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Child Playground Entry/Exit Tracking and Log Visualization System Using BLE Beacons and Smart Devices

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Abstract

Playground safety for preschool and early elementary school children has become an increasingly important issue for families and local communities. In semi-open playground environments, direct supervision by caregivers is often difficult, while conventional positioning approaches may be costly, infrastructure-dependent, or unreliable due to frequent signal obstructions. This study presents an integrated low-cost monitoring system that combines commercial BLE beacons, a single smart device installed in the playground, a push-notification server, and a caregiver smartphone application to detect children's entrance and exit events and visualize their playground usage logs. Rather than proposing a new localization algorithm, the main contribution of this work is the practical system integration and field validation of BLE-based entrance/exit detection in semi-open playground settings. The smart device continuously scans beacon RSSI values, applies Kalman-filter-based smoothing and threshold-based state transitions, and transmits detected events to the server, where daily, weekly, and monthly statistics are generated and visualized for caregivers. Field experiments conducted at five real playgrounds showed that the proposed system achieved over 99% entrance/exit detection accuracy with an average response time of less than 7 s. These results demonstrate that reliable playground entry/exit monitoring can be implemented at low cost, with simple infrastructure and practical deployment in residential environments.

Keywords: BLE beacon; child safety; playground tracking; push notification; children's activity logs

1. Introduction

The safety of young children in early childhood and lower elementary grades has become an important social issue that must be addressed collaboratively by families, educational institutions, and local communities. As dual-income households increase, high-density apartment complexes become more common, and private education and after-school activities expand, children are spending more time outside the direct line of sight of their caregivers. Semi-open spaces such as playgrounds within apartment complexes, daycare playgrounds, and neighborhood parks offer opportunities for physical and emotional development, yet they also introduce situations in which a child's location is temporarily unknown, and the risk of accidents or disappearance is elevated. These challenges are typical in urban living environments and highlight the need for technical support that can efficiently monitor a child's movement and rapidly detect potentially dangerous situations [1,2].

Recent advances in Internet of Things (IoT) and location-based services (LBS) have opened new possibilities for child safety management. While Global Positioning System

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(GPS)-based positioning performs well in large open outdoor spaces, its accuracy degrades in indoor or semi-open environments with many obstacles due to signal blockage, multipath, and noise. GPS tracking also tends to require higher power consumption and recurring communication costs, which can be limiting factors for low-cost, always-on monitoring systems [3]. To address these limitations, Bluetooth Low Energy (BLE) beacons have been widely adopted as a low-power, short-range wireless technology for proximity and location tracking. BLE can support scalable sensor networks at low cost, uses received signal strength indication (RSSI) for coarse distance estimation, and integrates naturally with commodity smartphones [4].

BLE- and IoT-based localization has increasingly been applied to child safety scenarios. For example, prior work has combined BLE and Wi-Fi signals to improve tracking performance in mixed indoor–outdoor environments and mitigate the weaknesses of single-technology approaches [5]. Other studies have proposed BLE–IoT systems that collect children's movement data in schools or playgrounds and deliver real-time notifications to caregivers via cloud-connected devices [6]. These studies demonstrate the feasibility of BLE-assisted child monitoring, but many of them focus either on controlled indoor environments or on system architectures that require multiple infrastructure components, additional gateway devices, or more complex deployment conditions.

However, from the perspective of practical deployment, several gaps remain. First, existing BLE-based child safety systems often rely on dedicated gateway hardware or comparatively complex back-end infrastructures, which can increase installation and maintenance costs for small residential playgrounds or community-managed facilities [7]. Second, many studies emphasize localization accuracy in classrooms, school buildings, or laboratory-like indoor testbeds, whereas relatively few provide empirical validation in semi-open playground environments where children move actively and line-of-sight is frequently interrupted [8]. Third, for many real residential use cases, the operational requirement is not centimeter-level positioning but robust and timely recognition of whether a child has entered, is staying in, or has exited the playground.

In this context, the contribution of this paper is not the invention of a new localization algorithm, but the integration and real-world validation of a low-cost BLE-based playground monitoring system tailored to semi-open environments. Compared with RFID-based child-tracking solutions, the proposed BLE-based design does not require dedicated reader hardware and can directly integrate with caregivers' smartphones, which simplifies deployment in residential playgrounds. The proposed system combines commercial BLE beacons, a single smart device installed in the playground, a push-notification server, and a caregiver smartphone application to support practical entrance/exit detection and log visualization. On the smart device, BLE RSSI values are continuously collected and stabilized using Kalman filtering, after which a lightweight threshold- and time-based state transition logic is applied to determine entry, stay, and exit events. The resulting events are transmitted to the server, where they are stored, aggregated into daily, weekly, and monthly summaries, and visualized through the caregiver application.

To evaluate the practical feasibility of this integrated system, field experiments were conducted at five real playgrounds. Rather than limiting the evaluation to a controlled laboratory setting, the study focuses on deployment-oriented performance indicators, including entrance/exit detection accuracy, response time, and simultaneous processing capability for multiple beacons. The experimental results show that the proposed system achieves more than 99% detection accuracy with an average delay of less than 7 s, indicating that low-cost entrance/exit monitoring can be realized with minimal infrastructure in real semi-open playground settings.

The remainder of this paper is organized as follows. Section 2 reviews prior work on BLE beacons, IoT-based child safety systems, and related cloud and edge computing approaches. Section 3 describes the overall architecture of the proposed system, including the push notification server, log management and statistical processing pipeline, and visualization components. Section 4 presents the experimental setup in real playgrounds and analyzes the performance evaluation results. Finally, Section 5 concludes the paper and discusses future research directions.

2. Related Work

This section reviews state-of-the-art methods in BLE-based localization, IoT-based child safety systems, and edge/cloud architectures, and discusses how these approaches relate to the problem of entrance/exit monitoring in semi-open playground environments. The reviewed literature is organized into four subgroups: (1) BLE RSSI-based localization and signal processing, (2) IoT-based child safety systems, (3) edge-centric and privacy-preserving architectures, and (4) gaps specific to semi-open playground scenarios.

