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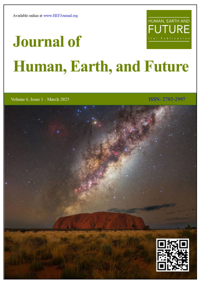

Improving Patient Turnaround Time in Malaysian Hospitals with Real-Time IoT BLE Location Tracking

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Abstract

This study aims to address challenges faced by Malaysian public hospitals in optimizing Patient Turnaround Time (PTAT) by implementing a Real-Time Patient Location Monitoring and Tracking System. Objectives include improving patient tracking to reduce delays and procedural inefficiencies, thus enhancing overall service quality and staff productivity. Methods and analysis involve designing a Proof of Concept (POC) based on Internet of Things (IoT) technology, specifically utilizing Bluetooth Low Energy (BLE) and Received Signal Strength Indicator (RSSI) values to estimate patient proximity to strategically positioned Access Points (APs) within hospital facilities. Through pilot tests, this system allows healthcare providers to monitor and locate patients in real time, facilitating timely service delivery. Findings indicate that the BLE-based location tracking system significantly reduces PTAT, minimizes patient movement delays, and boosts staff efficiency in handling patient flow. Novelty and improvement lie in leveraging BLE's low-power, cost-effective nature, offering a practical solution for real-time tracking that aligns with the unique operational needs of Malaysian hospitals. This IoT-based approach is a promising development for healthcare settings striving to enhance patient care standards through efficient resource and time management.

Keywords: BLE; IoT; Patients Turnaround Time (PTAT); Public Hospital.

1. Introduction

Hospital overcrowding, delays in patient care, and challenges with patient tracking are pervasive issues in healthcare systems worldwide, contributing to missed doctor's appointments and inefficient service delivery [1]. Patients often experience lengthy wait times before being attended to by medical staff, and in the interim, they may wander around hospital grounds, which complicates efforts to locate them when they are called. The difficulty in tracking patients efficiently within healthcare facilities has been documented as a key factor that affects service quality and operational efficiency [2]. Furthermore, the high prevalence of chronic diseases, coupled with the shortage of healthcare professionals due to Malaysia's contract system for doctors and nurses (Figures 1 and 2), aggravates these challenges [3]. Public hospitals in Malaysia, Thailand, and Singapore face similar challenges such as overcrowding, staffing shortages, and resource constraints. Malaysia struggles with limited access to advanced medical technology, particularly

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in rural areas. Thailand faces financial limitations, impacting access to equipment and leading to delays in care. Singapore deals with high patient demand due to an aging population and workforce constraints, causing longer waiting times. Despite these challenges, Singapore's hospitals are more equipped due to better infrastructure and resources compared to Malaysia and Thailand, although they still face strain from increasing patient volumes.

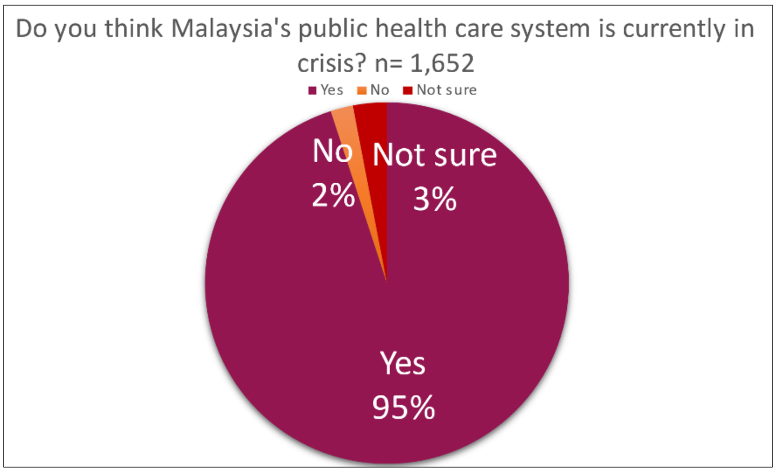

Figure 1. Codeblue: Dissatisfaction among Health Care Professionals and Workers in Malaysia's Government Health Service in 2023

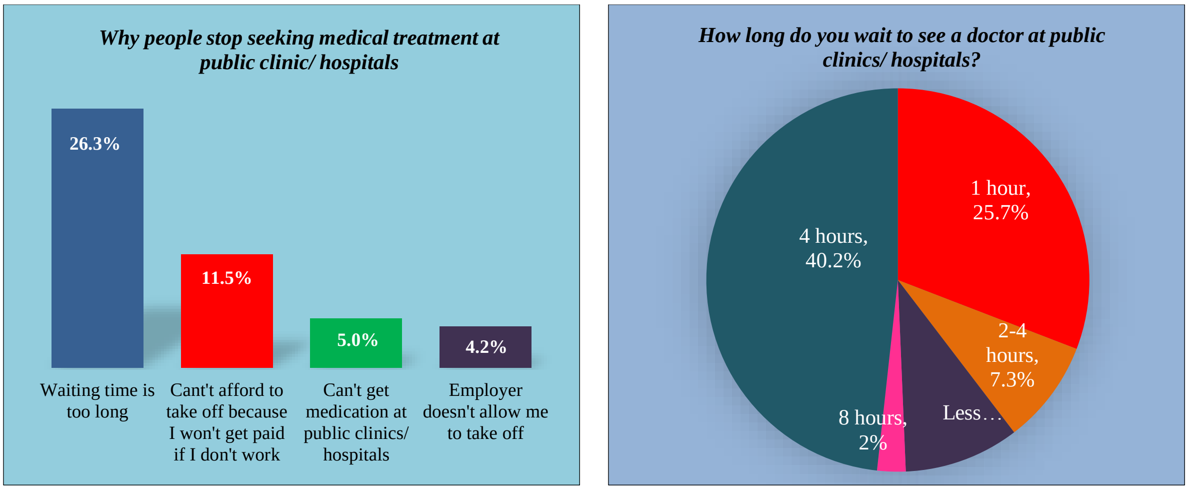

Figure 2. Malay Mail Online's survey reveals why people stop going to public hospitals for medical care

Recent studies have focused on integrating Internet of Things (IoT) and Bluetooth Low Energy (BLE) technologies for real-time patient monitoring [4-6]. However, few of these studies have specifically addressed PTAT optimization through patient location tracking [7-9] in high-traffic public hospitals, such as those in Malaysia [10]. For instance, the use of BLE and Received Signal Strength Indicator (RSSI) to enhance patient traceability has been explored in a few pilot studies, but comprehensive solutions tailored to Malaysian hospitals are limited. These findings underscore a significant gap: while tracking systems are emerging, there is limited research on their impact on PTAT in the context of public healthcare environments, particularly with the unique constraints of Malaysian facilities [11].

This study aims to address these gaps by developing a real-time patient location tracking system using BLE technology to enhance PTAT management. Our proposed system not only enables healthcare staff to locate patients accurately within the hospital but also seeks to optimize resource allocation, reduce patient wait times, and improve overall patient satisfaction. By presenting a Proof of Concept (POC), this study contributes to the growing body of knowledge on IoT-based healthcare solutions and offers a practical approach to addressing operational inefficiencies in Malaysian public hospitals. For instance, Figure 3 illustrates how PTAT is typically calculated. Streamlining hospital operations is vital to improving patient care, optimizing resource utilization, and boosting hospital productivity. A major hurdle lies in the inability of hospital staff to locate patients within the facility, leading to missed appointments, even when patients are present within the hospital grounds. According to Malaysia's Ministry of Health, such inefficiencies cause widespread dissatisfaction among the public, healthcare providers, and patients alike [10]. Enhancing the quality of care and managing hospital resources effectively is crucial, but creating an integrated solution for patient tracking and monitoring to optimize PTAT is a complex challenge, with few existing studies or solutions adequately addressing the problem.

