Development of an Indoor Positioning System for Smart Aging Applications

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By

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Lay Abstract

Indoor positioning technology acts as the foundation for several healthcare monitoring networks. An accurate and easy to use indoor positioning system will entail how effective the overall healthcare monitoring platform is. Additionally, indoor positioning itself can be accomplished in several different ways. Some of these approaches include the use of physical sensors to detect presence, signal strength approximations via some sort of communication protocol or even the use of secure entry via RFID identification tags. Currently, most of the systems that use one of these approaches require extensive setup and calibration processes and extensive knowledge of the tracking locations. However, this is not always practical especially when the system is integrated in a large-scale environment like a retirement home. A system with an easy-to-use setup and installation platform is needed to complete these high impact healthcare monitoring projects.

Abstract

The development of an Indoor Positioning System that requires a non-invasive setup and installation process is outlined in this dissertation. The Hardware, Mechanical and Software components are described in complete detail. The system operates using a hybrid of Bluetooth Low Energy (BLE) signal strength analysis and proximity sensor data collection to determine the location of a known Bluetooth compatible device. Additionally, a dynamic remote calibration protocol was developed to ensure a safe and smooth setup and integration process in any location the system is implemented. The system uses custom designed beacon modules that connect directly to outlets in designated rooms. These beacons relay sensor and BLE data to a Hub module that collects and stores all this data locally and on a cloud server. These features ensured that the IPS is a completely remote device that can be setup independently by the user. To our knowledge, this is the only Indoor Positioning System that does not require prior knowledge of the location of integration and the need for an in-person setup and calibration process. Additionally, despite the lack of an extensive setup and calibration process the system still operates at an accurate room detection percentage of 98%. To further prove its ease of use the system has been implemented in a clinical study where several older adults (65+) have integrated this system within their homes. This system has been designed to act as the foundation for larger scale healthcare monitoring applications.

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Finally, I would like to thank my friends and family who were a great support system throughout my years of research. Thank you, Jai, Harsh, Shiva and Malini you guys have always been so helpful throughout my time at McMaster, and it really helped take my mind off research when I needed to most. Thank you to my parents and sister for always supporting me and encouraging me to pursue post graduate studies.

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List of Abbreviations

AIP	Aging in Place
GPS	Global Positioning System
BLE	Bluetooth Low Energy
IMU	Inertial Measurement Unit
IOT	Internet of Things
IPS	Indoor Positioning System
MCU	Microcontroller
PIR	Passive Infrared
RFID	Radio Frequency Identification
RPi	Raspberry Pi
RSSI	Relative Signal Strength Indicator
SH	Smart Home
US	Ultrasound

Declaration of Academic Achievement

First Author

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Zon, M., **Ganesh, G**., & Fang, Q. (2022). Telemedical Smart-Home Framework for Automating Clinical Testing using Fuzzy Probability Based Context-Awareness Sensing and its Application in Parkinson's and Fall Risk Assessment. Submitted to IEEE Access.

Zon, M., **Ganesh, G**., & Fang, Q. (2022). Low-Cost Portable Smart Home System for Context-Aware Medical Applications and its use in Building Intelligent Life Alert Systems. Manuscript in preparation for submission.

Project Contributions

The design, testing and validation of the AIP-IPS highlighted in **Chapter 3** was conducted by me with the assistance of PhD student Michael Zon in the data collection and analysis components. Dr Qiyin Fang supervised the entire design process and encouraged several iterations which eventually led to a final design that was ready to implement in a pilot clinical study. Additionally, the AIP-IPS was used to complete context awareness sensing testing and validation that was conducted by Michael Zon.

I assisted Michael Zon in a scoping review by screening research articles and developing figures that were included in the publication submission. Additionally, for two additional context awareness sensing focused publications, I assisted in conducting experiments with Michael Zon and helped prepare and format figures that illustrated the results.

For the pilot clinical study described in **Chapter 4**, I assembled, tested, and delivered AIP-IPS systems for participants. Additionally, I developed the communication topology and data extraction processes for the AIP-IPS as well. Michael Zon and I worked on different applications using the collected data from clinical study participants.

Chapter 1 Introduction

Canada's aging population presents new challenges and opportunities for health, mobility, and technology research. By 2041, over a quarter of the national population will be 65 years or older [1]. In Ontario specifically, the older adult population is projected to double in this time [1]. As Canada's demographics shift, our priorities for health and technology must adapt to meet health-related needs and goals for Canadian older adults. Older adults have unique health and mobility concerns that accompany serious consequences to mobility, cognition, independence, and well-being. The safest monitoring locations for older adults are long term care facilities (LTC) where the facilities are designed to minimize the risk of physical injuries and access to staff dedicated to always aiding them. However, access to LTC's often depends on physical location and socio-economic status, leaving many community-dwelling older adults in the informal care of spouses, adult children, or friends. Nearly 6 percent of older Canadians (486,000) take on such roles, experiencing extreme levels of distress, burnout, with nearly 80 percent of informal carers stating that they "can't go on" [2]. Constant monitoring of older adults that are not "high risk" would be impractical and quite difficult for caregivers. Therefore, there is a need for remote monitoring of older adults to provide regular assessments of their health and wellbeing. Many research groups have developed remote monitoring systems and specifically indoor localization systems for smart aging in place applications.

1.1 Motivation

Indoor positioning technology is a broad research field with many different approaches and use cases. The present work uses indoor positioning as a method of implementing Smart AIP applications. AIP is a lifestyle for older adults that involves them staying at home instead of relocating to an institutionalized setting. According to the Rural Health Information Hub, 90% of older adults wish to stay in their own homes [3]. Understanding the needs of others and prioritizing them is the best way to promote safe AIP. Recent studies claim that around 11 to 22% of older adults who relocated to dedicated assisted living institutions could have managed within their homes or community-based care if the appropriate support was provided [4]. The appropriate support would include the implementation of smart aging technology, that would make several daily active living tasks significantly more manageable. Therefore, there is a need for research and innovation for the wellbeing of the older adult population. One specific area of AIP is the concept of remote monitoring. This would allow caregivers to always have access to vital health related information without the need to be physically present.

Indoor position tracking is similar Global Position tracking in the sense that they both acquire signals from several receivers and triangulate the location of a source based on these signals. A GPS uses satellites to receive signals whereas an IPS uses a more local communication network like WIFI, RFID, BLE, etc. An IPS can function in two different ways: coordinate based (x, y) location detection or room level proximity/presence detection. Several IPSs prefer to use a coordinate-based approach since it would provide a specific location point relative to a known location. Coordinate-based systems require extensive knowledge of the indoor tracking location and usually involve a lengthy setup and calibration procedure prior to implementation. Proximity/presence detection systems involve significantly less knowledge of the location prior to setup. However, they compromise the level of accuracy by limiting it to room level proximity/presence. Several existing IPS systems used in both research and commercial applications operate using the coordinate-based approach. These systems require a lengthy setup and installation procedure before they can even be tested. To the best of our knowledge, there are no Indoor Positioning System's that can be implemented with little knowledge of its location's topography and can be setup independently by the user themselves. The development of such a system would be ideal for older adults living in their own homes thus improving AIP.

Indoor tracking is a fundamental aspect of remote healthcare monitoring. The knowledge of a person's location at all times can be used to develop several different smart applications and better understand someone's daily active living pattern. Several commercial buildings utilize anonymous indoor localization systems to determine the number of individuals that enter and exit specific locations. An example of this would be the use of an IPS to determine the gender and age of customers visiting specific shops in a mall [5]. Similarly, indoor positioning is common in academia as they are used to develop smart aging applications to develop wayfinding applications, detecting early onsets of Dementia and the development of context aware healthcare monitoring systems [6][7]. When you combine the knowledge of a person's location with their real time healthcare parameters (vitals) you essentially develop a context aware smart system. An example of context awareness sensing for older adults could include monitoring the heart rate of a specific individual. You can differentiate an elevated heart rate's meaning based on the location and time of an individual. For older adults specifically one-use case could be immediately while climbing the stairs, an indoor positioning system would know they are in the stairwell and consider the elevated heart rate as something that is not a concern. Inversely, if the same elevated heartrate were to occur in the same older adult's bedroom it can be considered concerning. Scenarios like these can be analyzed using indoor positioning data and used to develop context aware healthcare monitoring systems.

1.2 Thesis Overview

The present work depicts the development of a Bluetooth based Indoor Positioning System that requires minimal knowledge of its installation location. The electrical, mechanical and software design components are outlined in detail. The testing protocols and setup/calibration procedures are outlined as well. The system was designed to be implemented in the homes of older adults therefore several limitations were placed on its design. A pilot clinical study involving around 30 older adult participants integrating this system within their homes was conducted and the qualitative and quantitative results from the initial stages of this study are presented later in this dissertation.

To begin, **Chapter 2** provides a thorough analysis of the existing literature on IPSs is presented. After understanding the rapid advances in this technology, we take a deeper dive into the various types of systems. The analysis of different algorithmic approaches and specifically which communication signals were used to develop these systems are outlined. Following this, the pros and cons of the existing positioning systems are discussed. Finally, a comparison between existing systems and the designed AIP-IPS concludes the literature review.

A concept that is emphasized in engineering design is the understanding of your problem before attempting to develop a solution. The problem this work aims to solve is the need for improvement in healthcare monitoring techniques for OA's. Specifically, the goal was to determine whether it is possible to design a system tailored for OA's that can be used in multiple context aware healthcare monitoring networks.

The solution is shown in **Chapter 3,** where the development and testing of the AIP-IPS is outlined in detail. A manuscript submitted to IEEE access highlights every aspect of the AIP-IPS with several figures and results that illustrate its effectiveness and setup/calibration process. The paper begins with a system design section that covers the electrical, mechanical and software design components in detail. This is followed by an explanation of the experimental methodology used to test this system. Then, the results of these experiments are presented followed by a discussion of what these results signify and the applications this system could be used for.

Chapter 4 details the use of the AIP-IPS in a pilot clinical study. The ethics approval, recruitment, setup, and preparation of the study are outlined in detail. The physical assembly of systems and data collection processes are highlighted as well. An analysis of the clinical study management process is also presented including what worked and didn't, what could be improved and more. Participant feedback was analyzed as qualitative data that further illustrates the clinical study process. Finally, the data extraction methodology and time synchronization of multiple sources of data collection was explained in detail. Our room detection algorithm along with a remote calibration procedure was illustrated as well.

To conclude, **Chapter 5**, summarizes the significance IPS development, its applications and specifically the AIP-IPS and its importance to the academia. The possibilities of improving the AIP-IPS using new advances in communication protocol topography and additional sensors are explored. Additionally, future work using the AIP-IPS, and the development of additional applications are discussed.

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Chapter 2 Background

Indoor positioning technology and its applications are an active area of research and development in smart systems. For example, in 2022, there were over 500 publications on IEEE Access and Sensors that involve indoor positioning technology. IPS technologies utilizing multiple different communication protocols [1] and machine learning algorithms [2] have been reviewed. In addition, several systematic reviews were published on specific indoor positioning applications including medical healthcare monitoring [3] and industry focused commercial applications [4]. This chapter will summarize the IPS technology by differentiating the types of IPSs and communication topologies used in their design, development, and testing procedures. The review will allow you to better identify the opportunities in design and implement an IPS that specifically tailors to the challenges in AIP related applications.