2.1. BLE RSSI-Based Localization and Signal Processing

BLE beacons have become a key enabling technology for IoT-based localization systems due to their low power consumption, short latency, and compact form factor. Recent work has focused on improving distance-estimation accuracy from BLE RSSI measurements using signal-processing and learning-based approaches. For example, Kalman-filter-assisted deep regression models have been shown to reduce noise in RSSI sequences and achieve sub-meter indoor localization accuracy [9]. Beacon configuration and deployment strategies have also been studied, including adaptive power-control schemes that balance tracking precision and energy efficiency across dense IoT deployments [10]. In addition, BLE mesh networks have been leveraged to support concurrent tracking of many devices through a single gateway, enabling multi-user monitoring in childcare and smart-home scenarios [11]. The propagation behavior of BLE signals in semi-open outdoor environments has been analyzed as well, with models that capture the impact of weather, humidity, and obstacles on RSSI attenuation, providing a foundation for more robust tracking in dynamic playground-like spaces [12].

While these methods demonstrate high accuracy in controlled indoor environments, they often rely on dense beacon deployments, precise calibration, and computationally intensive algorithms. For semi-open playground scenarios where the primary goal is not centimeter-level positioning but rather robust entrance/exit detection, such high-precision approaches can be unnecessarily complex and costly. In particular, trilateration-based methods and deep regression models may not be well-suited for low-cost, single-node configurations that must operate under frequent line-of-sight interruptions and rapidly changing environmental conditions. This suggests that a lightweight, threshold-based state transition logic combined with simple filtering (e.g., Kalman filtering) may be more practical for the target application.

2.2. IoT-Based Child Safety Systems

IoT-based child safety systems can be grouped into three broad categories: real-time location monitoring, hazardous event detection, and behavior prediction. Hybrid communication architectures combining BLE with long-range technologies such as LoRa have been proposed to monitor children across large school campuses while maintaining low power consumption [13]. Other studies have employed IoT sensor data with AI models to automatically detect abnormal or risky behavior patterns and trigger immediate alerts to caregivers [14]. Cloud-integrated dashboards have also been designed to visualize per-child location logs and reduce the cognitive burden on parents by presenting concise summaries rather than raw event streams [15]. More recent work has introduced AI-enhanced pipelines that fuse BLE RSSI data with vision-based models, such as transformer architectures, to classify children's activity patterns and identify spatio-temporal risk behaviors, moving from simple location tracking toward more cognitive safety management [16].

These approaches demonstrate the feasibility of data-driven child monitoring and highlight the trend from simple presence detection toward behavior analysis and continuous feedback. However, many of them are designed for controlled environments such as school buildings, school buses, or indoor playrooms, where sensor coverage is stable and infrastructure is well-managed. In contrast, semi-open residential playgrounds near children's homes are characterized by frequent line-of-sight interruptions, variable obstacle density, and rapidly changing usage patterns. Moreover, AI-enhanced pipelines that fuse BLE with vision-based models often require additional hardware (e.g., cameras), higher computational resources, and more complex deployment conditions, which can be prohibitive for small residential communities. From the perspective of practical deployability, a low-cost BLE-only system that focuses on entrance/exit event detection and log visualization may offer a more suitable balance between performance and implementation cost.

2.3. Edge-Centric and Privacy-Preserving Architectures

Most child-tracking systems collect and process data primarily in the cloud, which raises persistent concerns about latency and privacy. To mitigate these issues, edge-centric architectures have been explored, in which preliminary filtering and aggregation are performed on local nodes to reduce response times and offload the cloud [17,18]. TinyML techniques have been deployed on edge devices to detect anomalies in BLE signal streams in real time, thus enabling on-device safety checks with minimal resource usage. Lightweight convolutional neural networks have also been proposed to support behavior monitoring under strict power budgets, allowing continuous operation below a few watts [19]. From an infrastructure standpoint, local beacon localization schemes can minimize installation costs while still supporting community-scale safety services [20]. Privacy-preserving communication mechanisms, including Diffie–Hellman-based encryption and anonymization for children's IoT devices, have been integrated into BLE protocols to protect sensitive location data [21]. Furthermore, context-aware and semi-supervised calibration methods have been developed to adapt BLE ranging models to changing playground environments and to improve accuracy even when labeled training data are limited [22,23].

Edge-centric and privacy-preserving designs are clearly beneficial for reducing latency and protecting sensitive location data, especially in child-monitoring applications. However, many of these approaches still assume relatively complex edge infrastructures, such as dedicated edge nodes, multi-hop networks, or specialized TinyML hardware. For the target application of semi-open playground entrance/exit monitoring, a single smart device that serves as both a sensor and an edge node can significantly simplify the architecture while still achieving low-cost deployment. In addition, while privacy-preserving mechanisms are important, their integration often increases system complexity and may require additional user authentication and management overhead. The proposed system, therefore, adopts a pragmatic trade-off: it uses a single smart device as the edge node, applies basic RSSI filtering and state transition logic locally, and relies on server-side aggregation and push notifications for scalable operation.

2.4. Gaps Specific to Semi-Open Playground Scenarios

Despite the progress described above, many BLE–IoT child safety solutions remain tailored to specific, controlled environments such as school interiors, school buses, or indoor playrooms. In contrast, semi-open residential playgrounds near children's homes are characterized by frequent line-of-sight interruptions, variable density of obstacles, and rapidly changing usage patterns, yet there is comparatively little work on reliable entrance/exit tracking and caregiver notification in these settings. Moreover, systems that depend on dense beacon infrastructures or computationally heavy trilateration often involve high deployment and maintenance costs, which can be prohibitive for small communities and neighborhood-level facilities.

The reviewed literature reveals a clear gap between state-of-the-art BLE–IoT child safety systems and the practical needs of semi-open playground monitoring. Existing methods tend to prioritize high-precision localization or AI-driven behavior analysis in controlled environments, whereas the key requirement for residential playgrounds is reliable, low-cost entrance/exit detection with minimal infrastructure. This gap motivates the present study, which focuses on system integration and field validation of a low-cost BLE-based entrance/exit monitoring system specifically tailored to semi-open playground scenarios. By demonstrating empirical performance across multiple real playgrounds, this work aims to provide a practical deployment-oriented solution rather than a purely algorithmic improvement.