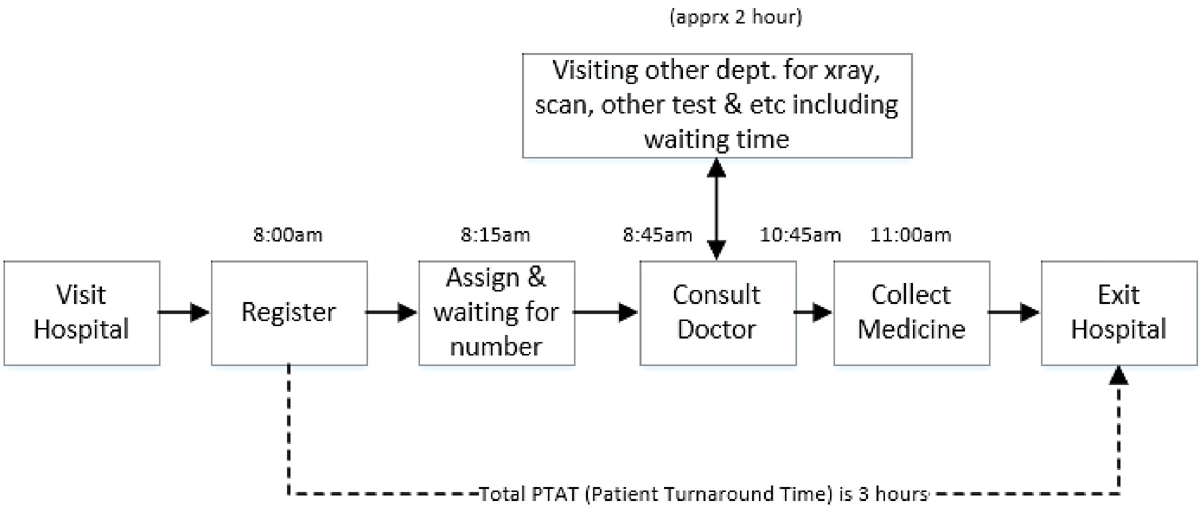

Figure 3. How Patience Turnaround Time is calculated

As healthcare systems advance toward "*Smart Healthcare*" [11], there is an increasing demand for real-time tracking and monitoring solutions to enhance patient care efficiency and reduce delays. Several recent studies by Huang et al. [7] and Halton [8] emphasize the potential of integrating IoT and Bluetooth Low Energy (BLE) technologies for continuous patient monitoring within healthcare settings [12, 13]. While BLE offers low-power, cost-effective tracking, IoT enables the collection, processing, and real-time analysis of patient location data, potentially addressing issues related to patient Turnaround Time (PTAT) and operational delays in public hospitals. The architecture of this system is depicted in Figure 4. Despite promising advancements, current research has largely focused on patient monitoring systems in controlled or private healthcare environments, often neglecting the specific needs and limitations of public hospitals with high patient volumes and limited resources [5, 14]. The Malaysian healthcare context, with its unique challenges like overcrowding, procedural delays, and resource constraints, has been underexplored in recent literature. This study seeks to fill these gaps by proposing a Real-Time Patient Location Tracking System specifically designed for Malaysian public hospitals, leveraging BLE and IoT to optimize PTAT management.

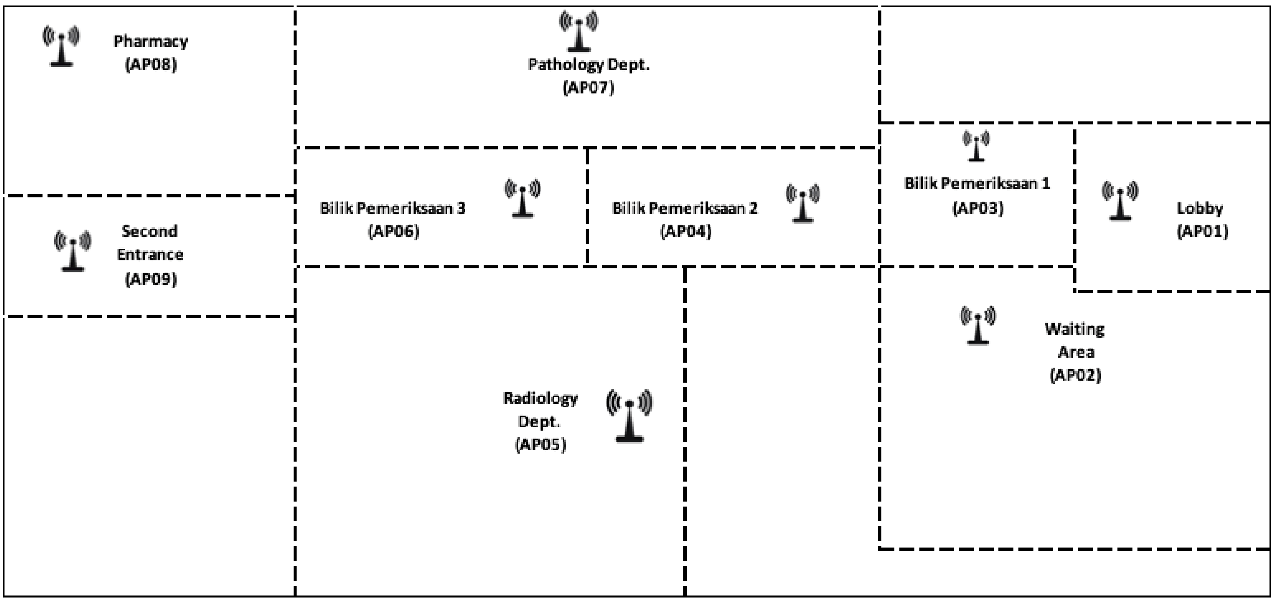

Figure 4. Architecture Layout Real Time Patient Location Tracking Solution

Upon admission, patients are provided with BLE-enabled wristbands containing essential information, such as a unique device ID. These wristbands communicate with strategically placed Access Points (APs) throughout the hospital, collecting location data that is processed and stored on a cloud-based system for real-time monitoring. This solution enables hospital staff to efficiently locate patients and streamline patient flow, potentially reducing missed appointments and increasing patient satisfaction. By addressing the unique operational needs of Malaysian hospitals, this study offers a targeted approach to PTAT optimization, contributing to both the literature on healthcare IoT and the practical improvement of public hospital operations.

Low-power wearable devices are employed to estimate patient locations by measuring RSSI values, as shown in the flowchart. Patients are provided with wrist-worn devices that receive RSSI signals from nearby Access Points (APs). The system server then uses a predefined mapping table of APs and their respective locations to identify the closest beacons emitted by the patient's wearable. These signals are subsequently mapped to specific subareas within the hospital, allowing for precise patient tracking and localization. To test the proof of concept, experiments were conducted using 3 Access Points and 8 wearable devices, as explained in Figure 5.