2.1 Indoor Positioning Systems

The ideology behind remote position tracking originated with GPS, a method in which a device can be tracked based of its triangulated signal communication with multiple satellites orbiting the Earth. Some functions of a GPS include, identifying a user's location, assisted navigation, location tracking, mapping, and timing. The GPS is an excellent tool for remote monitoring of mobile targets like vehicles. However, it lacks efficiency when used in indoor location applications, which limits the functions listed above to solely outdoor tracking applications. Thus, the development of the IPS began, a 2016 systematic review mentions that initially IPSs consisted of expensive and not readily available devices such as Active Badge (IR) and Active Bat (US) RF transmitters and receivers [5]. Active Bat uses ultrasonic signal communications and a trilateration algorithm to achieve precise centimeter level position tracking.

Similarly, Active Badge used infrared rays and receivers to determine centimeter level position coordinates. This transitioned to the use of more recent, cheaper, and effective wireless communication protocols like Bluetooth Low Energy (BLE) which operates at 2.4 GHz, Wireless Fidelity (WIFI) which operates at 2.4 and 5 GHz. These protocols are currently commonly used by commercial electronics which makes developing IPSs more feasible. The continued research, testing and development of IPSs using these communication protocols has led to significant advances in commercialized IPS technology.

2.1.1 Indoor Positioning for Aging Applications

One excellent application for indoor positioning is its ability to integrate itself within smart AIP applications. As mentioned in **Chapter 1**, AIP is a lifestyle and the purpose of indoor positioning research is to improve, analyze and learn how to optimize older adults' lives. The research work described in **Chapters 3 and 4** outline the development, testing and integration of a unique IPS used for AIP. Tracking an older adult's indoor location provides an excellent platform to develop several beneficial healthcare monitoring applications. Several researchers experiment and design IPSs tailored to older adults in various form factors.

Many IPSs are built for the sole purpose of use in aging research, this has led to the publication of systematic reviews that outline significant changes in technology aiding AIP applications for older adults. Morato et al outlined the research advancements in technology designed for older adults over the 2000 – 2020 decades [6]. Their review was conducted to emphasize the significance of aging research by providing readers with an overview of technological advancements in this research field.

Similarly, researchers can utilize indoor positioning technology for a variety of specific use cases with different communication topologies. For example, Zhang et al developed an IPS tailored to older adults using customized ultrawideband protocol and integrates a distance of arrival methodology to improve the detection accuracy [7]. This process is similar to BLE's angle of arrival parameter that has been recently introduced in the Bluetooth 5.2 protocol [8]. Thakur et al developed an IPS used specifically for fall detection in older adults [9]. Their work consisted of developing a wearable sleeve that collects IMU data and acts as a transmitter of RSSI to specifically located receiver beacons via BLE. To validate their device, they conducted specific daily activity experiments such as opening doors, turning on lights, sitting and standing on furniture, etc. Another use case that can be explored is the integration of GPS and IPS for complete mobile monitoring. Fernandes et al developed a hybrid system that accomplished this feat using ultrawideband communications for indoor detection and achieving a 700ms latency [10]. An IPS can be used for several different applications, however the most impactful use would be its role as the foundation of all smart healthcare monitoring systems for older adults. Continued research and data collection using indoor positioning will result in significant advances in aging in place research as well as beneficial improvements in the quality of life for older adults.

2.1.2 Indoor Positioning for Medical Applications

Indoor positioning is not limited to tracking humans, several pieces of important equipment and valuables are transported regularly throughout large multistory buildings like hospitals or research centres. Specifically, the use of an IPS for medical applications has been explored in research and commercially. A systematic review that highlights different systems used for this purpose clearly identifies its importance as it led to the development of commercial IPSs in Iran [11]. Their review illustrated the importance of medical equipment tracking in emergency situations as many scenarios occur where a certain tool or device is required, and its location is unknown.

With regards to medical device tracking systems, Namee et al developed a device using a GPS module coupled with a microcontroller and Narrow Band IOT (NB-IOT) receiver and attached it to medical equipment within hospitals [12]. Their motivation to develop such a system was based off the ability to provide hospitals with equipment borrowing records and the real time location of equipment. The GPS module calculates the latitude and longitude of the tracking device and relays that information to a cloud database when outdoors, similarly the NB-IOT based indoor location is updated every 10 minutes while within the hospital vicinity. Similarly, Tsai et al developed an IPS that uses RFID tags attached to medical equipment and tracked their location based off its relative signal strength from multiple receiver beacons [13]. Their system included a well documented user friendly front end platform to view data patterns like equipment usage frequency and the common locations equipment was placed. Medical equipment tracking will eliminate any human error resulting in delayed treatment or equipment misplacement in hospitals.

2.1.3 Indoor Positioning for Commercial Applications

The previous sections talked about using indoor positioning in small scale applications with fewer tracking devices and users. However, expanding this to a big data setting would be the goal with regards to commercialization. Some examples of commercialized IPSs are integrations within densely populated public spaces like shopping malls, university buildings, corporate offices, etc. López-Pastor et al developed a WIFI based IPS for the purpose of integration in shopping malls using smartphones as their tracking devices [14]. Their work focused on discovering marketing strategies that can be obtained with the data collected from consumer tracking patterns. An example they describe is differentiating users who enter a store and make a purchase and those who do not. They do this by placing beacons near the cash counter and recording a user’s time spent in this specific location. Similarly, the company Bluepath is a large organization dedicated to integrating indoor positioning technology in several different applications [15]. Some examples of their work include the installation of IPSs in museums, hospitals, shopping malls, construction sites and airports. Their work is not limited by just the integration of these systems, a pivotal component of their company is their ability to provide high quality data analytics for smaller corporations on user location traversal patterns. Bluepath is just one example of a company commercializing this technology, many other data collection organizations are either integrating indoor positioning with their existing systems or developing their own IPS to market, sell and collect data.

2.2 Communication Protocols for Indoor Positioning

The process of determining the position of a tracking device involves the analysis of signal strength using a communication protocol. By definition, a communication protocol is a system of rules that enables communication between two or more network devices [16]. Communication protocols continued to be developed and require publication and certification before they can be implemented in any manufactured electronic device. Protocols are reviewed by the Internet Engineering Task Force (IETF) and other organizations depending on the type of communication developed. The following subchapters outline the functionality of various communication protocols and how they are implemented to conduct indoor positioning tracking.

2.2.1 Bluetooth and Bluetooth Low Energy (BLE)

Bluetooth is a communication protocol commonly used with devices that wish to communicate with each other in short ranges (~10m). Bluetooth signals constantly fluctuate between 2.402 – 2.48 GHz to prevent the ability to hack connected devices [17]. The difference between Bluetooth and BLE is the amount of data that can be transferred and how much power is consumed. BLE uses the Frequency Hopping Spread Spectrum (FHSS) standard modulating 40 channels with 2MHz spacing [18]. Therefore, BLE communications is more commonly used for low power applications like wearable devices or sensor beacons whereas Bluetooth is used for more power demanding applications like wireless speakers, headsets, etc.

In indoor positioning, BLE is more commonly used, as both receivers and transmitters are commonly battery powered devices that require less power intensive communication. Moreover, the only information that's required to send/receive for indoor tracking is the signal strength which makes using BLE the obvious choice. A recent systematic review covering indoor fingerprinting techniques using BLE stated, BLE is significantly superior to traditional WIFI transmission methods" in indoor positioning applications based on a thorough analysis of existing literature [19]. The review outlines several different existing BLE based IPSs and classifies them based on algorithms and fingerprinting techniques. Similarly, another indoor positioning review paper that focuses specifically on Human Activity Recognition (HAR), outlines a comparison of using BLE vs. WIFI in a healthcare setting [20]. Based on their review of existing technologies, researchers prefer to use BLE as it is inexpensive and operates at the same frequency as WIFI, making it easy to integrate.

Bluetooth technology is a fantastic option that is commonly used for indoor positioning, however there are pros and cons when using this technology. One drawback is its limited range and constant fluctuations. To mitigate these issues there are several solutions that can be implemented. Bluetooth shielding can be used to focus signal acquisition from specific directions, RSSI filters can be used to remove irregular spikes and to improve positioning accuracy, additional beacons can easily be implemented as BLE devices are low cost to manufacture. Additionally, Bluetooth standards are constantly changing, and new features are being added. This is both good and bad for BLE based indoor positioning. The good part is a lot of these new features have improved signal quality and added additional functions like advanced signal properties (angle of arrival, angle of departure) [17,18]. The bad part is these changes almost always require physical hardware replacement. This would require researchers and manufacturers to make significant changes to their designs if they wish to update their system.

2.2.2 Wireless Fidelity (WIFI)

WIFI is a communication protocol that belongs to the IEEE 802.11 standard, it operates at various frequencies but most commonly 2.4GHz and 5GHz [21]. WIFI is the most common communication protocol that network devices use, it is implemented almost everywhere due to its primary role as the method of communication for internet. The process of WIFI based indoor positioning is the analysis of signal parameters obtained from the local area network (LAN) created when devices connect to a router. Introducing multiple routers will result in additional data collection and more accurate positioning information. Currently large-scale indoor positioning applications primarily use WIFI as their method of indoor position tracking due to its accuracy, power, and easy implementation.

Researchers have analyzed the performance of WIFI based indoor positioning systems extensively resulting in several review papers published over the years in this area. One paper focuses on the use of WIFI fingerprinting to accurately detect the precise location of a tracking device. Shang et al reviewed several WIFI based IPSs and highlighted the implementation of machine learning algorithms using collected signal strength data [22]. Some of the analyzed parameters include time of arrival (TOA), time difference of arrival (TDOA) and angle of arrival (AOA). Advanced parameters like these improve the quality of localization as it offers more precise data points that can be used by a variety of different positioning algorithms like trilateration or fingerprinting. Roy et al conducted a review of IPSs that use WIFI enabled smartphones as their tracking devices, allowing for anonymous indoor position tracking [23]. Their review analyzes several existing smartphone-based systems and illustrates the challenges involved when using smartphones as tracking devices in an indoor localization system (ILS).

Using WIFI as the controlling communication protocol in indoor positioning creates several challenges despite providing excellent signal parameters. For example, dedicated WIFI tracking devices are expensive ranging from, $50 to $100 each, thus heavily increasing the cost to develop a WIFI based IPS. Additionally, the use of WIFI consumes large amounts of energy due to the demanding nature and design of the protocol itself. Therefore, tracking devices will have shorter recording times as they will need to be charged. It is important to consider cost and power constraints when developing an IPS using WIFI. Therefore, large commercial IPSs use WIFI as they are not heavily constrained by development costs.

2.2.3 Radio Frequency Identification (RFID)

The RFID communication protocol involves the transfer of electromagnetic waves and physical contact to establish two-way communication between network devices [24]. A common use of RFID communication is for security, with unique identification tags and readers allowing entry/exit of secure locations. Researchers have extensively studied the RFID protocol and its various implementations. A recent conference paper by Catarinucci et al summarizes the latest developments in RFID communications and its applications involving localization systems [25]. RFID tags can be implemented to perform indoor positioning as well, using presence detection. Receivers can be placed outside entry points to various rooms and the user's location will be known whenever their corresponding RFID tag contacts a receiver beacon.

Using RFID is less common in indoor positioning applications as the physical contact between readers and tags is not always practical in real life scenarios. This restricts the implementation of RFID systems to locations that are willing to integrate or have an existing RFID based entry/exit system. Therefore, it would not be possible to implement such a system in several locations like elderly care facilities, residential homes, etc. However, just like BLE, RFID tags are inexpensive and do not require a significant amount of power to function efficiently. For a research setting, RFID is an excellent option.