3. Design and Architecture of Child Playground Entry/Exit Tracking and Log Visualization System

In this section, we explain the overall architecture, core operation logic, and push notification workflow of the proposed playground child entrance/exit tracking and log-visualization system based on BLE beacons and a single smart device. The system consists of three main components: BLE beacons carried by children, a smart device installed in the playground, and a push notification server with a companion mobile application for caregivers. The BLE beacons are used to detect whether a child is within the playground area, while the smart device estimates entrance and exit events from the received RSSI values. The resulting events are processed locally on the smart device, transmitted to the push notification server, and then stored and aggregated as entrance/exit logs; the processed statistics are visualized in the caregiver's mobile application. Figure 1 illustrates the overall system architecture. In Figure 1, each child carries a BLE beacon (child beacon node) that periodically broadcasts an advertising packet containing a UUID and RSSI information at an interval of 100–500 ms (①). The smart device installed in the playground receives these packets, analyzes the RSSI values in real time, and applies a state-transition procedure to classify the child's status into entry candidate, stay, exit candidate, and exit confirmed events (②). When an entrance or exit event is detected, it is first recorded in a local event logger on the smart device and then forwarded to the push notification server. The server accepts JSON-formatted event data from the smart device, generates a push notification to the parent application associated with the corresponding child (③), and stores the per-day event data in a statistical analysis database. The caregiver's mobile application subscribes to a push listener service that receives entrance and exit messages in real time, and, when requested, presents the child's playground activity statistics as graphical charts for daily, weekly, or monthly periods (④).

The smart device installed in the playground receives RSSI packets from the BLE beacons and estimates the actual distance $\boldsymbol{d}$ according to the path-loss model in Equation (1).

$$RSSI = A - 10n\log_{10}(d) + \varepsilon \tag{1}$$

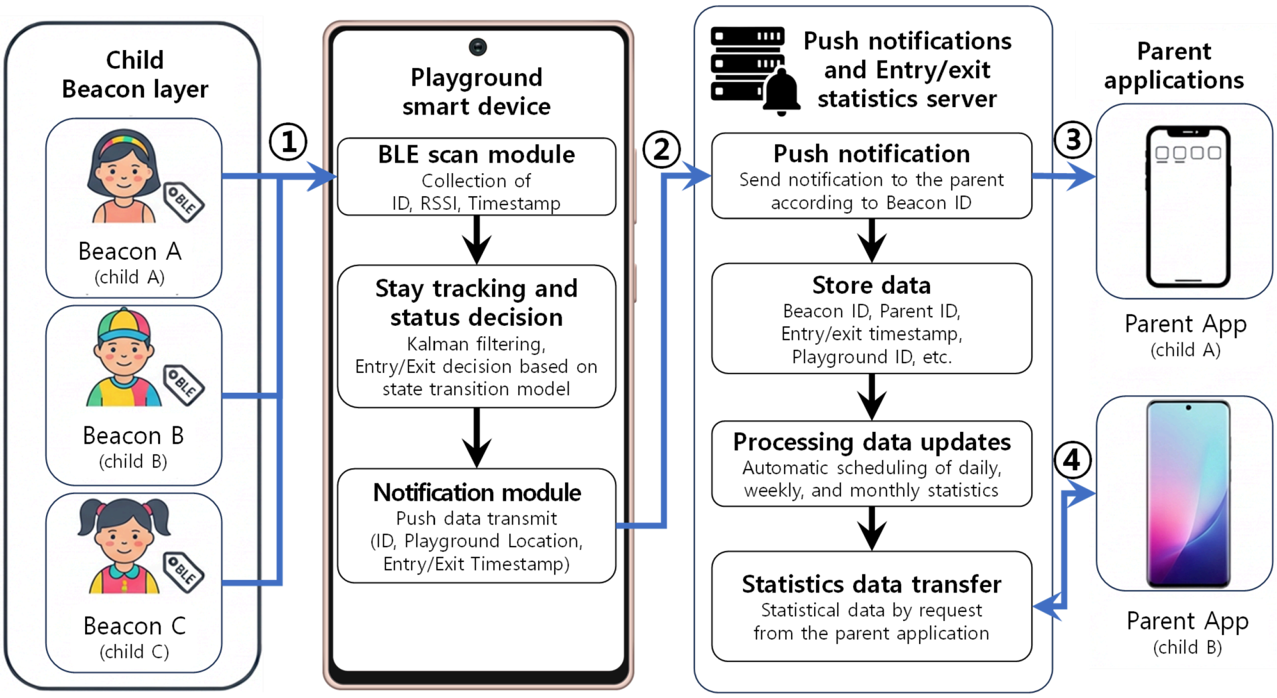

Figure 1. Structure diagram of child playground entry/exit tracking system.

Here, A denotes the reference RSSI value (in dBm) measured at a distance of 1 m, n is the environmental attenuation factor, and ε represents measurement noise caused by reflections, obstacles, and other disturbances in the environment. Because RSSI values fluctuate significantly under real-world conditions, this study applies a Kalman filter to stabilize the measurements before they are used for state decisions. The Kalman filter computes an optimal estimate from noisy observations through a two-step procedure consisting of a prediction step and an update step. In this work, the RSSI model is expressed by a state prediction in Equation (2) and a measurement in Equation (3), which respectively describe the temporal evolution of the underlying RSSI state and the observed RSSI values [24].

$$x_k = x_{k-1} + w_{k1} \quad (2)$$

$$z_k = x_k + v_k \quad (3)$$

In these equations, Equation (2) is used as a minimal state model for RSSI smoothing rather than as a dynamic model for actual behavior predictions. w_k and v_k denote the process noise and measurement noise terms, respectively, and the Kalman gain K_k determines the optimal weighting between the predicted state and the new measurement based on the relative magnitudes of these noise components. The updated RSSI estimate can then be written in the simplified form given in Equation (4), which effectively smooths short-term fluctuations and suppresses random spikes. As a result, the RSSI sequence used by the smart device becomes more stable, and the reliability of entrance and exit state transitions for each child is significantly improved.

$$\hat{x}_k = x_{k-1} + K_k(z_k - x_{k-1}) \quad (4)$$

Based on the filtered RSSI values, the child's playground usage state is categorized into four discrete levels, denoted **S0** through **S3**. Using both RSSI thresholds and temporal conditions, the entrance and exit procedures are formalized as a four-step state machine, as summarized in Table 1.

Table 1. Definition of state transition for child tracking.

State Name	Symbol	Main Condition
No presence/standby	S0	RSSI < −80 dBm or no signal > 2 s
Entry candidate	S1	RSSI > −75 dBm for ≥2 s
Stay	S2	RSSI ∈ {−75, −60} dBm, maintained for ≥3 s
Exit candidate/exit	S3	RSSI < −78 dBm for ≥3 s or no signal for ≥5 s

The threshold of −80 dBm indicates the absence of a detectable signal, whereas the threshold was set to −75 dBm in Table 1 because the beacon signal begins to be gradually received by the smart device as the child approaches the surrounding area of the device. In addition, the −78 dBm threshold and the 3 s criterion were designed as a hysteresis mechanism to reduce false exit detections. In practice, the minimum observed delay of 4 s resulted from the temporal buffer introduced to improve detection stability. In other words, the "longer than 3 s" condition serves as a safeguard to verify that the event persists, whereas the 4 s value represents the minimum latency measured under the experimental conditions.

