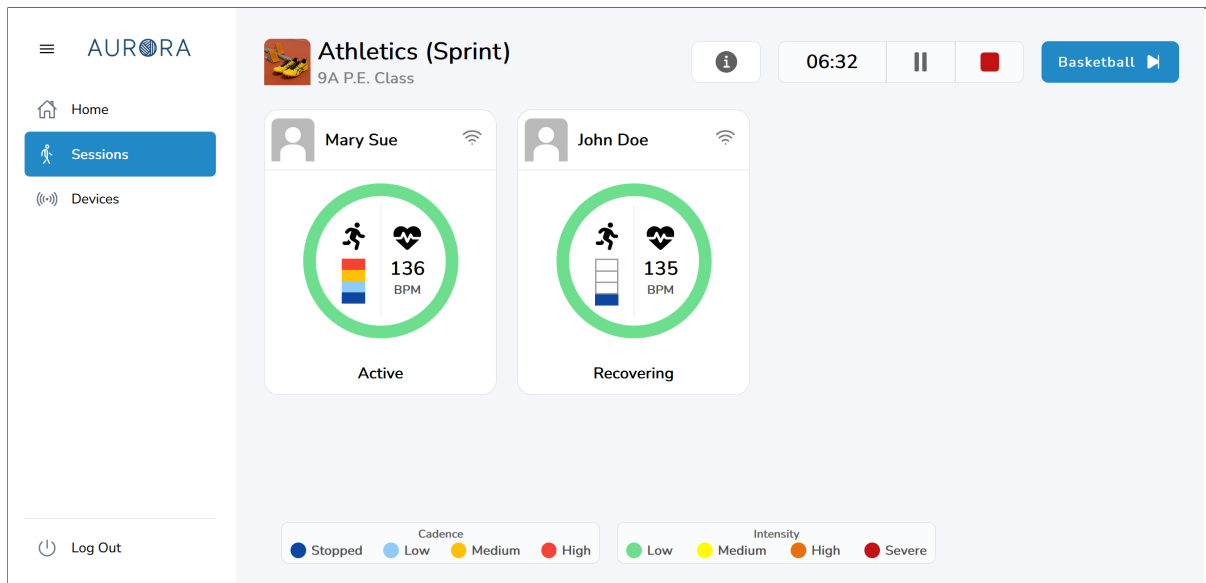


Figure 3: AURORA mobile application.

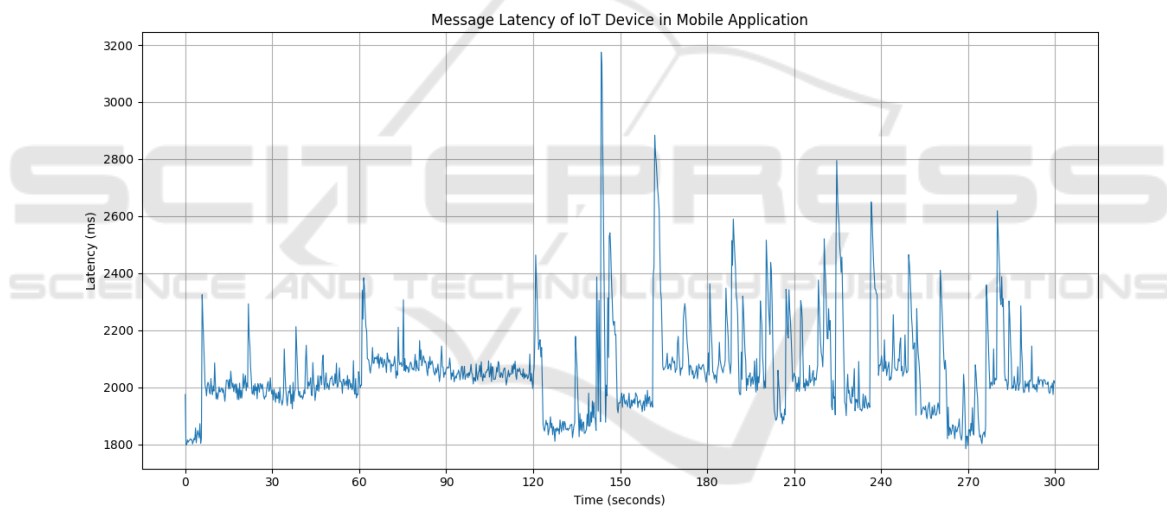


Figure 4: Message latency from IoT to Mobile Application.

defined as the time elapsed between data acquisition by the sensor and its reception by the mobile application. The system exhibited stable performance, with message transmission latency consistently ranging from 1.8 to 2.2 seconds. With some spikes observed, reaching up to 3.2 seconds. These findings indicate that the system is capable of supporting near real-time data handling requirements, providing end users with timely access to critical performance metrics.

## 5 DISCUSSION

The use of message brokers to manage the queues with massive data from sensors, produce results that are in line with findings from Ding et al. (Ding et al., 2023), whose MQTT-based system reported sub-second latencies under ideal conditions.

The Lambda Architecture adopted in this work enabled the unification of batch and stream processing layers, which proved beneficial for maintaining both real-time monitoring and comprehensive post-session analysis. This dual capability is particularly important in educational settings, where teachers benefit from

both immediate feedback and detailed retrospective insights.

Compared to prior IoT-based physical education systems, e.g., the work from Fresta et al. (Fresta et al., 2024), which relied on cloud processing, the proposed architecture uses a local, private network coupled with *Docker*-based containerisation, providing strong performance isolation and reduced dependency on internet connectivity. This setup also contributes to improved data security — an increasingly critical concern noted by Xu and Liu (Xu and Liu, 2023) and Liu et al. (Liu et al., 2024), who emphasise the importance of safeguarding students' personal health information in real-world deployments.

Nevertheless, some latency spikes were observed. While they did not impact overall functionality, they suggest potential areas for improvement in communication protocol optimization or network load balancing.

## 6 CONCLUSIONS AND FUTURE WORK

This paper presented a distributed IoT-based software architecture designed to enable real-time monitoring and analysis of student performance data in physical education settings. By leveraging a private local network, *Docker*-based service deployment, and the Lambda Architecture model, the system successfully integrated real-time data collection, processing, and visualization within a secure environment.

Experimental trials demonstrated that the system achieved consistent message transmission latencies between 1.8 and 2.2 seconds, with occasional spikes up to 3.2 seconds. These preliminary results demonstrated that the architecture is robust and reliable, managing considerable amounts of sensor-generated data with low latency. The system provided near-real-time data visualization, using a private network, ensuring security and privacy, and addressing critical ethical and data protection concerns in the context of student information handling.

The proposed solution, also empowers educators through intuitive mobile applications that facilitate session planning, live monitoring, and post-session analytics. Offering an educator-focused platform that aligns with pedagogical goals and privacy standards.

Future research will focus on advancing privacy-preserving mechanisms within edge computing frameworks. In particular, the integration of encryption and anonymization data processing techniques to ensure security while maintaining system scalability and usability.

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