2.2.4 Other Communication Methodologies

As initially mentioned, several additional communication protocols do exist and are used to perform indoor positioning. For example, ultrawideband (UWB) and infrared technology (IR) can be used for indoor presence detection. UWB is commonly used in military communication systems and operates in a wide frequency range of 3.1 to 10.6 GHz, thus its name UWB [26]. The communication protocol introduces additional properties to better calculate the location of a device. However, its limiting factor is how expensive it is to implement the hardware required, which is why it is mainly used in military applications. IR technology operates using a tracking device that constantly emits IR rays ranging between 830-950nm [22]. IR receiver beacons located in the tracking location will receive the emitted IR rays at various angle and distances. Using these acquired signal properties, localization algorithms are implemented to calculate the device's location. A recent review paper was published highlighting advanced technologies used for indoor positioning. The review paper focused more on the use of advanced IPS algorithms, however it mentioned the use of a two communication protocols that are less commonly used for indoor positioning. Some of these include ultrasound wave-based proximity detection and Zigbee RSS fingerprinting [27]. Another common feature explored in indoor positioning research is the use of multiple communication protocols collaboratively for position validation and enhanced accuracy. Merging different technologies is an excellent way to improve a system's accuracy and even explore how shared properties vary between protocols [28].

Zigbee and LoRaWAN are both short-range to mid-range radio frequency (RF) communication protocols that are often used in indoor positioning systems. These technologies are designed to enable low-power, low-cost wireless communication over relatively short distances, making them well-suited for use in indoor environments. Zigbee is a wireless networking protocol that is based on the IEEE 802.15.4 standard. It operates in the 2.4 GHz frequency band and uses a mesh networking architecture, which allows multiple devices to communicate with each other and with a central hub or gateway. This makes it possible to build networks of sensors or other devices that can transmit data over long distances, even if some of the devices are out of range of a direct connection to the hub. In an indoor positioning system, Zigbee devices can be used to transmit location data to a central hub, which can then be used to determine the location of the devices within the building. LoRaWAN, on the other hand, is a wireless communication protocol that is designed for use in low-power, wide-area networks (LPWANs). It operates in a variety of frequency bands, including the 915 MHz and 868 MHz bands, and uses a long-range, low-power radio technology called LoRa (long-range wide-area network). LoRaWAN networks are typically used to transmit data over long distances (up to several kilometers) at low data rates (a few hundred bits per second). In an indoor positioning system, LoRaWAN devices can be used to transmit location data to a central hub or gateway, which can then be used to determine the location of the devices within the building. Table 2.1 outlines differences in existing indoor positioning technology to further illustrate our decision to use BLE based signal analysis in the AIP-IPS. The table compares communication protocol-based position tracking as well as sensor-based proximity detection.

TABLE 2.1
Comparison of Various Indoor Positioning Technologies

Technology	Pros	Cons
RFID (Radio Frequency Identification)	Can be used to track the location of individuals or objects with high accuracy; can be integrated into a variety of devices and systems; relatively low cost	May require close proximity to a reader in order to function; may not be suitable for tracking fast-moving objects
BLE (Bluetooth Low Energy)	Can be used to track the location of individuals or objects with moderate accuracy; can be integrated into a wide range of devices; relatively low cost	May require close proximity to a beacon in order to function; may not be suitable for tracking fast-moving objects
WiFi	Can be used to track the location of individuals or objects with moderate accuracy; widely available in many buildings and public spaces; relatively low cost	May require a clear line of sight to a WiFi access point in order to function; may not be suitable for tracking fast-moving objects
PIR (Passive Infrared)	Can be used to detect the presence of individuals in a specific area; relatively low cost; low power consumption	May not be suitable for tracking the exact location of individuals; may be triggered by other sources of heat
Radar	Can be used to track the location of individuals or objects with high accuracy; can be used to detect moving objects; relatively low cost	May require a clear line of sight to the object being tracked; may not be suitable for tracking objects at close range
5G	Can be used to track the location of individuals or objects with high accuracy; can support high-bandwidth applications; relatively low latency	May require a 5G network to be available in order to function; may not be suitable for tracking fast-moving objects
LiDAR (Light Detection and Ranging)	Can be used to track the location of individuals or objects with high accuracy; can be used to detect moving objects; relatively low cost	May require a clear line of sight to the object being tracked; may not be suitable for tracking objects at close range

2.3 Indoor Positioning Algorithms

The process of determining the position or location of a tracked device/tag can be conducted through range-based approximation of trilateration or signal strength analysis via fingerprinting. When developing an IPS it is extremely important to decide which algorithm you wish to use and how you are going to use it. Fingerprinting would involve a significant amount of post processing as it would be difficult to perform in real-time since it relies on understanding a dataset to accurately determine position. Trilateration can be performed in real time; however, it compromises positioning accuracy and requires stable communications without interruptions.

2.3.1 Trilateration

Trilateration is the ability to determine position through a minimum of three known distances from the same reference point in a 2D space [29]. In indoor positioning these distances are calculated based off the signal strength values relative to specific receiver beacons. After determining these distances, the point of intersection (POI) between all three would be the (x, y) coordinate location of the tracking device. This process is illustrated in Figure 2.1, with circles representing the receiver beacons and the smartphone representing the tracking device.

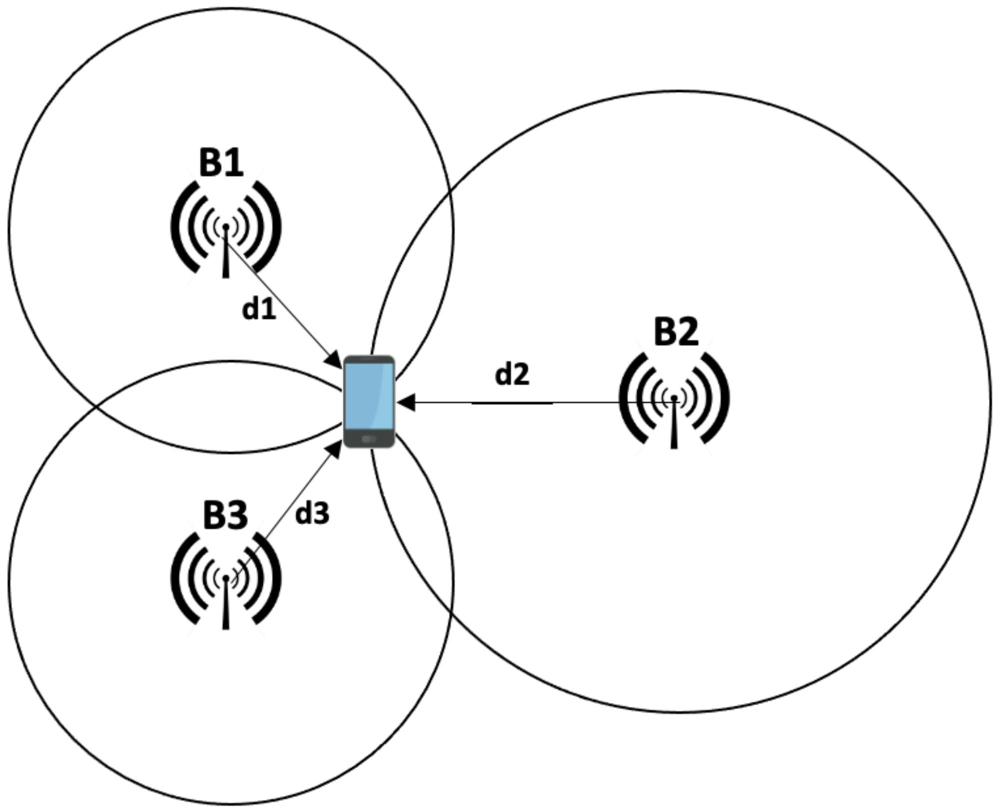

Figure 2.1: Trilateration Diagram with 3 Receiver Beacons (B1-3), 3 Euclidean Distance Vectors (d1-3) and Mobile Tracking Device

2.3.2 Fingerprinting

The literal meaning of the term fingerprinting means to leave an everlasting mark on an object through a fingerprint. However, in the context of indoor positioning, this process has a different meaning. The process of fingerprinting uses RSSI to determine the location of a known tracking device. The tracking device constantly relays RSSI data to receiver beacons, using these received values we can develop various thresholds for specific locations. This process would be the calibration stage where the setup process will usually involve using a user traversing a known tracked location while the receiver beacons collect RSSI data. Then a threshold would automatically be calculated relative to that location, using these thresholds you can determine a device's position at the room level. To gain a more precise location, multiple receivers can be implemented, and sub-room level positioning is also possible.

2.4 Existing IPS Technology vs AIP-IPS Technology

The above subsections have provided a detailed explanation of the types of IPS technology that currently exists and how they work. Indoor positioning is an immensely broad research field, with several differences in either IPS applications, integration, communication etc. However, one thing that almost every single developed IPS has in common is an extensive knowledge of the indoor location the developer wishes to integrate their system. For most cases, systems that achieve centimeter level position tracking require extensive setup, installation, and calibration procedures. This is more than reasonable for systems that are designed for applications which require such high precision and can afford to spend time, money, and resources to ensure they achieve this. However, it would not be practical to do this in certain applications like long term care facilities or residential homes. When beginning development of the AIP-IPS, COVID-19 had confined everyone within their homes, which proved to be the biggest design constraint. The AIP-IPS managed to work around these constraints and achieved accurate indoor positioning using a combination of BLE signal strength and sensor validation. The AIP-IPS is not brand-new technology, instead it uses a combination of existing indoor positioning technology and eliminates the need for extensive setup and installation procedures. The major difference between the AIP-IPS and existing systems is its ability to be self-installed allowing the user themselves to perform the installation and calibration process entirely on their own. **Chapter 3 and 4** will explain in detail this process with examples of older adults (who were part of a pilot clinical trial) installing this system easily within their homes.

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Chapter 3 A Turn Key Indoor Positioning System for Aging-in-Place Applications

This chapter was written as a manuscript for submission to a peer reviewed journal. It outlines the design and development process, testing, validation, and implementation of a unique IPS. The purpose of writing this manuscript was to provide the academic community with the ability to use this innovation for healthcare monitoring applications. A key feature of this IPS is it requires minimal setup and installation and utilizes a remote calibration process. To the best of our knowledge, there are no IPSs that can be implemented without knowledge of the indoor tracking floorplan. As mentioned in the literature review, IPS technology varies significantly every year, this work represents my contribution to this year's advancements.

Abstract

Objective: Indoor positioning system's (IPS) are part of the internet of things (IoT). In this work, we designed an IPS that identifies individual users; does not require floorplans; and allows the end-user to install/setup the system themselves. Additionally, a dynamic calibration process is implemented to learn room boundaries based on the distribution of the BLE signal strength. The system uses beacon modules that directly plug into regular wall outlets. These beacons relay sensor and Bluetooth data to a Hub module. *Methods:* Several testing procedures were followed to validate the functionality of the designed IPS. Raw and filtered relative signal strength indicators (RSSI) and variability of RSSI were measured during testing. Room detection was determined by comparing a user input location (ground truth) with the IPS detected location for over 300 tests. *Results:* The IPS produced a 96% accuracy of correctly detecting room location. When using the additional motion sensor alone, the IPS achieved a 93% accuracy. Testing the same system in different environments produced similar results at above 90% accuracy. *Conclusions:* The measured raw and filtered BLE RSSI values proved to be an accurate method of identify locations in conventional residential dwellings. The use of PIR motion and ultrasonic sensors information provided improved validity when compared with existing indoor positioning systems. *Significance:* The ease of use and modular design of this IPS makes it a good choice for implementation in larger scale smart healthcare monitoring systems.