According to Table 1, the state-transition procedure comprises four stages.

- **Entry candidate (S1):** When the child approaches the playground, the RSSI level increases; if this increase is maintained for at least 2 s, the state is classified as S1.
- **Stay (S2):** If the RSSI remains within a predefined stable range for more than 3 s, the child is clearly inside the playground, and the state transitions to S2.
- **Exit candidate (S3):** When the RSSI drops sharply or the beacon signal is not received for 3 s or longer, the child is regarded as leaving the playground, and the state changes to S3.
- **Exit confirmed (return to S0):** If no signal is received, or the degraded RSSI condition persists for at least 5 s, the exit is confirmed, and the state returns to S0.

Because this process applies a two-step decision (time window plus RSSI threshold) even in a single BLE receiver configuration, it effectively suppresses false triggers caused by short-term signal noise and prevents spurious entrance or exit detections.

The push notification server delivers entrance and exit events for each child's playground usage to the corresponding parent's mobile application and, at the same time, stores these events in the server-side database. Stored records are periodically aggregated by an automatic scheduling process: daily statistics are updated at 00:10 every day, weekly statistics are refreshed at 00:30 every Sunday, and monthly statistics are updated at 23:50 on the last day of each month, thereby automating the generation of visualization data. Figure 2 shows the ER (entity–relationship) diagram of the MySQL tables used to represent raw entrance/exit logs and their daily, weekly, and monthly summaries.

In Figure 2, the CHILD_BEACON table stores the BLE beacon ID and basic metadata for each child, while the PLAYGROUND_INFO table contains the name, location, and associated smart device information for each playground. These two tables are referenced when determining from which playground a given entrance or exit event was generated. The ENTRY_EXIT_LOG table records actual entrance and exit events, including fields such as event type, RSSI, and timestamp. The DAILY_SUMMARY, WEEKLY_SUMMARY, and MONTHLY_SUMMARY tables are used to visualize statistics in the parent mobile application; they are automatically updated daily, weekly, and monthly based on accumulated records in the ENTRY_EXIT_LOG.

The overall procedure for data transmission and visualization in the proposed system is illustrated by the sequence diagram in Figure 3. As depicted in Figure 3, once the playground smart device determines an event from the RSSI received from a child's BLE beacon, the push notification server accepts the corresponding event payload in JSON format, stores it in the database, and then looks up the parent's device token. If a valid token is found, the server enqueues the entrance or exit event into the messaging queue and immediately issues a push notification to the parent's smartphone application, which receives and displays the event in real time. In addition, when the parent application requests statistics, the push server returns the aggregated daily, weekly, or monthly data, and the mobile app renders these values as statistical charts that summarize the child's playground usage over the selected period.

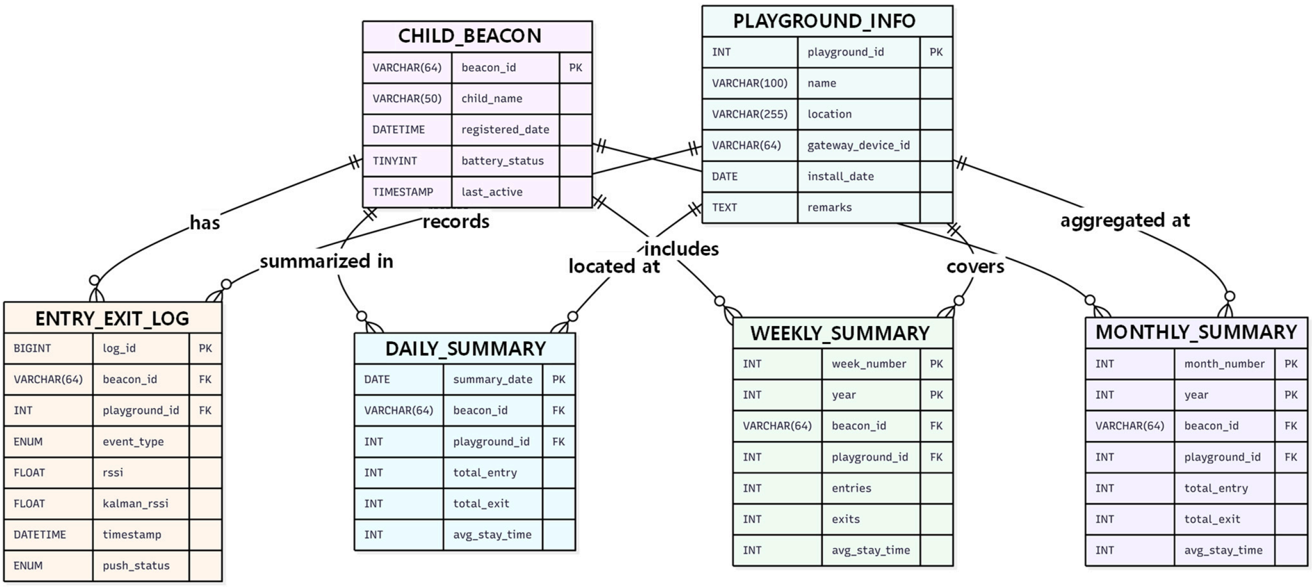

Figure 2. Database operation principle of the proposed system.