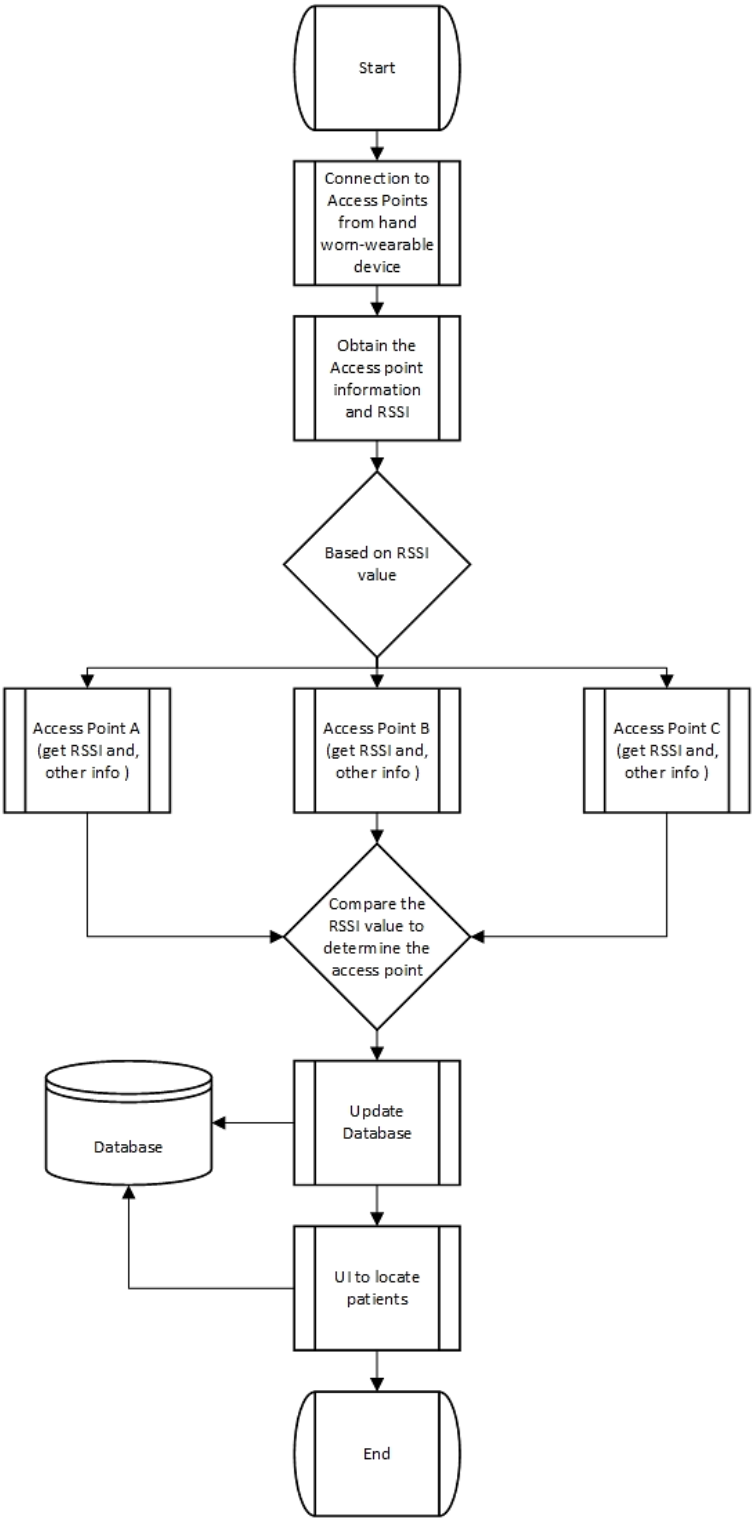

Figure 5. Flow chart of positioning algorithm

In the context of wireless communication systems like Bluetooth Low Energy (BLE), RSSI plays a critical role in determining signal quality and device proximity. RSSI measures the strength of the signal received [15] by the device's antenna, with higher (less negative) RSSI values indicating a stronger signal. As the signal travels over longer distances

[16, 17], it weakens, resulting in a lower RSSI value. Each BLE chipset has a unique threshold for maximum RSSI sensitivity (a minimum negative value), beyond which it can no longer detect incoming signals. RSSI is essential in applications like real-time patient tracking in Malaysian public hospitals, where precise patient location monitoring can significantly improve Patient Turnaround Time (PTAT). By leveraging RSSI, hospitals can ensure seamless tracking of patients throughout various stages of treatment, reducing wait times, optimizing workflow, and improving overall service quality. Each received data packet undergoes signal strength evaluation, enabling the system to provide continuous, real-time updates essential for time-sensitive healthcare operations. It's important to note that although RSSI (Received Signal Strength Indicator) reflects the strength [18] of an incoming signal, it does not represent the transmission power from the router or Access Point (AP). Instead, RSSI is affected by the receiving device's Wi-Fi or Bluetooth Low Energy (BLE) card performance, meaning that signal strength can vary depending on the sensitivity and capability of the receiving device.

The RSSI is obtained by quantizing detected signal energy, providing an accurate assessment of signal quality. This information is available across various layers of the communication protocol stack, such as the MAC, NWK, and APL layers, along with each packet's timestamp for further analysis [19]. Although both RSSI and dBm measure signal strength, they do so differently: dBm gives an absolute power level in milliwatts [20], while RSSI is a relative index that can vary across devices and manufacturers, often measured on a scale of 0 to 255. For example, Cisco uses a scale from 0 to 100, whereas Atheros employs a 0-60 scale. Despite these differences, the underlying principle remains consistent: the higher the RSSI value, the stronger and more reliable the signal. This variability in RSSI measurement scales, as defined by the IEEE 802.11 Wi-Fi standards, allows flexibility across different hardware, but in practical applications such as patient location tracking in healthcare facilities a higher RSSI translates to better signal reception, which is crucial for maintaining the accuracy and efficiency of real-time monitoring systems.

The experiment begins by measuring the reference average RSSI at a 1-meter distance for Bluetooth applications [21]. Additionally, the maximum RSSI value at a 5-meter distance, corresponding to the set transmission power, is also recorded. Table 1 presents results from this initial phase, obtained using a BLE device with the nRF52832 chipset (illustrated in Figure 6). This experiment utilizes the nRF52832, a Bluetooth 5.2 System on Chip (SoC) with a maximum RSSI sensitivity of -96 dBm [22, 23].

Figure 6. nRF52832 chipset

Table 1 demonstrates that the typical RSSI values for both devices at a 0-meter distance are approximately -35 dBm. Similar trends were observed at the other measured distances, although a slight difference was noted at the 1-meter mark. The variation, a mere -1 dBm, is minimal and does not suggest any inaccuracy in the collected data. At a distance of 5 meters, the two devices measured maximum average RSSI values ranging from -88 dBm to -94 dBm. These values will be utilized as reference points. If the measured RSSI is higher (closer to 0 dBm), it indicates that the user's distance exceeds 5 meters.

Table 1. RSSI Measurement Results for 2 Devices under Line-Of-Sight Condition

Device Number (n)	Condition	Distance (m)	Average RSSI $RSSI_{avg}$
1	No obstacle – Line of sight	0	-34.01
2			-36.43
1		1	-50.01
2			-52.13
1		3	-67.12
2			-68.15
1		5	-88.45
2			-89.14

As illustrated in Figure 7, the experimentation in this study follows three primary steps:

- Setting Up the Environment – Configuring the environment for obtaining RSSI measurements and conducting initial testing.
- Proof of Concept (POC) – Validating the proposed technique to ensure its feasibility and effectiveness.
- Pilot Test – Applying the recommended approach in a real-world setting to test its practical application.

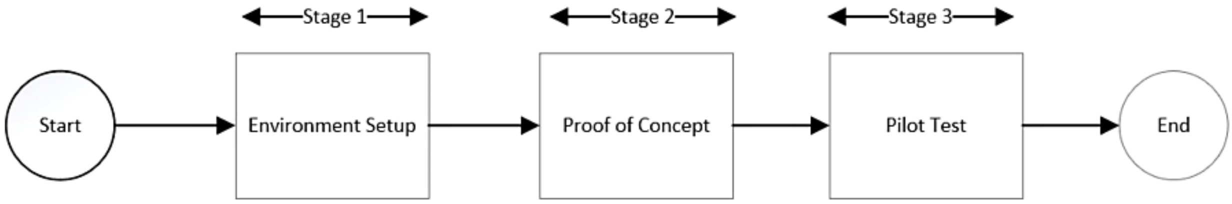

Figure 7. Stages of the Experiment

It's important to note that this strategy and testing methodology [24] can be replicated with other BLE devices as well, ensuring versatility in different experimental scenarios

2. Methods

2.1. Stage 1 - Environment Setup

Proximity-based solutions, such as point-of-interest (PoI) applications [25], are increasingly being used in healthcare settings to enhance patient flow and improve efficiency. In hospitals, PoI systems can provide users with real-time information about their location, guiding them to specific departments or treatment areas, thereby reducing unnecessary delays. Additionally, these systems can track and recover lost or misplaced items, such as medical equipment or personal belongings, using Bluetooth tags. In such implementations, Bluetooth Low Energy (BLE) tags periodically broadcast frames, which are detected by nearby access points (APs). The Access Points (APs) then relay tag data to the server via the access controller (AC). For Points of Interest (PoI) applications, the system determines the nearest points or departments relative to the patient's calculated location. This real-time tracking optimizes patient flow within the hospital, significantly reducing wait times and enhancing overall Patient Turnaround Time (PTAT). By integrating BLE technology and proximity-based tracking, Malaysian public hospitals can improve patient movement, operational efficiency, and service delivery, creating a more streamlined healthcare experience.