3.1 Introduction

The knowledge of a user's position along with external data parameters like environmental sensor data or vital signatures enable the development of healthcare monitoring applications. In addition, storing the user's location changes over longer periods of time will provide useful information that relates to behavior analysis and activity monitoring [1]. The Global Positioning System (GPS) is currently the dominate positioning technology, which has been embedded in transportation, mapping, and guidance systems everywhere. For applications predominately indoors, however, GPS is of limited usage due to the difficulty in communicating with GPS satellites as well as the increased requirement for positioning precision. Indoor environments propose a great challenge when it comes to position tracking because of the obstacles and interferences to wireless electromagnetic signals from the building structure. A system that can successfully overcome these challenges will prove to be extremely beneficial for many reasons. Indoor position tracking opens a gateway to several unique applications. A simple example would be automating light fixtures based on presence of certain individuals or devices, which would classify as an IoT application. The knowledge of room detection can be used to analyze room transition patterns and potentially apply wayfinding applications like the one used by Giuliano et al in a museum [2]. It is important to set a fully functioning foundation for an Indoor tracking system because it would serve as the backbone to a plethora of application ideas. The technical, medical, and general applications provide immense benefits and integrating them with a powerful indoor positioning system at its core is our goal.

Indoor tracking has a significant impact when implemented in a clinical setting, it opens several approaches to health monitoring intervention platforms when combining time and location data with measured health parameters. The use of this data would be critical in the development of real time context aware healthcare monitoring applications. For example, the use of indoor tracking would be beneficial for Alzheimer's and Dementia patients who have a history of getting lost by wandering away from their home. Additionally, the IPS would provide caregivers in long term care facilities a method of monitoring multiple patients efficiently. Caregiver burnout is a serious concern, technology that aims to assist caregivers can have a positive impact for the safety of both caregivers and older adults [3]. This project is working to create a technology that is shaped by the insights of older adults and their goals/needs for independence, in addition to providing support and respite for caregivers.

Position tracking is commonly performed by analyzing signal properties of communication protocols to identify a user / device's location. An early 2021 systematic review by Pascacio et al covered the various communication protocols used to develop existing IPS technologies and outlined their similarities and differences [4]. Currently, common IPSs determine location using either Bluetooth, WIFI or RFID communication protocols. WIFI is often used as a preferred indoor tracking method because of its speed and integration. However, using WIFI to perform indoor tracking requires extensive battery power usage on tracking devices, which limits the time a user can be tracked. WIFI based systems are ideal for indoor tracking in large indoor spaces like hospitals or industrial buildings. H.-P. Bernhard et al propose the development of an

WIFI based presence detection system for an automotive assembly factory [5]. Their system would track the location of assembled cars moving from various testing locations and the location of their corresponding parts that are either added/removed. RFID is like WIFI with high fluctuations in signal strength and a limited measurable distance, however it has a lower power consumption. RFID is harder to implement because most commercial wearable devices like smartwatches and cellphones have BLE and WIFI integrations instead. [6]. Additionally, RFID signal strength has a lower detection distance when compared to BLE signals. Bluetooth Low Energy (BLE) works within a 30m radius and has multiple parameters that can be assessed for location tracking applications. Some of these properties include, relative signal strength indicator (RSSI), Angle of Arrival/Angle of Departure (AOA, AOD), and TX power [7]. Bluetooth based IPSs are optimized to determine position at almost the centimetre level which makes them ideal for indoor tracking applications.

The two main types of IPSs are proximity/presence-based vs coordinate (x, y)-based. Mokhtari et al uses BLE tags and a proximity-based approach to perform room level detection and activity monitoring [8]. Their research concluded that proximity-based systems struggle with accurate detection during longer recording periods because of data saturation with several room transitions. Noertjahyana et al developed a similar system except using the trilateration approach [9]. The IPS developed in our manuscript focuses on room level detection (proximity) with the use of RSSI and motion/ultrasonic sensor feedback. Their IPS uses a combination of BLE and sensor data to confirm whether the tracked individual is present in a room. The main advantage here is that a proximity-based detection system can be implemented at any point of interest, without prior knowledge of room topography. In contrast, the trilateration approach is dependent on processing power and improves as the number of beacons relaying information increases. Trilateration uses several matrices of calculated RSSI based distance values to coordinate an exact x, y position within a known indoor location setting.

Smart devices should prove beneficial to the user, be comfortable, non-intrusive, and easy to integrate. Successful smart home devices must be able to dynamically adapt to any home environment and still function at the highest efficiency possible. Many existing IPS require knowledge of detailed building topography for successful implementation and functionality. This means that these systems would require extensive work on their setup and calibration process. Signal integrity is the most important aspect of all data acquisition systems. The BLE communication protocol is constantly evolving and is currently stable at in its 4th generation BLE 4.0. The 5th generation has newly been established and improves on some of the struggles of 4.0, however sufficient documentation renders it unapplicable for this use case. In this work, an IPS is developed that requires no prior knowledge of room topography with a minimal setup and configuration process. However, it still maintains a high degree of precision and accuracy using BLE signal analysis and environmental sensor data. The system uses compact wall adapter beacon enclosures in conjunction with smartwatches/BLE tags as tracking devices. The system prioritizes being extremely easy to integrate and configure while retaining an extremely high degree of indoor presence detection accuracy.

One fundamental aspect of this system is its adaptability within various indoor environments. Previous literature on indoor tracking proves that in an indoor space, the presence of furniture and wall introduce high levels of signal loss and are the source of RSSI fluctuation [10,11]. Therefore, there is a need for an IPS that can successfully adapt within any indoor environment regardless of fluctuations. Developing an IPS that does not have to be preprogrammed based off building topography and room layout is another reason why adaptability is vital. This system would avoid several challenges created by currently developed IPSs. Some of these challenges include the need for a floorplan to design an optimal setup configuration prior to installation. Additionally, this system would avoid the need for any professional installation procedures such as wall mounting beacons in hard-to-reach locations, which is commonly required. A system like this would make integration within large buildings like hospitals or retirement homes significantly easier and still maintain a high degree of efficiency.

3.2 System Design

The IPS consists of several physical BLE beacon modules that relay signal strength and sensor data to a hub module. Figure 3.1 illustrates the working principles of the designed IPS, it highlights the major functional groups and their communication routes. Each IPS beacon consists of a microcontroller connected to several sensors through a custom designed printed circuit board (PCB). The casing encloses all the hardware, includes mounting slots for the sensors and contains an integrated wall plug option for power. For post processing and data storage all data from beacon modules is received by the hub module and is sent to a Raspberry Pi that saves all the data locally.

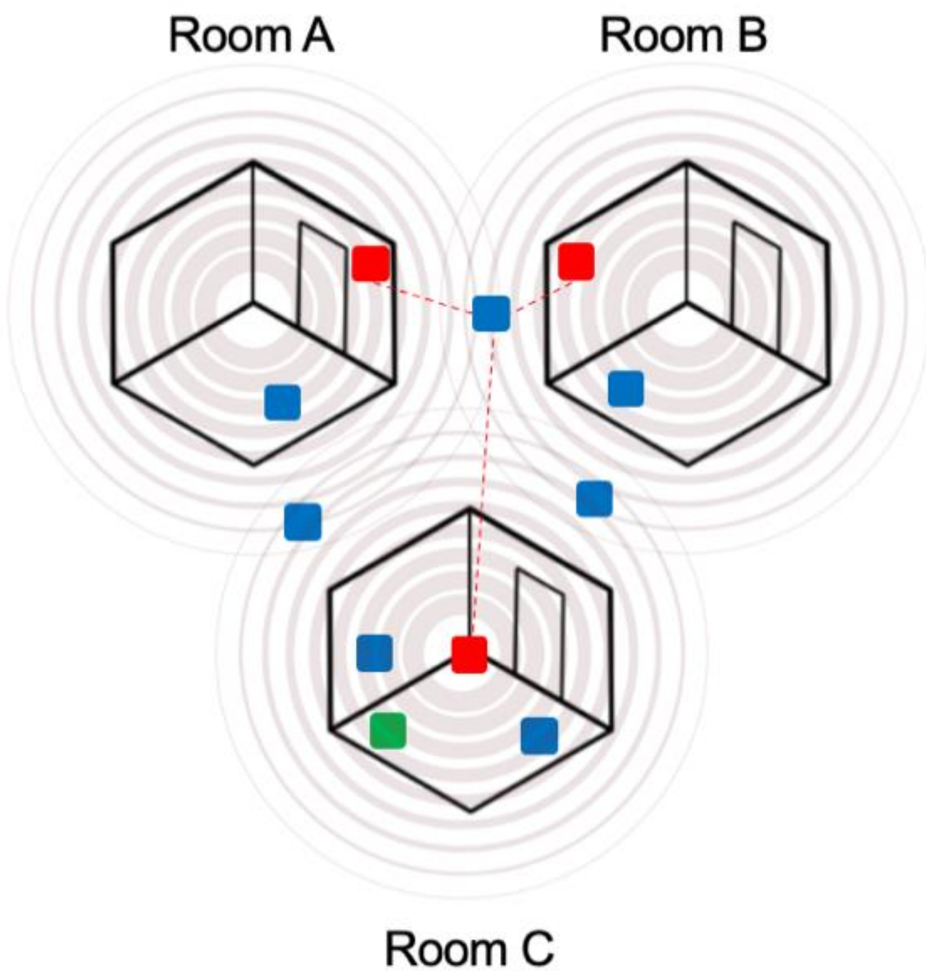


Figure 3.1: IPS System level design diagram, Red: Room beacon, Green: Raspberry Pi Hub, Blue: BLE tag (iTag's and smartwatches)

3.2.1 Hardware and Electrical

The overall hardware system consists of three major components: sensors, microcontrollers and BLE tracking devices. The sensors and microcontrollers are physically connected to each other whereas the BLE devices can be standalone and communicate with each microcontroller using Bluetooth signal communication. Each beacon consists of four sensors (Ultrasonic, PIR Motion, Ambient Light, and Temperature) connected to a single microcontroller (ESP32). The beacons require a 5V power source to operate, which is why AC-DC adapters are integrated within the enclosure itself. Figure 3.2 illustrates the Hub – Multiple Beacon approach used. The red outline corresponds to multiple BLE beacon modules connected to outlets in the tracked rooms. The green outline consists of one hub module that contains a microcontroller and Raspberry Pi connected via micro-USB. This hardware setup ensures all data arrives at a central location and is processed on a separate device.

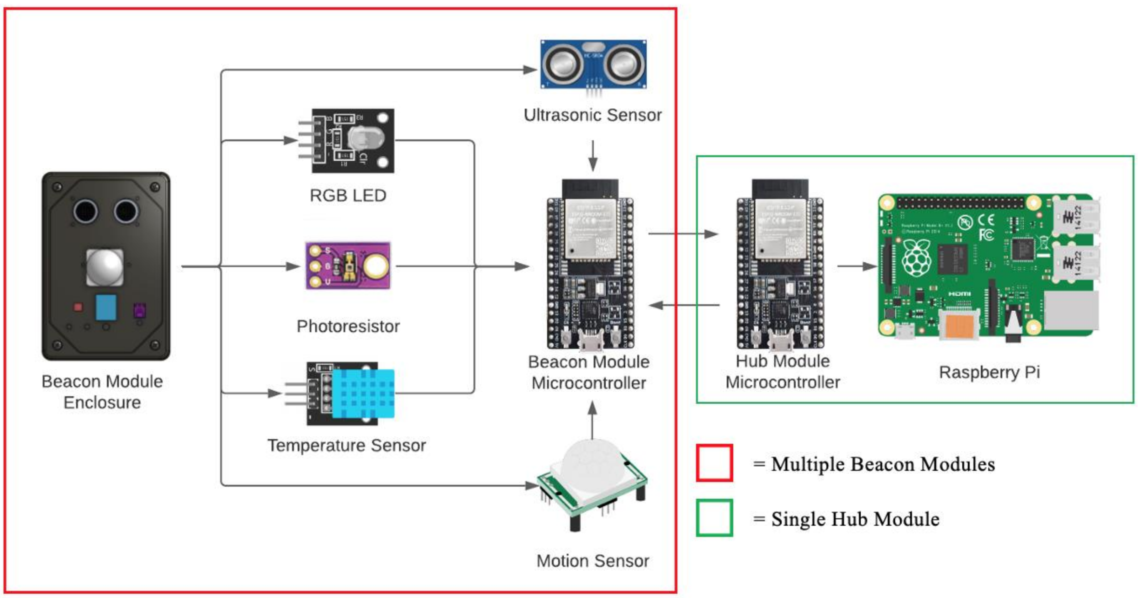


Figure 3.2: Hardware Flow Diagram, Red: Beacon Module Component Composition, Green: Hub Module Component Composition

3.2.2 Software and Data Architecture

The software component of the IPS is split amongst the different devices being used. The microcontroller uses the C++ programming language to perform BLE signal acquisition and filtering along with all the sensor data collection. The Raspberry Pi 4 uses Python to perform data parsing methods and wireless transfer of BLE and sensor data to a Google Firestore cloud database. The data acquisition process and relationship between the components within the IPS is shown in Figure 3.3.