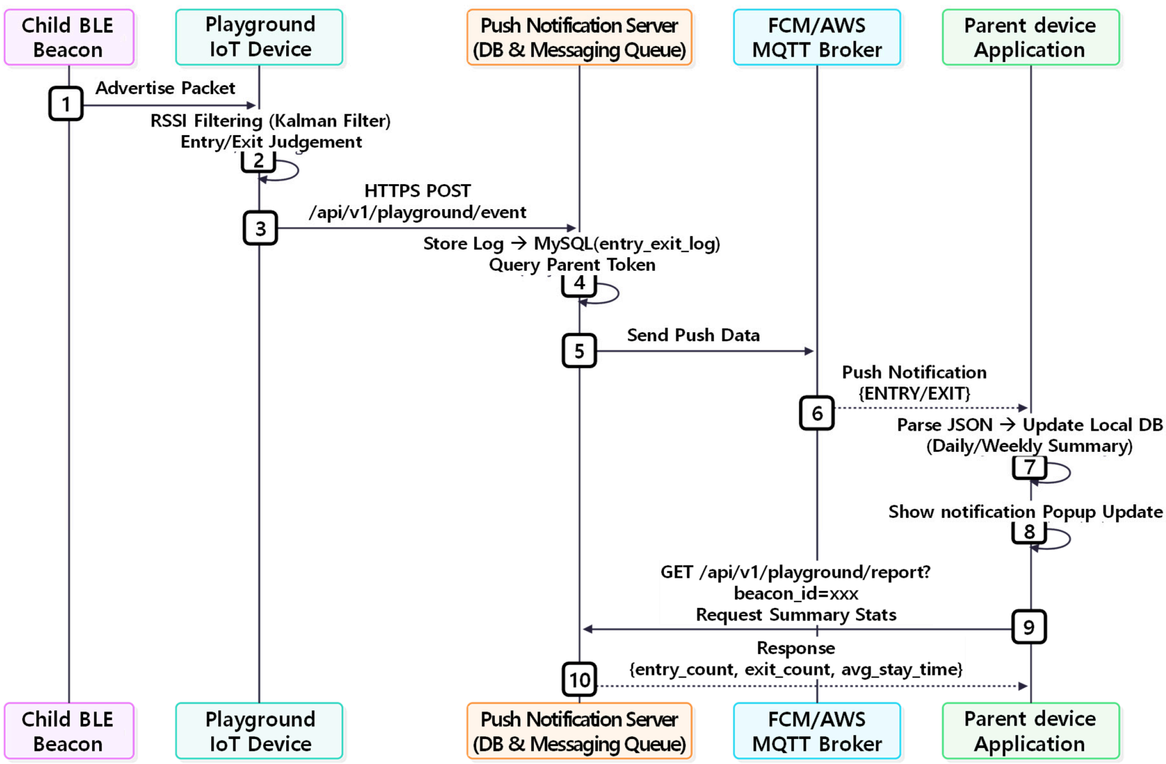

Figure 3. Data transmission sequence diagram of the proposed system.

4. Experiments and Evaluations

To evaluate the performance of the proposed application and system, field experiments were conducted at five playgrounds located in apartment complexes in Incheon, Republic of Korea. At each playground, a single smart device (Samsung Galaxy Note 20 Ultra) was installed, and one test participant carried a single BLE beacon while repeatedly entering and exiting the playground over a 20 min session. The dwell time between entrance and exit was constrained to be at least 5 min per visit to emulate realistic play durations. This experiment was performed once per day over a period of 30 days, and the collected data was used to analyze entrance/exit decision accuracy and detection latency.

The communication environment for the system was based on a shared Wi Fi 2.4 GHz network, and the backend infrastructure for push notifications and data storage employed MySQL 8.0 together with Firebase Cloud Messaging. The RSSI sampling interval on the playground smart device was set to 0.3 s, and the BLE beacons used in the experiments were Beacon E7 devices manufactured by B-Fon.

For performance evaluation, three key metrics were measured and analyzed.

- **Decision accuracy (%)**

The ratio of correctly classified entrance/exit events is computed using Equation (5).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \quad (5)$$

In Equation (5), TP (true positives) denotes events that occurred and were correctly detected by the system, while TN (true negatives) represents cases where no event occurred, and the system correctly did not signal an event, i.e., normal decisions. FP (false positives) corresponds to cases in which no real event occurred but the system incorrectly reported one, and FN (false negatives) indicates that a real event occurred but was not detected by the system, capturing detection errors. In this study, detection accuracy is computed by comparing the system's entrance/exit classification results, derived from BLE beacon RSSI signals, against the ground-truth event logs collected during the experiments.

- **Detection response time (s)**

During the experiments, the operator manually recorded the actual time when each entrance and exit occurred in the playground, and this was compared to the timestamps at which the system detected the corresponding events from the BLE signals. For each event, the detection latency was obtained as the difference between the real event time and the system detection time, and the average response time was then calculated over all entrance and exit events. The average delay time refers to the difference between the actual event time and the system detection time for each event, including local RSSI sampling, state decision logic, server transmission, and push notification delivery.

- **Simultaneous beacon processing capability**

This metric evaluates the system performance when a single smart device processes multiple BLE beacon signals concurrently. The experiments verified whether entrance and exit events for several participants entering or leaving the playground at the same time, or in overlapping patterns, were logged without omission and whether notifications were delivered accurately to all corresponding caregivers' applications.

A comparative experiment was first conducted between a simple RSSI threshold-based method and the proposed approach. The baseline method does not apply RSSI filtering; instead, it determines an entry event immediately when the observed RSSI exceeds the entry threshold θ_{in}, and determines an exit event immediately when the RSSI falls below the exit threshold θ_{exit}. For a fair comparison, both methods were configured with the same BLE scanning interval (0.3 s) and identical threshold values θ_{in} and θ_{exit}.

Event detection performance was evaluated using Precision, Recall, and F1-score for both entry and exit events. TP is defined as a case where an actual entry or exit occurs and is correctly detected by the system. FP refers to a case where the system incorrectly detects an event that did not occur, while FN refers to a case where an actual event occurs but is not detected by the system. Precision, Recall, and F1-score were computed as follows.

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision \times Recall} \tag{8}$$

To obtain detailed experimental results, ten participants repeatedly entered and exited the playground at arbitrary times within a 30 min period. Each participant performed a total of nine trials (three trials per playground) across three different playgrounds. The experimental sites included a small apartment-complex playground, a neighborhood park playground, and a kindergarten-affiliated playground. Each playground had a semi-open structure with an area of approximately 150–200 m^2 and included typical facilities such as slides, swings, sand play areas, and benches. Table 2 summarizes the statistical results for the detection delay of entry and exit events in the playground environments. As shown in Table 2, the proposed method produced no false positives for either entry or exit events and demonstrated improved Precision by effectively reducing false detections observed in boundary-crossing situations in the baseline method. As a result, it can be confirmed that the proposed method maintains Precision, Recall, and F1-scores of 0.95 or higher for both entry and exit event detection.

Table 2. Detection accuracy of entry and exit events.

Event Type	Method	TP	FP	FN	Precision	Recall	F1
Entry	Baseline	85	9	5	0.904	0.944	0.924
	Proposed	89	0	1	1	0.989	0.994
Exit	Baseline	83	11	7	0.883	0.922	0.902
	Proposed	90	0	0	1	1	1

The entry and exit detection delay is defined, as in the previous experiment, as the time difference between the actual entry/exit moment and the time at which the system outputs the corresponding event. For each playground and event type, the mean, standard deviation, minimum, maximum, and 95th percentile were computed to compare the response characteristics of the proposed method and the baseline method.