The experimental setup designed to simulate the deployment of a Real-Time Patient Location Tracking Solution leverages the existing Wi-Fi network along with a detailed hospital floor layout plan. This configuration includes setting environmental parameters such as the Access Point (AP) names, models, channels, and frequency bands. APs are strategically located on the floor plan, and their positions and configurations are optimized to enhance performance. The anticipated results are subsequently analyzed, and the data collected during the experiment is uploaded to a central database. As illustrated in Figure 6, the APs are arranged within the clinic's layout to collect RSSI values, which are utilized to determine the distance between the patient's device and the nearest AP. By pinpointing the strongest RSSI values, the system can identify the closest AP, thus providing real-time updates on the patient's location. This setup is essential for assessing the system's effectiveness in a practical clinical environment, ensuring reliable tracking of patient movements throughout the facility.

To enhance clarity, the detailed selection criteria for hospitals and departments involved in pilot testing. Criteria might include factors such as patient volume, department type (e.g., Emergency, Outpatient), or readiness for IoT technology. Additionally, specifying the pilot phase duration would offer insight into the robustness of the study. Metrics for evaluating success below in the later topic include the percentage reduction in Patient Turnaround Time (PTAT), accuracy of patient tracking, and feedback from staff and patients on ease of navigation and reduced wait times. On the data analysis methods by detailing any statistical approaches or models used to evaluate the IoT solution's impact on Patient Turnaround Time (PTAT). For instance, clarify whether specific statistical tests, such as paired t-tests, were applied to compare PTAT before and after implementing the tracking solution. Regression models helped assess the correlation between tracking accuracy and PTAT reductions. Additionally, descriptive statistics or data visualization methods, like time series, illustrate changes in patient flow and waiting times, providing clearer insights into system effectiveness.

The study involved the use of 5 nRF52832 System on Chips (SoCs), powered by 5V lithium-ion batteries [26]. A Proof of Concept (PoC) was conducted to validate the proposed method under optimal conditions and assess distance estimation. During the PoC, two nRF52832 devices measured RSSI values across varying distances while maintaining line-of-sight (LOS) conditions for accuracy. Access Points (APs) were placed strategically to collect data packets from the BLE client devices, and using two BLE modules allowed for the detection of measurement discrepancies. The chipsets broadcast packets to the AP every 50 milliseconds (though this interval could vary based on the scenario), while the AP scanned for incoming packets every 5 seconds. Once collected, the data was uploaded to a database for further analysis. This dataset included essential information such as the Medium Access Control (MAC) address, Access Point details, device name, RSSI value, and timestamp (date and time). This thorough dataset was crucial for evaluating the system's performance and confirming the exactness of the RSSI-based distance estimation.

With a maximum transmission power (Tx) of -4 dBm, the nRF52832 chipset is particularly suitable for testing low-calibrated Tx techniques for proximity tracking. In this paper, the Tx power was adjusted to -8 dBm, which was identified as the optimal setting, resulting in an RSSI of -96 dBm at a distance of 5 meters [13]. Throughout the Proof of Concept phase, measurements ranging from -100 to -200 dBm were employed to ensure the consistency and accuracy of the data. The experiment took place in a controlled environment, free from external network interference and physical obstacles, to uphold the integrity of the results [14]. To simulate wearable devices worn on the wrist, both the transmitter and receiver were placed at a height of 0.5 meters, ensuring a direct line of sight for optimal signal reception. The setup for the Proof of Concept experiment is shown in Figure 8, and Table 2 provides a sample of the data collected during the scanning process. This careful configuration was crucial for validating the technique under ideal conditions, ensuring precise location tracking and reliable RSSI measurements.

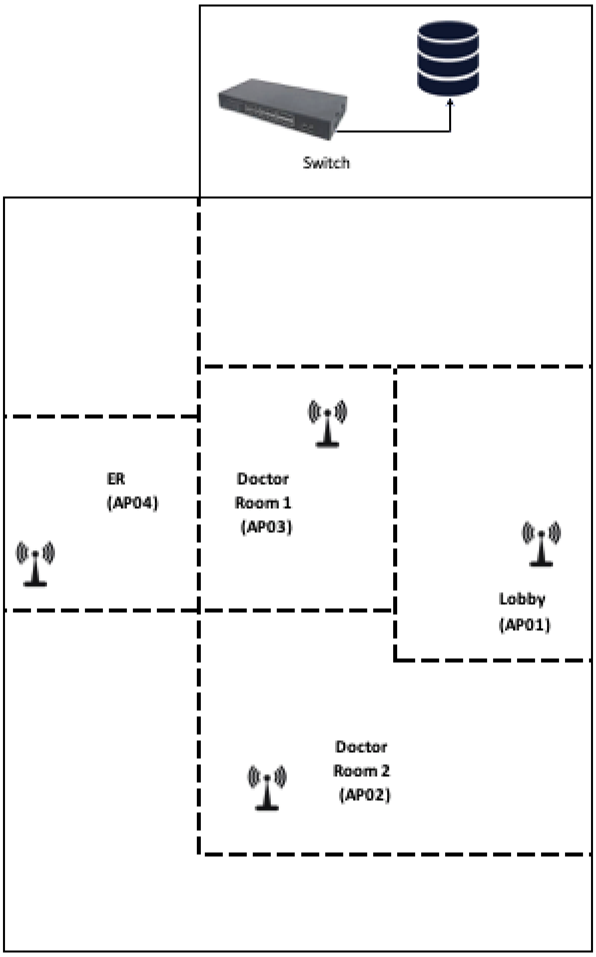

Figure 8. Stage 1 Experimentation Set Up

Table 2. Sample of Captured Data

Access Point	AP Address	Device Name	Device Address	RSSI Value	Date	Time
AP01	00:1D:46:12:3E:C7	BLETag1	01:1D:34:11:3C:B5	-65 dBM	14/08/2024	09:40:12
AP02	01:1D:46:10:3C:F8	BLETag2	02:1D:46:11:3C:B9	-34 dBM	14/08/2024	09:43:53
AP03	00-14-22-01-23-45	BLETag3	04:1D:45:11:3F:B10	-23 dBM	14/08/2024	09:50:55
AP01	00:1D:46:12:3E:C7	BLETag4	05:1D:23:11:3E:B11	-51 dBM	14/08/2024	09:55:47
AP04	00-1F-32-21-13-1C	BLETag5	01:1D:54:11:3B:B12	-31 dBM	14/08/2024	09:58:32

Data collection was carried out and structured within a database in accordance with the framework established during the proof of concept. To reflect real-world scenarios, the devices were positioned at a height of 7 meters, representing the typical usage of wearables in a healthcare context. In this phase, four devices were utilized to assess the system's performance in managing multiple users at once and to evaluate the number of effective scans from various angles of arrival (AOA) [27]. This multi-device setup was crucial for assessing the scalability of the approach and its effectiveness in handling a larger number of users while maintaining reliable and accurate location tracking.