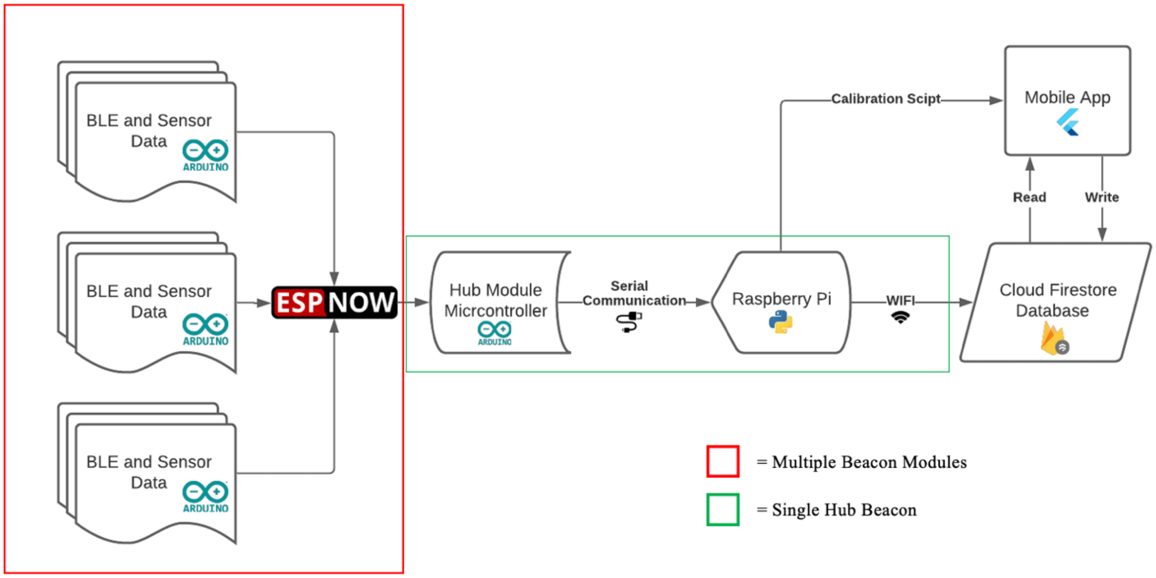


Figure 3.3: Software and Data Transfer Flow Chart, Red: Beacon module sensor and BLE data communication pathway from rooms to the hub module, Green: Hub module post processing data management, allocation, and calibration process pathway

Four types of communication protocols are used in the IPS: ESP-NOW, WIFI, BLE and USB-UART Serial. The first is the ESP-NOW communication platform, it is the key method of sending BLE signal strength and sensor data between microcontrollers without the need for WIFI. ESP-NOW is a 2.4GHz frequency-based communication protocol developed by Espressif [12]. It uses a peer-to-peer communication methodology, which is why we chose to design a Hub Module – Multiple Beacon Module approach. The beacon modules receive advertising packets from known smartwatches and tags using BLE communication and sensor data from the physical sensors on the beacon. The signal strength from these devices is stored momentarily on the microcontrollers and are sent along with sensor data to the hub module using ESP-NOW communication. The hub module will constantly receive data flow from several beacons within the indoor environment.

Anytime data is received by the hub microcontroller, it will relay this data to a Raspberry Pi via serial communication. Physically, the hub will contain both a microcontroller and Raspberry Pi that are connected serially via micro-USB. All transferred data is saved locally on the physical raspberry pi device and is additionally periodically sent to Google Cloud Firestore to monitor IPSs externally.

The calibration process consists of an online database that receives user input locations while wearing their tracking device. For example, to calibrate a beacon placed in your bedroom the user would enter their location relative to room they want to allocate that beacon with (e.g., middle, left, right of the room). After this, they will be prompted to walk around the perimeter of the room for a period of 20 seconds to collect the maximum RSSI range of the room. During this period, the system dynamically records signal strength values rapidly from all surrounding beacons and determines a range of RSSI fluctuation patterns within the room itself and its sublocations.

3.2.3 Beacon Design

The beacon module is a custom designed electronic device that encompasses sensor measurement, BLE signals and Wireless communication using a microcontroller to process these data points. Each module uses the ESP32-Devkit-C as its microcontroller unit. The ESP32 is the core of the IPS as it handles all BLE and sensor data communications. The electrical and mechanical components are labelled as the IPS enclosure in Figure 3.4. Inside each beacon module is a custom-built PCB that connects all the sensors and microcontroller and eliminates the need for perf boards or breadboard-based connections.

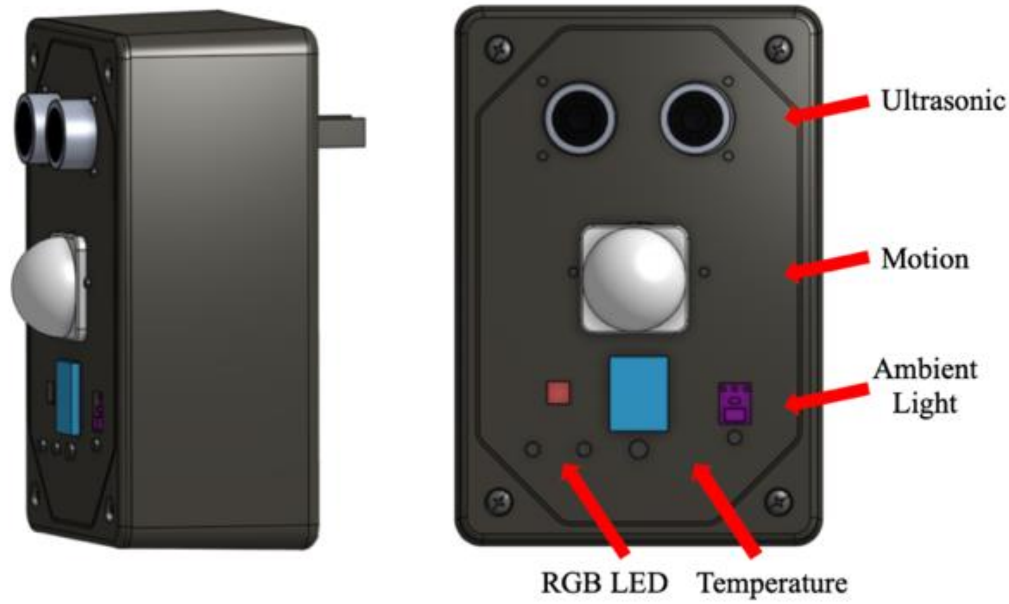


Figure 3.4: Beacon Module Enclosure with Labelled External Sensors

The enclosure is a PLA composed 3D printed case that was designed using Solidworks 2019 CAD software. It consists of a lid that contains mounting options for sensors and a base that encloses the AC-DC adapter and ESP32 PCB shield. The PCB was designed using Autodesk Eagle and contains two layers with all sensor connections and microcontroller mounting on the top layer.

3.3 Methods

3.3.1 Experimental Setup

The functionality and performance of the IPS were evaluated in two residential houses with simulated activities. Testing parameters were documented and tabulated prior to conducting each individual test in Table 3.1. The two houses where experiments were conducted are located in suburban residential neighborhoods in the City of Mississauga and Hamilton (McMaster Smart Home for Aging-in-Place (SHAPE) facility), both of which are in the Greater Toronto

Metropolitan Area (GTA). Conducting the same experiments in two different locations allowed for analysis of environmental changes and improved validity in the system's functionality. The suburban residential neighborhood setting provides a typical wireless signal environment, e.g., WIFI, Bluetooth, cellular networks, etc. Both houses are typical single-family dwellings with multiple stores (two floors plus basement). The house in Mississauga (House 1) contains typical residential household electrical outlet settings (one per wall). The SHAPE facility (House 2) is a house with special electrical wiring systems that has multiple outlets per wall.

The experiments required human test subjects are labelled as subject 1 and 2 respectively. Additionally, only two types of devices were used for the tests, the Amazfit Bip Smartwatch and a generic iTag. Certain tests do not have their orientation labelled because the device is constantly moving and does not remain in one fixed orientation relative to the beacon.

TABLE 3.1
Experimental Test Log and Parameters

Test Subject	Type of Test	Tested Device	Height Ground Level (m)	Device Position	Device Location	Orientation Relative to Beacon
Subject 1	RSSI Stability (1m)	iTag	1.54	Around Neck on Pendant	House 1 - Family Room	Directly Facing Beacon
Subject 1	RSSI Stability (2.5m)	iTag	1.54	Around Neck on Pendant	House 1 - Family Room	Directly Facing Beacon
Subject 2	RSSI Stability (1m)	Amazfit	0.48	On Right Wrist	House 1 - Family Room	Directly Facing Beacon
Subject 2	RSSI Stability (2.5m)	Amazfit	0.48	On Right Wrist	House 1 - Family Room	Directly Facing Beacon
N/A	RSSI Stability (1m)	Amazfit	0.65	Flat on Desk	House 2 - Basement	Facing Upwards
N/A	RSSI Stability (1m)	iTag	0.65	Flat on Desk	House 2 - Basement	Facing Upwards
Subject 1	Room Detection - RSSI	Amazfit	0.65 - 1.27	Wrist	House 1	N/A
Subject 2	Room Detection - RSSI	iTag	0.65 - 1.27	Wrist	House 1	N/A
Subject 1	Room Detection - RSSI	Amazfit Smartwatch	0.65 - 1.27	Wrist	House 2	N/A
Subject 2	Room Detection - RSSI	iTag	0.65 - 1.27	Wrist	House 2	N/A
Subject 1	Location vs Ground Truth	Amazfit	0.65 - 1.27	Wrist	House 2	N/A
Subject 2	Location vs Ground Truth	Amazfit	0.43 - 1.06	Wrist	House 2	N/A
Subject 1	Location vs Ground Truth	iTag	0.65 - 1.27	Wrist	House 1	N/A
Subject 2	Location vs Ground Truth	iTag	0.43 - 1.06	Wrist	House 1	N/A

3.3.2 RSSI Fluctuation and Filtering

Initial testing was conducted to determine static fluctuation in RSSI when a smartwatch and iTag are in a still position. Stability tests were performed at fixed distances of 1, 2.5, 5 and 10m from a single beacon in two different test environments. Tests were performed in an interval of 100 seconds with a test subject standing at a fixed position with the device of choice. During this interval, the relative signal strength indicator (RSSI) is plotted. The objective of this experiment is to observe the effects of RF interference on BLE signal strength and determine how effective filtering is on these noisy RSSI signals. Additionally, the key differences observed between distance and signal strength will prove that the use of signal strength analysis is an effective method to determine location or presence. Equation (1) will be used to calculate the distance based off measured RSSI values for both raw and filtered data. The measured power would be the estimated RSSI at 1m distance from the beacon. This value varies depending on the beacon used to measure RSSI. N is an environmental factor that ranges between 2-4 and is determined after correlating the calculated distances with fixed ground truth distances. The RSSI value is the measured signal strength. Using this equation, the resulting distance vs time graphs will be plotted for further analysis.

$$Distance = 10^{\frac{(Measured\ Power\ - RSSI)}{10 \times N}} \qquad \text{Equation 3.1}$$

3.3.3 Room RSSI Variation

To ensure room detection would be as accurate as possible, RSSI fluctuations were measured in various rooms within the McMaster Smart Home and Residential Home. For this experiment, a user would be wearing a smartwatch on their wrist or an iTag pendant around their neck while they walk around a room for a period of 100 seconds. Tests were conducted in 4 rooms at both testing locations. The purpose of this experiment is to record RSSI variations through rooms of various sizes. Analyzing this data helped with designing a calibration algorithm and observing how RSSI varies based on room size visually.