To obtain detailed results, the experiment was conducted in the same manner as the previous setup: ten participants entered and exited each playground at arbitrary times within a 30 min period, and the experiment was repeated three times per playground. Table 3 summarizes the statistical results of entry and exit event detection delays across the three playgrounds.

As shown in Table 3, the proposed method achieved an average entry detection delay of approximately 5.7 s and an average exit detection delay of approximately 7.6 s in the apartment playground. In the neighborhood park playground, the average delays were 5.3 s for entry and 7.4 s for exit, while in the kindergarten playground, the delays were

5.2 s for entry and 7.1 s for exit. Furthermore, based on the 95th percentile, entry and exit events were detected within 10 s across all three environments. Although the baseline method exhibited shorter average delays in some environments, it was more sensitive to instantaneous RSSI fluctuations, resulting in increased variance and higher maximum delay values.

Table 3. Statistics for performance comparison of entry and exit detection delays.

Playground	Event Type	Method	Means (s)	Std (s)	Min (s)	Max (s)	95 (s)
Apartment	**Entry**	Baseline	4.1	3.2	0.5	18.3	9.8
		Proposed	5.7	2.1	1.2	8.8	6.3
	Exit	Baseline	5.3	4.5	0.6	22.7	11.1
		Proposed	7.6	2.6	1.8	8.4	7.8
Neighborhood	**Entry**	Baseline	4.7	3.8	0.8	17.3	10.1
		Proposed	5.3	2.3	1.7	9.1	7.3
	Exit	Baseline	5.9	4.9	0.8	20.3	13.7
		Proposed	7.4	2.7	2.0	8.7	7.4
Kindergarten	**Entry**	Baseline	4.9	3.7	0.9	19.1	9.6
		Proposed	5.2	2.3	1.6	8.7	6.5
	Exit	Baseline	5.4	5.1	0.8	21.6	12.3
		Proposed	7.1	2.9	1.7	9.1	7.7

Next, the results of the 30-day single-participant experiments conducted at five playgrounds are summarized in Figure 4. As shown in Figure 4, the average entrance/exit decision accuracy across all playgrounds was 99.2%, and the proportion of incorrect notifications was approximately 0.8%, occurring primarily when the RSSI values were close to the decision thresholds. The mean accuracy ranged from a minimum of 98.9% (Playground 3) to a maximum of 99.6% (Playground 4), and all playgrounds achieved at least 98.8% accuracy on average, indicating that the entrance/exit decision algorithm operated stably across diverse environmental conditions. The standard deviation of the mean accuracy was about 0.25%, which suggests that the system exhibits strong spatial adaptability across different playground layouts. These results demonstrate that the proposed solution functions as a practical child-safety monitoring platform with robust performance regardless of structural differences in playground environments.

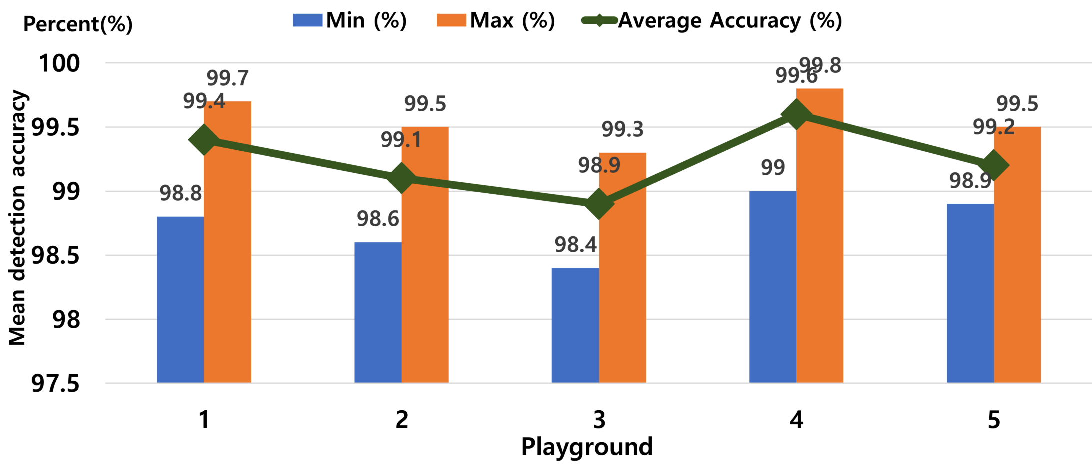

Figure 4. The result of the detection accuracy for 5 playgrounds.

For the response-time evaluation, the test supervisor recorded the actual times of each entrance and exit using a stopwatch, and these times were compared with the corresponding detection timestamps in the system logs to compute the detection delay. This experiment was carried out in parallel with the accuracy measurements over the same 30-day period, and the results are shown in Figure 5.

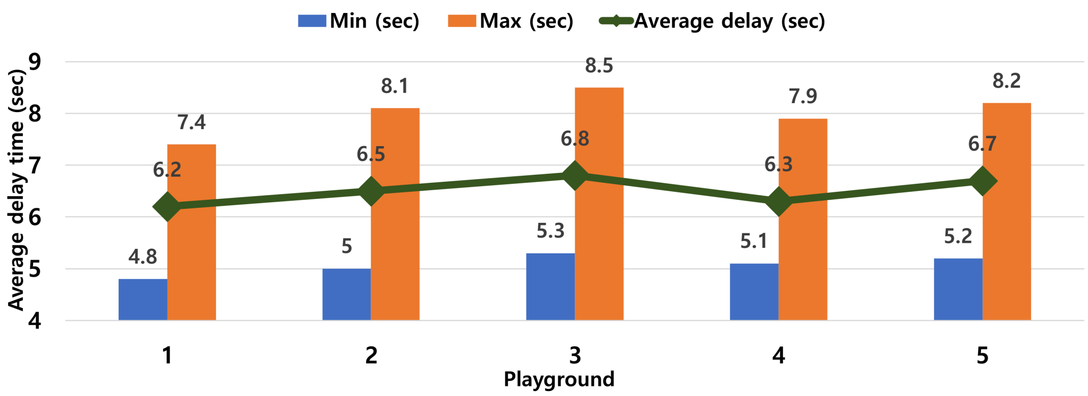

Figure 5. Measured response time comparison.