2.2. Stage 2 - Experimentation Stage

In the second stage of the Proof of Concept (PoC), testing involved 20 devices—16 wearable devices and 4 Access Points (APs). The experiment measured distances ranging from 1 to 5 meters, with various positions to simulate real-life scenarios. Figure 9 shows the PoC setup, where the system identifies the closest Access Point ("Person 1") based on RSSI values. These values vary with distance, with stronger signals detected at shorter distances [15, 28]. With 4 APs in total, the goal of the POC is to verify whether the proposed approach can accurately track patient location and function effectively before progressing to the next stage of development. This experiment is critical in validating the solution's potential for improving Patient Turnaround Time (PTAT) in Malaysian public hospitals by ensuring precise, real-time location tracking.

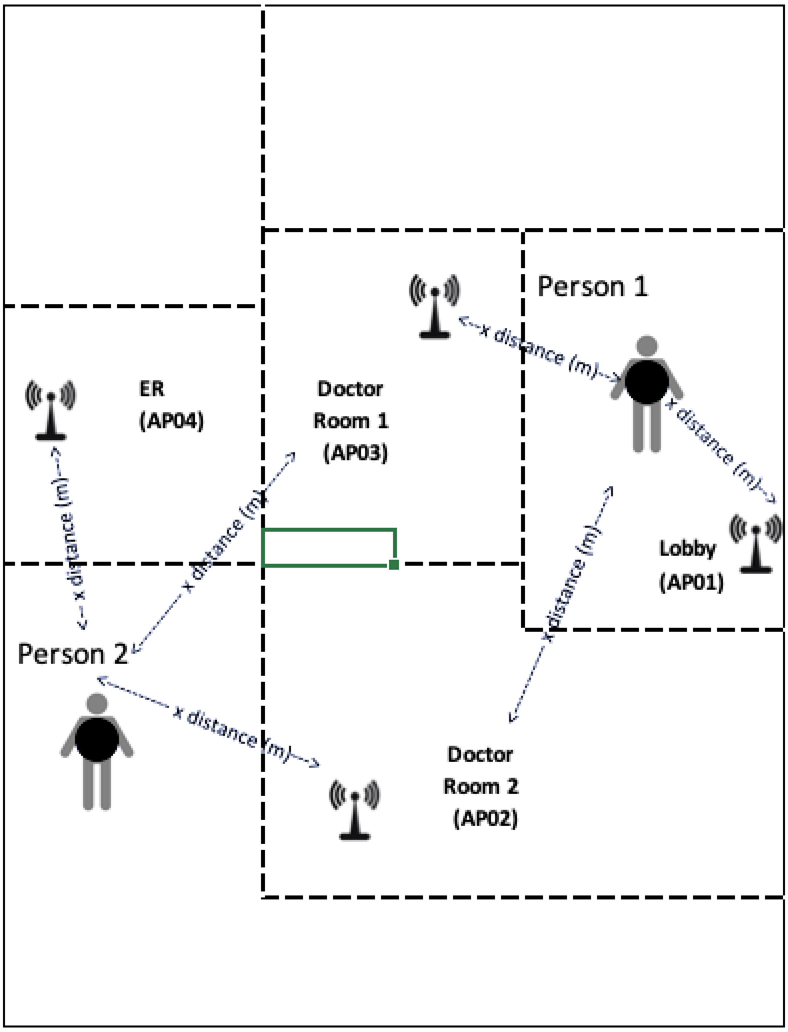

Figure 9. Stage 2 Experimentation Set Up

2.3. Stage 3 – Pilot Test

In stage 3, a Pilot Test was carried out in an indoor setting with five participants to replicate real-world conditions. The test area featured various doors and walls, and users moved around to create natural obstructions. This phase is crucial, as it assesses the feasibility of implementing the approach in practical scenarios. Each user was equipped with a BLE wearable device featuring the nRF52832 chipset, and they wore the devices for a duration of 2 hours. The users were instructed to move between departments, starting from the main lobby. Every time a user passed an Access Point (AP), a record was generated that captured the RSSI value, enabling continuous location tracking. The testing was conducted within a 1 to 5-meter range, with each session lasting at least 30 minutes. After the 2-hour session, the wearable devices were retrieved, and the data was analyzed by comparing device-stored information with system-generated records. Each patient was assigned a unique BLE tag, such as "BLETag1" or "BLETag2," linked to their name for accurate tracking. A sample of the collected data is presented in Table 3. This stage ensures the system's effectiveness in a dynamic hospital environment, aiding in the optimization of Patient Turnaround Time (PTAT) in Malaysian public hospitals.

Table 3. Summary Data of Experimentations

Access Point	AP Address	Device Name	Device Address	RSSI Value	Date	Time
AP01	01-23-45-67-89-AB	BLETag1	01:1D:46:11:3E:B8	-45 dBM	16/08/2024	10:31:32
AP02	01:1E:45:11:3C:B8	BLETag2	02:1D:46:11:3E:B9	-12 dBM	16/08/2024	10:34:45
AP03	00-14-22-01-23-45	BLETag3	04:1D:46:11:3E:B10	-50 dBM	16/08/2024	10:56:22
AP01	01-23-45-67-89-AB	BLETag4	05:1D:46:11:3E:B11	-13 dBM	16/08/2024	11:53:45
AP04	00-14-22-01-23-BC	BLETag5	01:1D:46:11:3E:B12	-9 dBM	16/08/2024	11:32:01
AP04	00-14-22-01-23-BC	BLETag1	01:1D:46:11:3E:B12	-67 dBM	16/08/2024	11:41:43
AP03	00-14-22-01-23-BC	BLETag3	04:1D:46:11:3E:B10	-90 dBM	16/08/2024	11:22:12
AP04	00-14-22-01-23-BC	BLETag5	01:1D:46:11:3E:B12	-65 dBM	16/08/2024	11:21:19

3. Analysis and Results

Signal pattern analysis was performed in various environments, including a meeting room, corridor, and eight designated locations. Additionally, signal patterns were collected from these eight predefined areas, as illustrated in Figure 4. The Access Point was installed on the ceiling at a height of 2.7 meters, with the power button facing downward for all experiments. BLE Access Points and wearable devices were deployed in various locations, including doctors' offices, the X-Ray Room, Health Education Unit, Laboratory, Treatment Room, Emergency Room, and entrances. A single access point was used per location, with 20 wearable devices worn by patients and staff. Figure 4 provides a layout diagram showing the strategic positioning of the devices for comprehensive signal pattern analysis.

3.1. Predefined Routes Movement of One Patient Experiment

During the first user experiments involving movement, a specific participant utilized the wearable device, as depicted in the Figure 10, and crossed from one location to another, a predefines route from main Lobby to the Second Entrance with one wearable device (MAC address capture), as illustrated in Figure 10 and the results in Table 4 The instances when the user passed the designated Access Point at each location were meticulously recorded, serving as our ground truth for evaluation. To assess the accuracy of predicted locations, we considered them correct if the method successfully identified the patient's presence at the respective locations during the recorded times.