3.3.4 Location vs. Ground Truth

A method of validating whether a user is in the detected room was required to successfully assess the quality and efficiency of the IPS. This validation experiment was performed using a custom designed mobile application that seeks user input on a user's current room location. The mobile app required a user to enter a room, wait 10 seconds and validate the room they are currently in (Ground Truth). This selection is then compared with the calculated location that the IPS determined based off signal strength (Location). 150 room selections were completed by two separate test subjects as they traversed between either 4 or 5 rooms depending on the test location.

3.3.5 Sensor Based Room Detection

The addition of sensors along with BLE signal strength analysis provides meaningful data that can be analyzed in real time or post processed. The IPS is equipped with a PIR motion sensor (HC-SR501), Ultrasonic Range Finder (HC-SR04), Ambient Light sensor (TEMT6000) and a DHT-11 temperature sensor. The ultrasonic and PIR motion sensor were primarily used for motion detection with temperature and ambient light used for context awareness applications. Following a similar process as test #3 (Location vs Ground Truth), the motion and ultrasonic distance measurement thresholds were compared with a user input location. For example, when walking into "room 1" the expected sensor output from room 1's beacon should detect presence via the motion sensor and fall within the calibrated threshold for the ultrasonic sensor. The mobile app required a user to enter a room, wait 10 seconds and validate the room they are currently in (Ground

Truth). This selection is then compared with the calculated location that the IPS determined based off the motion sensor and ultrasonic sensor outputs. 150 room selections were completed by two separate test subjects as they traversed between either 4 or 5 rooms depending on the test location.

3.3.6 Room Transition and Detection Speed

Performance testing of the IPS involves determining how fast it can detect room changes and presence. This experiment consisted of a user traversing between two adjacent rooms of similar size while the time difference between timestamped presence detection is compared to determine detection speed. The same experiment was repeated for rooms that are at greater distances apart from each other.

3.3.7 RSSI Filtering

The filtering performed in this paper consists of a simple exponential filter applied on raw RSSI values in real time. An exponential filter works using a recursive algorithm and prioritizes the previously filtered value along with a filter weight to accurately determine the newly filtered value y_n as shown in equation (2). The variable x_n holds the measured raw RSSI value and the variable y_{n-1} holds the previously calculated filtered value. When analyzing the filter's performance, the most important variable to consider is "w" the weight factor. Several researchers use similar filters that operate using a weight factor or similar constants like the Kalman filter and Particle Filter [13,14].

$$y_n = w \times x_n + (1 - w) \times y_{n-1} \qquad \text{Equation 3.2}$$

Throughout experimental analysis of RSSI fluctuation data, various filter weights were used, and newly filtered datasets were obtained. However, for the functional IPS, an optimal filter weight was desired. To accurately determine what value of "w" is required further analysis of the exponential filtering on RSSI values was required. To determine this value, the root mean square (RMS) of filtered RSSI fluctuation datasets were calculated and plotted. Each dataset contained 100 RSSI values that were filtered using weight factors that varied from 0-100%.

3.4 Results

3.4.1 RSSI Fluctuation and Filtering

Figure 3.5a displays an RSSI vs Distance graph from average RSSI measurements taken during interval tests in the McMaster Smart Home basement. The figure shows raw and filtered RSSI levels, and their calculated distances based off Equation 3.1.

The raw and filtered RSSI values of the Amazfit smartwatch at distances (1, 2.5, 5 and 10 meters) are graphed and illustrated in Figure 3.5c. Graphed raw RSSI values show rapid changes at every measured distance while maintaining a reasonably distinguishable range. Graphed filtered RSSI values show smaller changes and have clearly distinguishable ranges. The observed RSSI ranges are approximately -50 to -60 at 1m, -55 to -65 at 2.5m, -65 to -75 at 5m and -75+ at 10m.

In addition to the plotted raw and filtered RSSI, the measured datasets were analyzed to determine standard deviation, mean RSSI and variance. The calculated standard deviation values of the Amazfit smartwatch during the 10m test in the Residential Home was 1.68 – Filtered. In the McMaster Smart Home, the 10m test results was 1.90 – Filtered. Testing was performed using an additional device known as an iTag for comparison between smartwatch and BLE tag RSSI values. The calculated standard deviation values of the iTag during the 10m test in the Residential Home were 2.57 - Raw and 1.56 – Filtered. In the McMaster Smart Home, the 10m test results were 2.21 – Raw and 1.74 – Filtered.

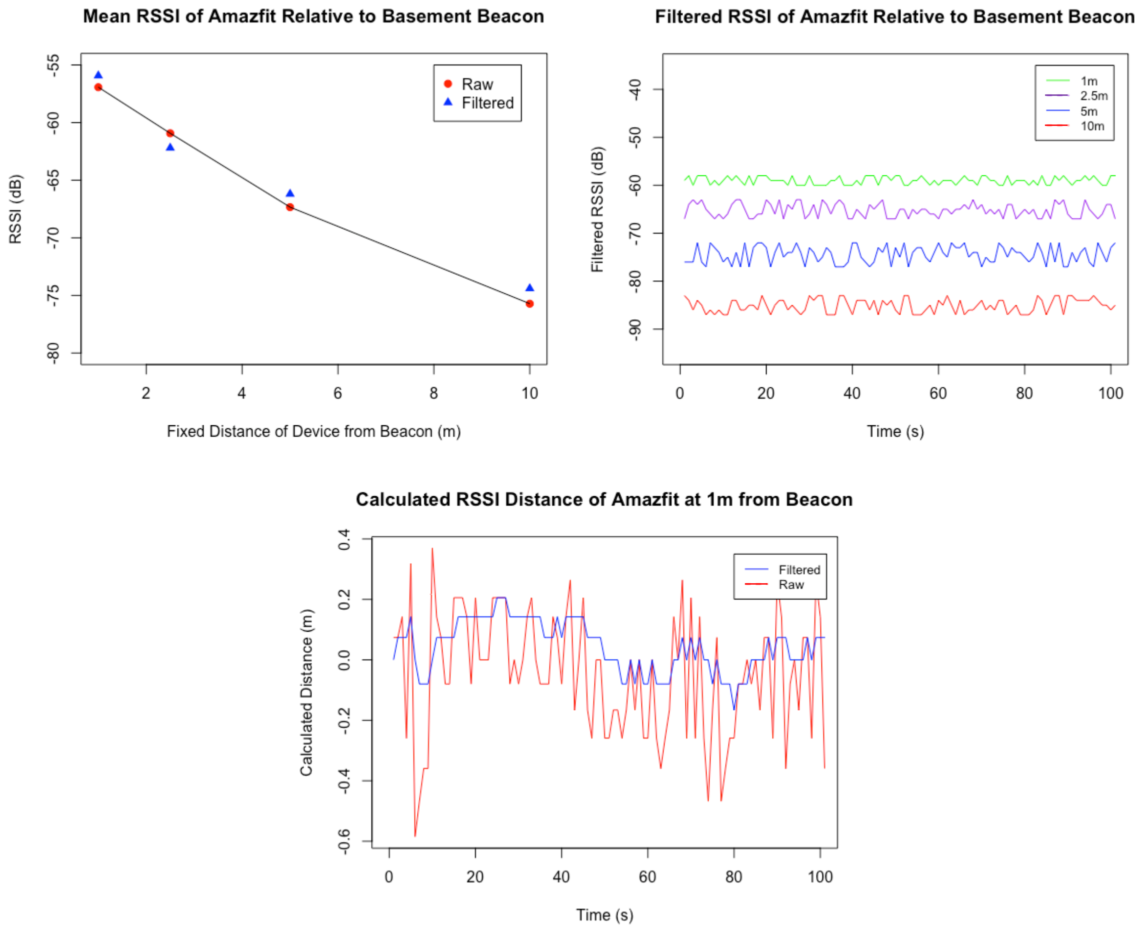


Figure 3.5a: Mean Measured RSSI at Fixed Distances (1, 2.5, 5 and 10m) in the Smart Home Basement, **3.5b:** Filtered RSSI at Fixed Distances (1, 2.5, 5 and 10m) in the Smart Home Basement, **3.5c:** Calculated RSSI based Distance Measurements of Amazfit Smartwatch at a fixed 1m relative to the IPS Beacon in the Smart Home Basement

3.4.2 Room RSSI Variation

Measured RSSI changes from both the Amazfit smartwatch and iTag while moving within a single room were measured and graphed. Graphed RSSI in the washroom of the residential and smart home show a similar range for both devices as shown in Figure 3.6a, b. Bedrooms and workspaces produced higher RSSI variation where RSSI reached a minimum value -88 dB and maximum of -55 dB. In the case of the washroom RSSI data, the maximum value recorded was -46 dB and the minimum was – 64 dB.

Further analyzed properties like standard deviation, maximum and minimum RSSI were calculated displayed in Table 3.2. A maximum standard deviation of 5.68 was calculated from the Amazfit smartwatch in the residential home bedroom. A maximum standard deviation of 5.61 was calculated from the iTag in the residential home office room. In the McMaster smart home, similar maximum standard deviation values were calculated and are greater than 5 as well.