In Figure 5, the average detection delay was 6.5 s, with a standard deviation of 1.1 s. This latency reflects the combined effect of the BLE packet interval (0.3 s), the Kalman filtering window, and the time required to transmit data to the push notification server. From these results, it can be observed that the difference between the actual event time and the notification time is approximately 6.5 s on average, which is sufficiently low to support practical real-time operation given the periodic nature of BLE signaling and the end-to-end communication delay of the push infrastructure.

To assess simultaneous beacon processing capability, an additional experiment was performed in which 10 participants, each carrying one BLE beacon, repeatedly entered and left a single playground for 20 min at random intervals, spending at least 5 min on each visit before exiting. This scenario was designed to verify whether the smart device can scan multiple BLE beacons concurrently and whether any logs are lost when multiple events occur at the same time. Some participants re-entered the playground more than once, and the average number of entrances per participant was approximately two, resulting in 40 entrance/exit events in total; the corresponding results are summarized in Table 4.

Table 4. Result of simultaneous entry/exit experiment.

Beacon Group	Entry + Exit	True Positives	False Positives	False Negatives	Detection Accuracy
1 and 2	8	8	0	0	100%
3, 4, and 5	12	12	0	0	100%
6, 7, and 8	12	11	0	1	91.7%
9 and 10	8	8	0	0	100%
Total	40	39	0	1	97.5%

Among the 40 events, 39 were correctly detected and delivered as push notifications, and only one event was missed due to a short exit (re-entry within 5 s), where the timing fell within the hysteresis window of the state machine. No false detections were observed. Despite scanning all beacons at a 0.3 s interval, no packet collisions or queue overflows occurred, and the detection logic remained stable even when all 10 participants entered or exited in close temporal proximity. These findings confirm that the proposed system maintains its performance under multi-beacon conditions and can monitor multiple children simultaneously in a real playground setting.

In addition to real-time push notifications of entrance and exit events, the parent mobile application also provides an intuitive visualization of the aggregated entrance/exit logs stored in the server's MySQL database. Figure 6 shows a statistical view in which the child's playground usage is plotted as daily graphs. In Figure 6, the horizontal axis represents days 1 through 30, and the left vertical axis shows the total playground usage time per day. This view enables caregivers to quickly grasp the child's daily activity level at the playground.

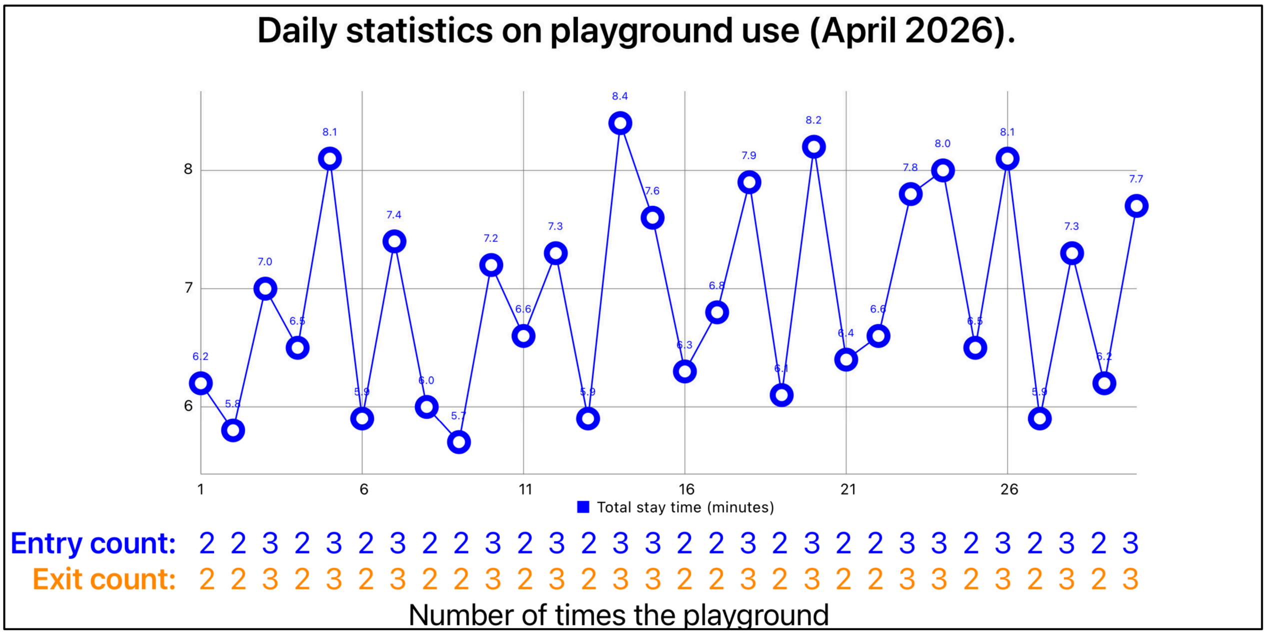

Figure 6. Screenshot of the parent application showing the daily summary.

The application automatically summarizes these daily data into weekly statistics and presents them in the graph shown in Figure 7. In Figure 7, the horizontal axis corresponds to weeks 1 to 5; as in Figure 6, the left axis shows the total playground stay time per week as a line plot. While weeks 2 through 4 exhibit similar levels of activity, week 1 and week 5 show a noticeably lower count, which can be attributed to the fact that five (from 1 to 5 April) and four (from 27 to 30 April) days are included in those weeks within the 30-day period. This representation allows parents to visually examine the regularity and trends of their child's outdoor play behavior over several weeks.

Finally, the monthly visualization is provided as a more compact summary graph in Figure 8. In Figure 8, the number of playground entries and exits by the child is represented using a bar chart, while the child's playground usage time is shown using a line graph indicating the average usage time, maximum usage time, and minimum usage time. Figure 8 allows caregivers to understand the overall level and range of the child's playground usage briefly. In summary, the parent mobile application functions not only as a real-time notification tool for entrance and exit events but also as a data dashboard that supports pattern analysis and long-term tracking, enabling more systematic management of children's playground usage habits.