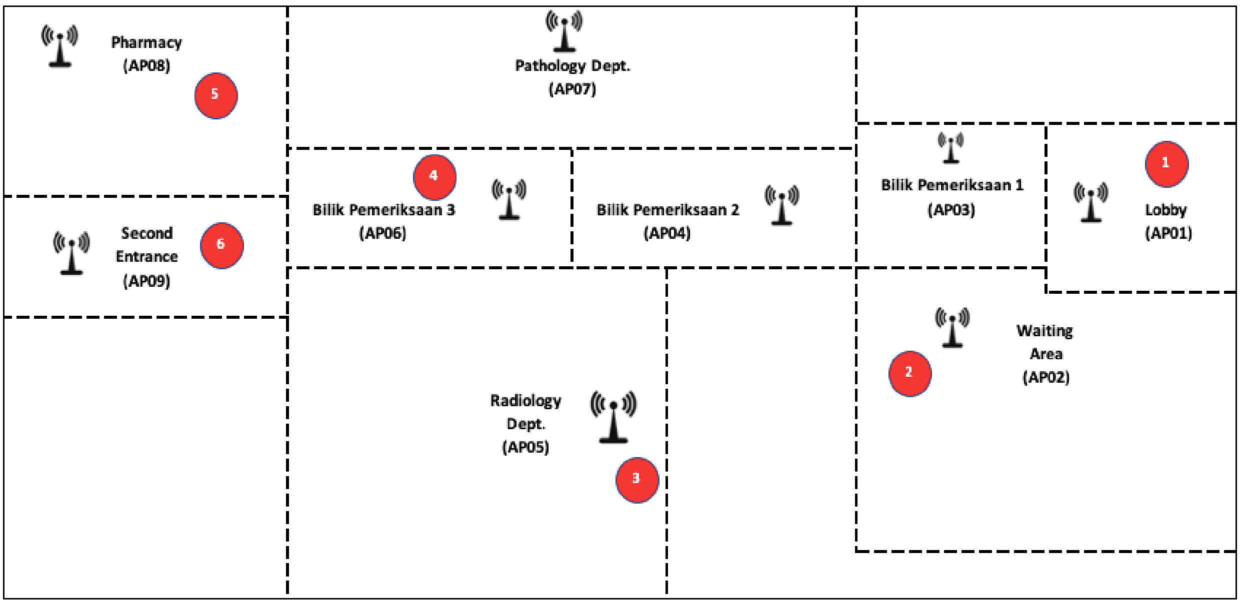

Figure 10. The pre-defined routes for moving patients' experiments performed from the Lobby to the Second Entrance

Table 4. Access Point Captured During The pre-defined routes for moving one patient experiments based on Figure 10

No.	Mac	RSSI	Date/Time	AP01 1	AP02 2	AP05 3	AP06 4	AP08 5	AP09 6
1	01:1D:46:11:3E:B8	-59	2023-07-12 08:19:04	•					
2	01:1D:46:11:3E:B8	-60	2023-07-12 08:19:56		•				
3	01:1D:46:11:3E:B8	-62	2023-07-12 08:21:01			•			
4	01:1D:46:11:3E:B8	-60	2023-07-12 08:22:55				•		
5	01:1D:46:11:3E:B8	-60	2023-07-12 08:24:30					•	
6	01:1D:46:11:3E:B8	-59	2023-07-12 08:26:46						•

In this approach, the user was allocated to the location associated with the latest date and time method within a specific timeframe. This thorough evaluation sought to determine the effectiveness of the methods in accurately tracking patients' locations during their movements, offering important insights into the reliability and accuracy of the location prediction techniques used.

- Patient 1 BLE wearable device MAC address → 01:1D:46:11:3E:B8

3.2. Predefined Routes Movement of Two Patients Experiment

This study encompasses a dual-patient movement experiment where two participants engage with wearable devices, traversing predefined routes from the main Lobby to the Second Entrance. The movement is tracked using a single wearable device, with its MAC address captured for identification, as depicted in Figure 10. The outcomes of this experiment are summarized in Table 5. The precise recording of instances when participants pass through the designated Access Points forms the basis of our evaluation. These recorded occurrences provide a ground truth for assessing the accuracy of predicted locations. To be considered accurate, a prediction must correctly identify the presence of patients at the specified locations during the recorded times. This evaluation criterion ensures a reliable and thorough assessment of the location prediction method used in the study.

- Patient 1 BLE wearable device MAC address → 01:1D:46:11:3E:B8
- Patient 2 BLE wearable device MAC address → 02:1D:46:11:3E:B9

Table 5. Access Point Captured During The pre-defined routes for moving two patient experiments based on Figure 10

No.	Mac	RSSI	Date/Time	AP01 1	AP02 2	AP05 3	AP06 4	AP08 5	AP09 6
1	01:1D:46:11:3E:B8	-59	2023-07-12 10:20:06	•					
2	02:1D:46:11:3E:B9	-69	2023-07-12 10:20:16	•					
3	01:1D:46:11:3E:B8	-60	2023-07-12 10:20:58		•				
4	02:1D:46:11:3E:B9	-58	2023-07-12 10:21:20		•				
5	01:1D:46:11:3E:B8	-62	2023-07-12 10:22:05			•			
6	02:1D:46:11:3E:B9	-61	2023-07-12 10:23:09			•			
7	01:1D:46:11:3E:B8	-60	2023-07-12 10:25:05				•		
8	02:1D:46:11:3E:B9	-59	2023-07-12 10:26:08				•		
9	01:1D:46:11:3E:B8	-60	2023-07-12 10:26:50					•	
10	02:1D:46:11:3E:B9	-62	2023-07-12 10:27:45					•	
11	01:1D:46:11:3E:B8	-59	2023-07-12 10:27:58						•
12	02:1D:46:11:3E:B9	-61	2023-07-12 10:28:29						•

3.3. Free Flow Movement of One Patient Experiment 1

In the initial phase of our patient movement experiments, we conducted free-flow trials to assess the performance of a wearable device worn by a specific participant. The participant using the device while traversing from the main Lobby to the Second Entrance via a free-flow route, with the associated MAC address captured. This movement is further depicted in Figure 4, and the corresponding results are presented in Table 6.

- Patient 1 BLE wearable device MAC address → 01:1D:46:11:3E:B8

Table 6. Access Point Captured During The free flow routes for moving one patient experiment 1 based on Figure 4

No.	Mac	RSSI	Date/Time	AP01 1	AP02 2	AP05 3	AP06 4	AP08 5	AP09 6
1	01:1D:46:11:3E:B8	-78	2023-07-12 14:45:10	•					
2	01:1D:46:11:3E:B8	-71	2023-07-12 14:46:34		•				
3	01:1D:46:11:3E:B8								
4	01:1D:46:11:3E:B8	-69	2023-07-12 15:01:55				•		
5	01:1D:46:11:3E:B8								
6	01:1D:46:11:3E:B8	-49	2023-07-12 15:46:03						•

The experiment involved meticulously recording instances when the participant passed through designated Access Points at various locations, serving as our ground truth for evaluation. These recorded instances are crucial for assessing the accuracy of the wearable device in identifying the participant's presence at specific locations within the hospital. The evaluation criteria considered the method successful if it accurately identified the participant's presence at the designated locations during the recorded times.

3.4. Free Flow Movement of Two Patients Experiment

During this phase conducted on the second day of the test, two individuals were equipped with BLE wearable tags to undergo movement experiments. We executed free-flow trials to evaluate the effectiveness and functionality of the wearable device as worn by the participants. This experiment involved 9 Access Points, as shown in Figure 11. Participants, using the device, navigated from the main lobby to the second entrance via a free-flow route, during which their associated MAC addresses were captured. The intricate details of this movement are expounded upon in Figure 11, while the outcomes and relevant data are meticulously outlined in Table 7. This comprehensive analysis serves to provide a thorough understanding of the device's performance during real-time movement scenarios.