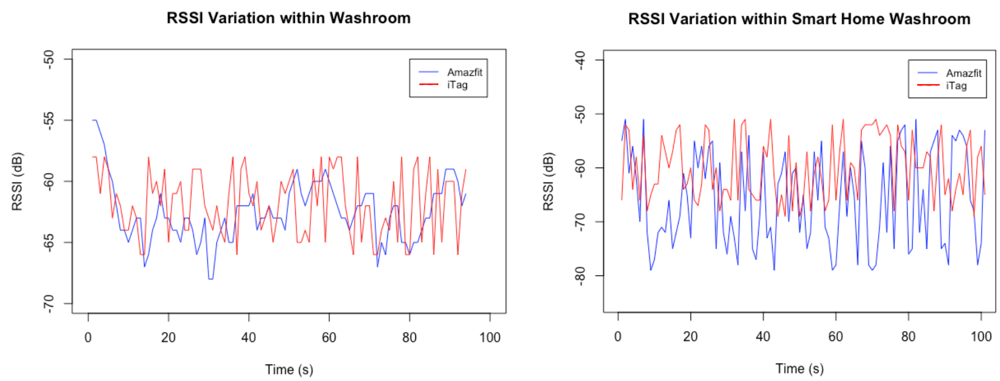


Figure 3.6a: Measured RSSI vs Time in the Residential Home Washroom, **3.6b:** Measured RSSI vs Time in the McMaster Smart Home Washroom

TABLE 3.2
RSSI Signal Properties of the Amazfit Smartwatch and iTag for RSSI Variation

Room RSSI Measurement	**iTag**				**Amazfit Smartwatch**			
Test Type	**Mean (dB)**	**Max (dB)**	**Min (dB)**	**Std. Deviation**	**Mean (dB)**	**Max (dB)**	**Min (dB)**	**Std. Deviation**
House 1 – Residential Home								
RSSI Fluctuation - Bedroom	-76.45	-56.00	-84.00	4.67	-73.66	-55.00	-80.00	5.68
RSSI Fluctuation - Washroom	-59.65	-48.00	-61.00	2.54	-56.76	-52.00	-64.00	2.89
RSSI Fluctuation - Office	-74.43	-59.00	-88.00	5.61	-77.65	-59.00	-86.00	5.43
RSSI Fluctuation - Bedroom 2	-54.32	-46.00	-58.00	2.43	-56.51	-50.00	-61.00	2.87
House 2 - SHAPE Facility								
RSSI Fluctuation - Bedroom	-66.84	-57.00	-82.00	5.23	-68.40	-51.00	-78.00	5.32
RSSI Fluctuation - Washroom	-56.67	-52.00	-61.00	2.45	-53.45	-46.00	-59.00	2.13
RSSI Fluctuation - Office	-71.21	-61.00	-84.00	5.12	-65.64	-54.00	-74.00	5.17
RSSI Fluctuation - Kitchen	-54.89	-51.00	-60.00	2.77	-58.63	-49.00	-60.00	3.25

3.4.3 Location vs. Ground Truth

Mobile app entries determined locations were compared, the detection results are displayed in Table 3.3. The IPS achieved a calculated percentage accuracy of 96.7% in the residential home and 95.33% in the smart home.

TABLE 3.3
User Input Location vs Ground Truth Location Test Results

Room Detection Analysis Parameters	Subject 1	Subject 2	Total
House 1 – Residential Home (4 Rooms)			
Number of Tests	150	150	300
Total Correct Location Matches	146	144	290
Incorrect Location Matches	4	6	10
% Accuracy	97.33	96.00	96.67
House 2 - SHAPE Facility (5 Rooms)			
Number of Tests	150	150	300
Total Correct Location Matches	144	142	286
Incorrect Location Matches	6	8	14
% Accuracy	96.00	94.67	95.33

3.4.4 Sensor Based Room Detection

Mobile app entries and recorded sensor values were compared, and the detection results are displayed in Table 3.4. The motion sensor achieved a total 93% accuracy. The ultrasonic sensor at a 200 cm threshold produced a lower accuracy of 78.67%. Temperature and ambient light sensors were tested for functionality and successfully relayed their measured values in real time after a beacon is connected.

TABLE 3.4
Tabulated Results of Motion and Ultrasonic Range Detection Testing

Motion and Ultrasonic Detection Analysis	Subject 1	Subject 2	Total
Motion Detection Testing			
Number of Tests	150	150	300
Correct Motion Detection (Presence Detected)	141	138	279
Incorrect Motion Detections (Presence Not Detected)	9	12	21
% Accuracy	94.00	92.00	93.00
Ultrasonic Detection Testing (2m Threshold)			
Number of Tests	150	150	300
Correct Ultrasonic Detection (Within Threshold)	126	110	236
Correct Ultrasonic Detection (Not Within Threshold)	24	40	64
% Accuracy	84.00	73.33	78.67

3.4.5 Room Transition and Detection Speed

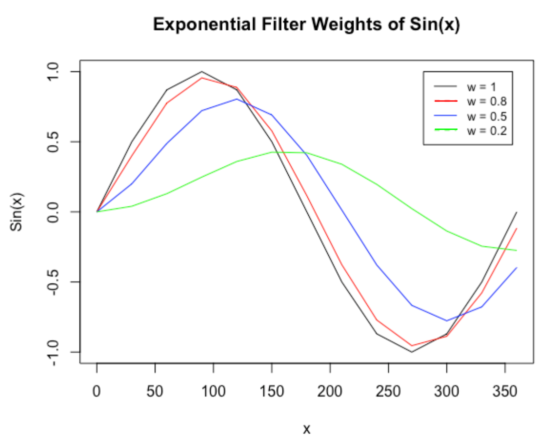
Each room transition was performed 15 times for both the Amazfit smartwatch and iTag. An average speed in seconds was calculated based off the 15 tests and reported in Table 3.5. Adjacent room transitions displayed average speeds of 1.47 and 2.23 seconds in the residential home and 2.57, 1.50 and 2.83 in the McMaster Smart Home. The far room transitions displayed average speeds of 5.20 and 6.55 seconds in the residential home and 5.97 and 6.29 in the McMaster Smart Home.

TABLE 3.5
Tabulated Results of Room Transition and Detection Speed Testing

Room Transition and Detection Speed Testing	Amazfit	iTag	Average Speed (s)
House 1 - Residential Home Detection Speeds in Seconds (4 Rooms)			
Bedroom to Washroom (Adjacent)	1.56	1.37	1.47
Washroom to Prayer Room (Adjacent)	2.54	1.91	2.23
Prayer Room to Office (Far)	4.53	5.87	5.20
Office to Bedroom (Far)	5.69	7.41	6.55
House 2 - SHAPE Facility Detection Speeds in Seconds (5 Rooms)			
Washroom to Office (Adjacent)	2.81	2.32	2.57
Office to Kitchen (Adjacent)	1.12	1.88	1.50
Kitchen to Dining Room (Adjacent)	2.53	3.12	2.83
Dining Room to Bedroom (Far)	5.62	6.31	5.97

3.4.6 RSSI Filtering

Testing of the generic sinusoidal function revealed that the phase shift is not affected by the filter, however the amplitude is, as shown in Figure 3.7a. The sin(x) function remains the same at a weight factor of 1 (100%) and gradually smoothens as weight is decreased. It is evident that at lower weights (w = 0.5 and 0.2), the filtered function responds slowly to changes that are evident in the original signal (w = 1). Using the filtered Sin(x) function's graphed response, a similar process was applied to a singular dataset from the RSSI fluctuation tests to produce Figure 3.7b. The RMS curve follows an exponential growth between 0-20 weight % and then steadily increases.



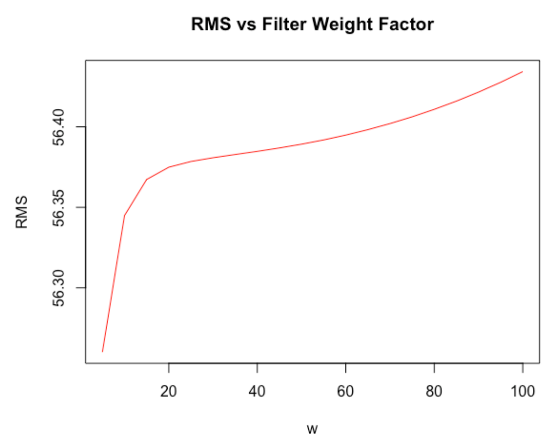


Figure 3.7a: Exponential Filtered Sin(x) Function at Varying Weight Factors, **3.7b:** RMS value as a function of Weight Factor for the RSSI Stability Dataset (1m)

3.5 Discussion

3.5.1 Objectives and Design Features

Throughout the development of this IPS several objectives were targeted. Our aim was to develop a system that can measure indoor locations at the room level, accurately determine room transitions, identify traversal pathways of specified BLE devices, correlation of room detection with timestamped sensor data, self-installation with minimal or no house visits, a reasonable cost to develop and secure data collection. The results of our validation tests directly align with several objectives mentioned above and are further outlined in detail below. The physical design of the IPS beacons and hub deal with the objective of self-installation. Beacons are built to be connected directly into wall sockets to eliminate the need for battery replacement or charging. The hub module follows the same process and has one additional connection to either a home router or ethernet port anywhere within the home. This design made the system extremely user friendly asking for minimal effort from the user during setup and installation. The reasonable cost objective was achieved as the system (assuming 5 beacons/rooms on average) costs approximately $200 to build. To ensure all data remains secure all collected sensor and Bluetooth data remains on the hub module device saved locally. The communication of data between beacons to the hub all operates on a secure 2.4GHz channel without any need for internet connectivity. The design, testing and validation of this IPS took all these objectives into consideration throughout the entire engineering design process.

3.5.2 RSSI Fluctuation and Filtering

It is evident that the RSSI at a stable position produced high levels of fluctuation due to RF interference within an indoor environment. Obstacles like furniture and metal properties within walls can have a serious impact on the RSSI values [15]. When raw RSSI is left alone there is substantial overlap between values at short distances as shown in the results from Figure 3.5c. When the exponential filter is applied to the raw values, determining the relative distance of a device is significantly easier as shown in Figure 3.5b. This decrease proves that filtering the RSSI values provides a significant advantage for the indoor tracking algorithm.

With regards to the main objective of room detection, a clear difference in measured RSSI is evident as distance increases. RSSI strength decreases as the tracked device moves further away from the beacon. Figure 3.5b and c show a clear difference in the efficiency of using filtered RSSI vs raw RSSI. Filtered RSSI plots produced significantly less deviation making it easier to correlate a distance to determine presence.

3.5.3 Room RSSI Variation

Rooms will produce varying RSSI values when a user is moving around the beacon's relative location. Analyzing these values allows us to determine a range and calculate the standard deviation of RSSI for each room. The variation proved to be significantly lower in smaller rooms when compared to larger rooms as depicted in Table 3.2. To accurately detect if a user is within that room multiple factors must be considered along with the RSSI values. This test proved that a calibration setup is required to accurately determine room presence based of a dynamically measured threshold. Room size variation made detecting indoor position at the sub room level difficult for the smaller room sizes. Potential ways to compensate for this would be to enhance the calibration algorithm to react differently on RSSI changes in smaller rooms compared to larger ones.

3.5.4 Location V.S. Ground Truth

Comparison between user input locations and detected locations resulted in a high % accuracy for the overall IPS. A difference of around 1% was observed in the calculated % accuracy between the two test locations. This result supports the IPSs ability to adapt to new indoor environments. The physical act of transitioning between rooms causes the IPS to receive multiple RSSI signals that are within a similar range to the closest available beacons. The similarity in RSSI range is the cause of the incorrect location detection. To mitigate this problem, filtering of RSSI values can be improved along with the inclusion of a more extensive calibration process during integration. Future experiments will be conducted using more than two test subjects and more than five rooms to detect. Additionally, a greater number of room transitions would be added to the testing procedure. The results of this experiment truly ensured that the system was correctly detecting the presence of an individual traversing within their home. It aligned with the objective of using IPS data to observe room traversal patterns and pathway guidance application development.

3.5.5 Sensor Based Room Detection

Results proved that the motion sensor would be an ideal backup for room detecting validation as it produced a high % accuracy for room detection. The ultrasonic sensor produced a significantly lower % accuracy, with several false positive room detections. Limitations on ultrasonic threshold distance and angle are the reasons for the lower accuracy. The ultrasonic sensor has a maximum distance measurement of 200cm directly in front of its detector. Whereas the PIR motion sensor has a 5m hemispherical radius in front of the detector. A drawback to using physical sensors for room detection is the location of the beacons will become limited. The detector heads from the motion and ultrasonic sensors must be facing an open area to accurately detect if a person walks in front of or past it. The beacons are designed to act as wall adapters and throughout most residential and clinical settings outlets are often covered by furniture or equipment.