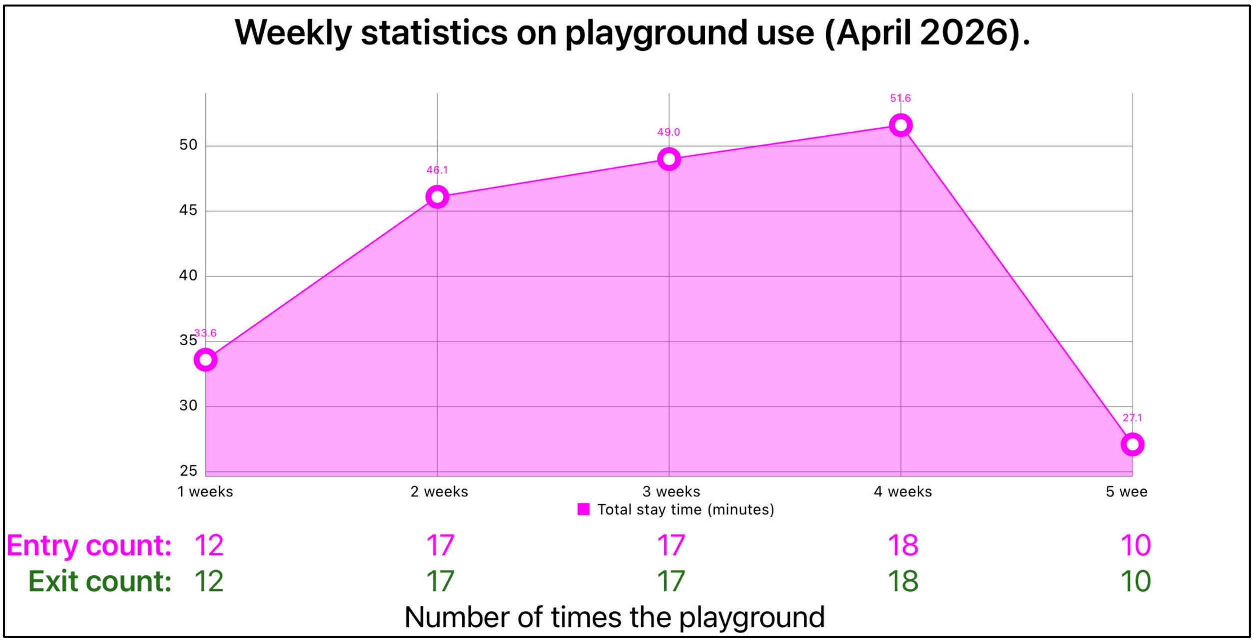

Figure 7. Screenshot of the parent application showing the weekly summary.

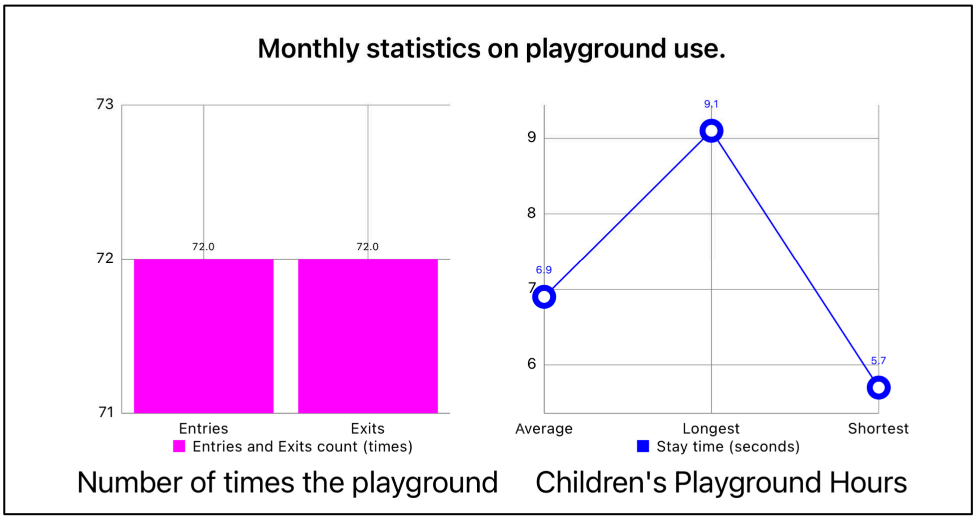

Figure 8. Screenshot of the parent application showing the monthly summary.

5. Conclusions and Future Research

This study presented an integrated low-cost child playground monitoring system that combines commercial BLE beacons, a single smart device, a push notification server, and a caregiver mobile application to detect entrance and exit events and visualize playground usage logs. The main contribution of the work lies not in proposing a new localization algorithm, but in demonstrating that a lightweight BLE-based system can be practically integrated and deployed for entrance/exit monitoring in semi-open playground environments. By applying RSSI-based detection with Kalman-filter-based smoothing and threshold-driven state transitions, the system enables real-time event recognition and automatic generation of daily, weekly, and monthly usage statistics.

Field validation was conducted over 30 days across five real playgrounds, showing an average entrance/exit detection accuracy of approximately 99%, an average response time of 6.5 s, and a push-delivery success rate exceeding 99%. In an additional multi-beacon experiment involving ten concurrent participants, the system achieved 97.5% detection accuracy, indicating that the proposed architecture can support simultaneous monitoring of multiple children in practical playground settings. These findings suggest that reliable child playground monitoring can be achieved at low installation cost, with simple infrastructure, and operational feasibility for residential complexes and neighborhood facilities.

Future work will focus on two main directions. First, we plan to develop a deep-learning-based behavioral prediction model that leverages long-term logs of playground entrance and exit events, with the aim of building applications and systems capable of forecasting individual usage patterns and issuing early warnings for potentially risky situations. Second, we intend to refine the integration between edge devices and the cloud to further reduce end-to-end latency, while strengthening data protection through TLS 1.3-based encryption and enhanced user authentication mechanisms. The experimental results indicate that the proposed system enables real-time child safety management even on low-cost IoT infrastructure, and follow-up studies are expected to extend its applicability to a broader range of environments, such as schools and kindergartens. Finally, we plan to develop a heatmap visualization of BLE beacon activity for each playground. Furthermore, since the proposed method relies on RSSI signals in semi-open environments, its stability may be affected by weather variations. Accordingly, additional experiments will be conducted to evaluate the performance of the proposed method under different weather conditions, including snow, rain, and temperature changes.

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Institutional Review Board Statement: This study did not require ethics approval as no personal, medical, or sensitive data were collected. The experiments were conducted solely to evaluate the technical performance of the system using BLE beacon signals, and no personally identifiable information was recorded.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: Restrictions apply to the availability of these data. Data used belongs to the owner/operator. The users' visit list of savings used in this article can be requested from the author.

Conflicts of Interest: The author declares no conflicts of interest.

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