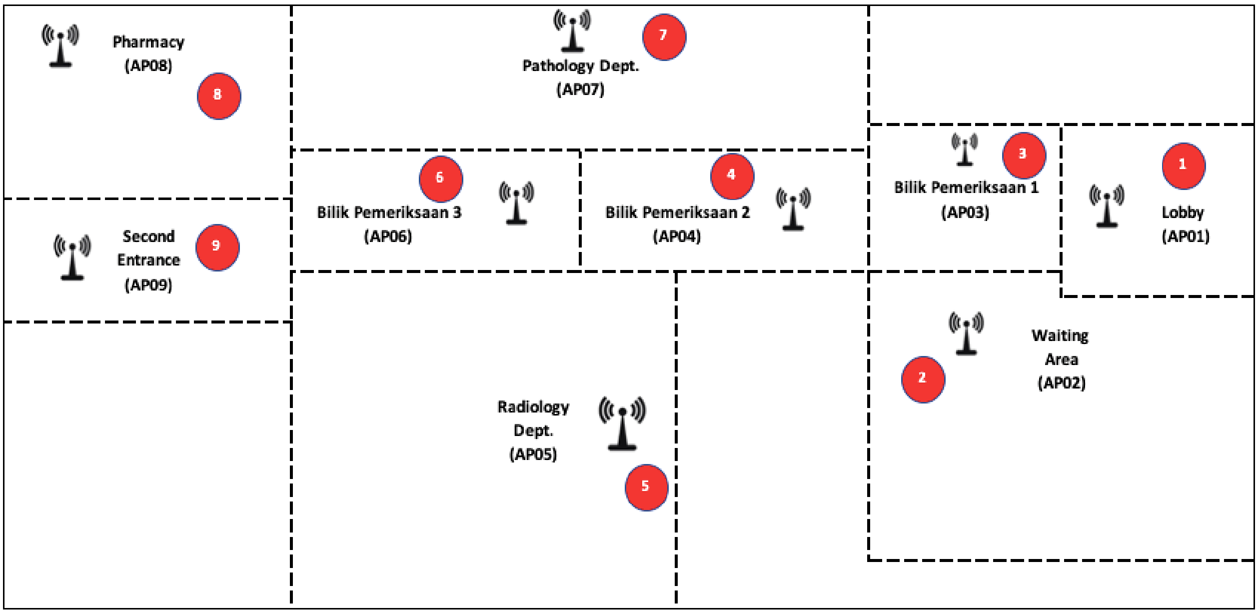

Figure 11. The Possible routes for moving patients' experiments performed from the Lobby to the Second Entrance

Table 7. Access Point Data Captured During The free flow routes for moving two patients experiment based on Figure 11

No.	Mac	RSSI	Date/Time	AP01	AP02	AP03	AP04	AP05	AP06	AP07	AP08	AP09
1	01:1D:46:11:3E:B8	-89	2023-07-13 09:15:19	•								
2	02:1D:46:11:3E:B9	-75	2023-07-13 09:18:20	•								
3	01:1D:46:11:3E:B8	-87	2023-07-13 09:18:38		•							
4	02:1D:46:11:3E:B9	-58	2023-07-13 09:20:32		•							
7	01:1D:46:11:3E:B8	-63	2023-07-13 09:50:41				•					
8	02:1D:46:11:3E:B9	-45	2023-07-13 09:25:33					•				
9	01:1D:46:11:3E:B8	-90	2023-07-13 10:03:15								•	
11	01:1D:46:11:3E:B8	-78	2023-07-13 10:31:42									•
12	02:1D:46:11:3E:B9	-51	2023-07-13 10:28:29									•

An insightful observation stemming from the experiment underscores the distinct movement patterns of the participants. Patient 1, identified by the MAC Address 01:1D:46:11:3E:B8, did not traverse through Access Points AP03, AP05, AP06, and AP07 during specific instances. Similarly, Patient 2, distinguished by the MAC address 02:1D:46:11:3E:B9, did not pass through Access Points AP03, AP04, AP06, AP07, and AP08 at certain times. The non-passage through these Access Points resulted in the wearable device not capturing any information during those specific intervals, indicating the absence of the patients in those particular locations during the recorded periods.

3.5. Random Movement of Five Patients Experiment

On the third day of testing, five patients were equipped with BLE wearable tags for a series of movement experiments aimed at evaluating the device's functionality under real-world conditions. The tests were randomized to assess the device's performance, with 9 Access Points strategically placed, as shown in Figure 11. The participants utilize the wearable device as they navigate from the main Lobby to the Second Entrance via a randomly determined route. Throughout this movement, the associated MAC addresses were systematically captured. The intricate details of these movements are further explained in Figure 11, while the ensuing outcomes and pertinent data are meticulously documented in Table 8 and subsequent tables in detail of the movement. This comprehensive analysis aims to provide a thorough understanding of the device's performance under real-time, dynamic movement scenarios, offering valuable insights into its capabilities and effectiveness in diverse hospital environments.

- Patient 1 BLE wearable device MAC address → 01:1D:46:11:3E:B8
- Patient 2 BLE wearable device MAC address → 02:1D:46:11:3E:B9
- Patient 3 BLE wearable device MAC address → 04:1D:46:11:3E:B10
- Patient 4 BLE wearable device MAC address → 05:1D:46:11:3E:B11
- Patient 5 BLE wearable device MAC address → 01:1D:46:11:3E:B12

Table 8. Overall Access Point Data Captured During Random Routes for moving Five patients experiment based on Figure 11

No.	Mac	AP01	AP02	AP03	AP04	AP05	AP06	AP07	AP08	AP09
1	01:1D:46:11:3E:B8	•	•				•		•	•
2	02:1D:46:11:3E:B9	•		•				•		•
3	04:1D:46:11:3E:B10	•	•		•	•			•	•
4	05:1D:46:11:3E:B11	•	•			•	•			•
5	01:1D:46:11:3E:B12	•			•				•	•

In summary, our free-flow patient experiments involved a detailed examination of the participant's movement with a wearable device, capturing MAC addresses and assessing accuracy based on meticulously recorded ground truth data at designated Access Points throughout the hospital. The results, as presented above provide valuable insights into the effectiveness of the wearable device in tracking and identifying patient locations within the healthcare facility.

4. Discussion

4.1. Enhancing Patient Turnaround Time (PTAT) Through Real-Time Localization and Movement Monitoring

One significant challenge in healthcare facilities is hospital congestion, which leads to increased patient wait times as they await processing and medical attention. During this waiting period, patients often move around the hospital, making it difficult for staff to locate them promptly. This becomes particularly problematic when a patient is called by a doctor from another department or after the doctor has finished attending to another patient, leading to confusion and delays. The inability to determine a patient's exact location can cause delays in treatment. Real-Time Patient Localization and Movement Monitoring systems play a vital role in improving Patient Turnaround Time (PTAT). These systems allow staff to quickly identify a patient's whereabouts, ensuring they are available when needed, thereby reducing unnecessary delays and enhancing overall hospital efficiency.

Upon arrival, each patient is provided with a BLE-tagged wristband containing essential data such as a unique ID number and the nearest Access Point (AP). These access points, installed strategically throughout the hospital, continuously collect the patient's location data as they move through the facility. This data is then transmitted to a cloud-based database for real-time processing and analysis. With real-time localization, staff can monitor patient movement accurately, ensuring that patients are in the right place at the right time, minimizing instances of missed appointments or delays caused by locating patients. This streamlined process significantly reduces congestion, optimizes resource allocation, and improves the overall patient experience, making hospital operations more efficient.

Based on the Proof of Concept (PoC), implementing real-time tracking solutions is expected to greatly improve Patient Turnaround Time (PTAT), as shown in Figure 12. By allowing healthcare staff to track patient movements accurately, the technology facilitates better patient management and quicker service delivery. This leads to optimized patient flow, reduced waiting times, and more timely care, which enhances operational efficiency and overall patient satisfaction.

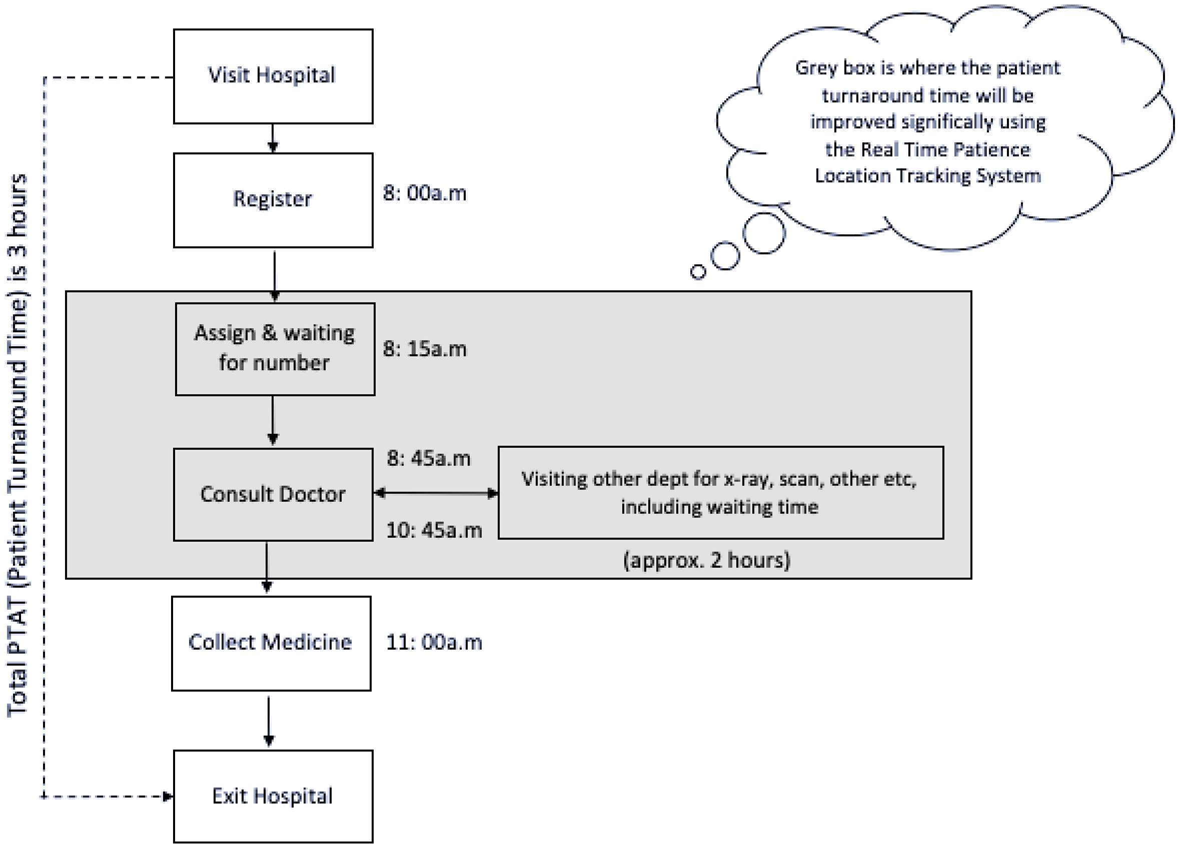

Figure 12. POC Results

The Real-Time Patient Location Tracking and Movement Monitoring Solution significantly reduces patient turnaround time by enabling quick identification of patient locations. This allows staff and doctors to promptly contact and provide care, minimizing delays caused by patients being unavailable or wandering. As a result, hospital operations become more streamlined, ensuring timely reporting and better care delivery. Table 9 illustrates a comparison of the key benefits achieved by deploying the Real-Time Patient Location Tracking System, highlighting improvements in patient flow, reduced wait times, and overall efficiency in patient management.

Table 9. Before and After Impact of Real Time Patient Location Tracking and Movement Solution

Description	Before	After
Registration	✓	✓
Patient missed Doctor's consultation due whereabout in hospital	✓	×
Trackable after registration	×	✓
Locate the Patient where about within hospital	×	✓
Faster Doctor consultation	×	✓
Improve the Quality of Service (QoS)	×	✓
Optimize the throughput of the departments	×	✓
Saving Time	×	✓
Cost saving	×	✓
Patients are happy	×	✓

The implementation of the real-time patient location tracking system has resulted in significant improvements across various areas of hospital operations. Before the system was implemented, patients' whereabouts within the hospital were often unknown, leading to missed doctor consultations and delays. After implementation, patient locations were tracked in real-time, enabling faster consultations, improved quality of service (QoS), optimized department throughput, and better overall patient satisfaction. These advancements also resulted in time and cost savings, both for patients and healthcare providers, contributing to an overall improvement in hospital efficiency and patient happiness.

Table 10 explains the current study focuses on improving patient flow and reducing waiting times in Malaysian public hospitals through real-time location tracking using Bluetooth Low Energy (BLE) and IoT technology. In comparison, previous studies utilized different tracking technologies: RFID-based tracking, which increased patient management efficiency; GPS-based tracking, which enhanced accuracy in large hospital settings; and Wi-Fi-based monitoring systems, which enabled quicker patient tracking and care. Each study employed distinct technological approaches, offering varying levels of accuracy, sample sizes, and implementations, but all aimed at improving hospital operations and patient care.

Table 10. Compare the Results of the Present Study with Previous Studies

Study	Methodology	Technology Used	Findings	Key Difference
Current Study	Real-Time Patient Location Tracking	Bluetooth Low Energy (BLE), IoT	Improved patient flow, reduced waiting times	Focus on real-time BLE tracking in Malaysian public hospitals
Martínez Pérez et al. [29]	RFID-based tracking	RFID	Increased efficiency in patient management	Different tracking technology (RFID vs. BLE)
Apte et al. [30]	GPS-based location tracking	GPS	Enhanced accuracy in large hospital settings	Larger sample size, GPS technology vs. BLE
Li & You [31]	WiFi-based monitoring system	Wifi	System enabled quicker patient tracking and care	Different technology stack (Wi-Fi)

5. Conclusion

Our experiments have demonstrated that real-time patient location tracking can significantly decrease wait times for patients in public hospitals in Malaysia. This underscores the necessity of addressing specific hospital requirements and utilizing cutting-edge technologies like BLE and the IoT to enhance Patient Turnaround Time (PTAT). In our proposed approach, we implemented an effective Real-Time Patient Location Tracking system using BLE. Utilizing RSSI for distance estimation through successful signal scans, we achieved accurate results. The findings suggest that real-time tracking can significantly improve patient management by reducing delays and ensuring patients are promptly located for treatment, thus enhancing overall healthcare efficiency. Received Signal Strength Indicator (RSSI) values for estimating patient location within the hospital. However, RSSI has limitations in real-time tracking, especially in complex indoor environments like hospitals. Factors such as signal interference from medical equipment, structural barriers, and multipath reflections (signals bouncing off walls or objects) can distort RSSI readings, reducing accuracy. Additionally, variations in BLE device sensitivity can lead to inconsistencies in distance estimation. These limitations may impact the precision of patient tracking and require supplementary techniques, such as Kalman filtering or multi-sensor fusion, to enhance accuracy in complex hospital settings. For improved tracking reliability, further research should investigate solutions to mitigate these challenges and refine distance estimates based on RSSI in healthcare environments.

The findings suggest that integrating BLE technology into hospital operations is a practical and effective method for enhancing PTAT. This solution offers healthcare providers a reliable tool for minimizing patient wait times and streamlining care delivery, ultimately improving hospital efficiency. Looking ahead, future implementations could incorporate even lower-power BLE chipsets to further conserve energy and enhance tracking sensitivity. Such innovations would make the Real-Time Patient Location Tracking system even more effective, ensuring long-term sustainability and scalability in improving patient flow.

6. Declarations

6.1. Author Contributions

Conceptualization, G.R.M.A. and K.S.M.A.; methodology, G.R.M.A. and S.M.; software, G.R.M.A.; validation, S.M. and K.S.M.A.; formal analysis, G.R.M.A. and S.M.; investigation, G.R.M.A.; writing—original draft preparation, G.R.M.A.; writing—review and editing, G.R.M.A., K.S.M.A. and S.M.; supervision, K.S.M.A. and S.M.; project administration, K.S.M.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to data collection from actual public hospitals in Malaysia.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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