3.5.6 Room Transition and Detection Speed

Results showed significantly longer detection times for rooms of further distances which was expected due to the time it takes to physically traverse larger and further rooms. Commercial indoor positioning systems can determine room location at less than 1 second speeds with prior knowledge of room layout and building topography [16]. Some possible reasons for the longer detection time observed would be the ESP NOW communication delay. BLE data is sent across a different communication channel at a different operating frequency. Additionally, the added filtering process could potentially add a significant delay due to processing incoming and past RSSI data before room detection analysis even begins. Further testing and validation need to be performed to confirm these concerns and determine if these are reasons for the longer speeds. Future work would involve exploring methods to increase the measured detection speed to achieve similar speeds without the need for knowledge of room layout. The detection speed and room transition data aligned with our objective of using IPS data to observe room traversal patterns and pathway guidance application development.

3.5.7 RSSI Filtering

The RSSI changes based off the implemented exponential filter significantly improve the signal quality. Results from the fluctuation and room variation tests prove that the filter aids the IPSs ability to accurately detect rooms. From Figure 3.7b, there is a large spike in the RMS value through the 0-20% weight range. From previous testing, it was noted that larger weight factors significantly increased the processing time and power consumption. Therefore, the optimal weight would be to use 20% as it is the smallest weight that maintains a smooth filter at the fastest possible processing speed.

3.6 Conclusion

Indoor position tracking continues to improve in methodology and implementation as technology advances. Presently, existing systems can use WIFI, BLE, RFID and preprogrammed topographies to track devices at almost the centimeter level. However, the system design in this paper performs location tracking at the room level without any preprogramming requirements using a dynamic calibration process and filtered BLE RSSI signal strength analysis. In addition, the system can validate its own location tracking using motion and ultrasonic sensor detection. Several experimental procedures were followed to validate this system's ability to accurately determine the location of both a BLE tag and smartwatch. The RSSI quality, variation, calculated location vs. ground truth and sensor room detection were tested and validated. The purpose of this study was to track human subjects wearing smartwatches or pendant tags, however the IPS can be used to track devices that have BLE sticker tags attached to them. Potential future implementations of the IPS could potentially include real time indoor tracking of constantly moving medical instruments like ultrasound machine carts and crash carts in hospitals. The IPS is the ideal device for use as a central core to large scale health care monitoring systems.

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Chapter 4 Clinical Study Applications

A pilot clinical study was conducted to thoroughly assess the AIP-IPS in a realistic setting. The study targeted older adults and required them to integrate the AIP-IPS within their home's for at least a 1-month period. The study involved the participant wearing a smartwatch at all times except while placing it on charge overnight. One goal of the study was to prove the rationale behind developing an IPS that can be installed by the user themselves and calibrated remotely. The study was a collaborative effort involving a PhD student, undergraduate student, and supervisor Dr. Qiyin Fang. My contribution to the study was the assembly, testing and validation of systems built for study participants. Additionally, I developed some initial stage data collection algorithms that helped aggregate the large datasets that were collected. Michael Zon (PhD), worked on research ethics protocol and applications, enlisting participants and post processing analysis of aggregated datasets. His work focused on the development of context awareness algorithms using the AIP-IPS [1]. Ishita Paliwal (BSc) worked on research ethics protocols and REB applications, enrollment of study participants and obtaining consent from those interested in the study.

4.1 Clinical Study Description

The clinical study consisted of 5 phases: Pre-Clinical, Testing and Validation, Phase 1 and the current status of the study, Phase 2. To be eligible for the study, our only requirement was that you must be an older adult of at least 60 and speak fluently in English. During the pre-clinical phase, interested participants were given pre-screening questionnaires and participated in either a phone or online meeting to address any questions or concerns with the study parameters. The meeting would provide us with verbal consent before proceeding with the study and determining which rooms the participants were comfortable being tracked.

Table 4.1 shows that the pilot study consisted of around 16 older adult participants who are located primarily within the Hamilton and Burlington regions. The indoor location's we implemented the system in where mostly detached residential homes and apartment suites. The study collected a large amount of sensor and BLE signal data. The smartwatches would collect step count, heart rate and accelerometer data while the room beacons would collect ambient temperature, humidity, and light. Additionally, for validating BLE based positioning the room beacons were equipped to provide motion sensor alerts and ultrasonic distance values. The study was designed with the goal of obtaining large datasets that provided 1-3 months' worth of positioning and sensor data [Table 4.1]. Three pairs of participants included in this pilot study were married couples which provided an additional demographic when compared with single participants [Table 4.1].

TABLE 4.1
Overview of Pilot Clinical Study Participants

Participant ID#	Initial Contact	Number of Beacons in Home	Study Duration
SP222/223	June 22, 2021	4	Oct 27, 2021 - Mar 14, 2022
SP224/225	June 22, 2021	4	Nov 2, 2021 - Mar 14, 2022
SP226/227	July 7, 2021	5	Dec 1, 2021 - Mar 14, 2022
SP228	July 7, 2021	N/A	N/A
SP229	July 7, 2021	5	Nov 10, 2021 - Mar 14, 2022
SP230	Oct 7, 2021	N/A	N/A
SP231	Oct 7, 2021	5	Nov 10, 2021 - Mar 14, 2022
SP232	Oct 19, 2021	4	Did not complete
SP233	Nov 3, 2021	5	Dec 15, 2021 - Jan 26, 2022
SP234	Nov 15, 2021	5	N/A
SP235	Jan 21, 2022	4	Mar 15, 2022 - Present

The testing phase consisted of assembling custom IPSs for study participants that completed the pre-clinical phase. This process would vary with each participant as every home is different. Due to several COVID-19 restrictions, the setup and installation that would normally be conducted by us graduate students were restricted. However, this was not an issue as the AIP-IPS utilized a remote calibration process and involves minimal effort from the user with its unique wall adapter beacon design. The included setup instructions explained the process of plugging beacons into labelled rooms, how to setup and use the MacSmartHome app on the smartwatch (tracking device) and connect the Hub to a wired ethernet connection.

Phase 1 consisted of the initial stages of data collection, validation, and troubleshooting. Throughout this stage, iterations were made to implemented systems based off early feedback from participants. Some examples of iterations that were pivotal changes included a redesign of the beacon enclosure due to its large size blocking additional outlets. Another iteration was the implementation of real-time sensor and RSSI data validation using Google Cloud Firestore™. Initially, our design only used Firestore™ as a remote calibration tool, however after installing the first system it was clear we needed a way to remotely monitor beacons to ensure accurate data quality. The real-time data would be uploaded to a cloud database every time it is received on the Hub module. We developed a Python script that sorted this data based on different study participants and validated that data from every beacon in each home is receiving data every 15 seconds.

Currently, the study is at Phase 2 where data trends and context awareness algorithms are being implemented on the large datasets we have obtained. I contributed to this phase by developing a time synchronization topology using Python. The time synchronization process is explained in detail in subsection 4.3.2. Additionally, the pre and post survey responses are analyzed to provide future students using the AIP-IPS some feedback on how it can be improved.

4.2 Collected Qualitative Data

Whenever a study involves human participants, it is pivotal to implement methodology that obtains qualitative data. Obtaining feedback from people who are actively using your technology is the ideal way to iterate and improve on a design. Moreover, the application of the AIP-IPS requires our target demographic of older adult's to find this system easy to use and set up within their home's. In this study, we received several qualitative data points in the form of online surveys via Google Forms. The following subsections will explain in more detail some of our findings and their relevance.

4.2.1 Pre-Clinical Study Survey Results

A pre-clinical survey was sent to participants as part of the screening process before sending them their assembled IPS. Table 4.2 shows the age demographic of our study participants and even provides us with a brief idea of their falling tendencies. From Table 4.2, it's clear that there are more female participants than male ones. Additionally, it's worth noting that few participants claim to have difficulty with balance. The ones who did respond yes, also responded with a yearly fall count greater than 2. It is important to have a diverse demographic of study participants as it ensures diversity in collected data. We have recruited a diverse group of study participants through age, gender, and physical characteristics. Certain parameters obtained from this survey will be used to develop the context aware emergency detection framework [2]. Some key components of this framework would include demographic data to help determine optimal and concerning measurable health parameters such as heart rate and blood pressure for each study participant. Similarly, knowing previous fall frequency is also helpful when implementing context aware algorithms. For example, a participant who falls frequently may have larger fluctuations in their recorded smartwatch's IMU values when compared to a participant who falls less.

TABLE 4.2
Pre-Clinical Survey Demographic

Participant ID	Study completed?	Sex	Age (yrs)	Height (cm)	Weight (kg)	Self-reported difficulty with balance?	# of Falls in the Last Year
SP222	Y	F	62	183	84	N	0
SP223	Y	M	75	170	79	Y	2
SP224	Y	F	69	157.48	70	Y	6
SP225	Y	M	70	170.18	74.8	N	0
SP226	Y	M	72	175	68	N	0
SP227	Y	F	71	160	68	N	0
SP229	Y	F	60	172.72	61	N	0
SP231	Y	F	66	162	88	N	6
SP232	N	M	70	178	83.5	N	0
SP233	N	F	67	160	82	N	1
SP234	N	F	70	175.26	68	N	0
SP235	N	F	76	167.64	72.6	Y	4

The pre-clinical survey was designed to obtain information regarding participant's activities to determine which rooms would be ideal to place beacons in. Responses to some daily activity frequency and difficulty are shown in Table 4.3. From the responses we obtained, this group of study participants consider themselves active as they do not have difficulty walking long distances and responded that they often exercise. Additionally, none of the participants require any form of walking assistance nor are any handicapped. Something almost every participant stated as a sitting activity for them is watching TV and reading, which would lead researchers to expect a significant portion of room location data to correlate where the TV and books are located. Additionally, activity recognition itself is a large component of aging research, several IOT systems that use indoor positioning are designed for activity recognition [3][4]. Therefore, having this knowledge prior to implementation enables the possibility of adding tailored applications like these to an existing system in the future.

TABLE 4.3
Pre-Clinical Survey Participant Activity Responses

Participant ID	Frequency of Sitting Activities	Frequency of going Outside for a Walk	Frequency of Exercise	Use of walking aid	Difficulty Walking 0.5 km?	Difficulty Walking 2 km?	Difficulty Climbing 1 Flight of Stairs?	Example Sitting Activities
SP222	3	3	2	N	0	0	0	reading, crochet, TV, online games, online courses
SP223	3	3	1	N	0	1	0	TV, online games, online courses
SP224	3	3	1	N	0	0	0	reading, movies
SP225	3	3	2	N	0	0	0	computer
SP226	3	1	0	N	0	0	1	TV, reading, Soduku, finances, conversations, socializing
SP227	3	1	0	N	0	0	0	TV, Soduku, MahJongg,
SP229	3	2	3	N	1	2	1	reading, TV, phone
SP231	3	3	0	N	0	0	0	reading, computer, TV, travelling by car
SP232	3	3	2	N	0	0	0	crosswords, Soduku, reading, TV
SP233	3	3	3	N	0	1	0	quilting, reading, TV
SP234	3	3	3	N	0	0	0	reading, TV, guitar playing, drawing, writing
SP235	3	3	3	N	0	1	0	reading, crochet, making bedrolls, TV, word games

***Ranking Scale: - 1 (LOW) – 5 (HIGH), Ex "4" would represent high frequency or high discomfort**

4.2.2 Post-Clinical Study Survey Results

Comparatively, the post-clinical survey was sent online after study participants had completed their stage of the study and returned the AIP-IPS. The post-clinical survey consisted of more specific questions that detailed the setup, installation, and usage beacons (room and hub) and tracking devices (smartwatch). Reviewing these responses and using the feedback from the preliminary participants, we were able to rapidly implement helpful iterations to the AIP-IPS.

Feedback on the beacon and hub setup procedure was of most importance because the AIP-IPS was developed with self-installation as one of the main design criteria. Table 4.4 shows us that the inconvenience of the installing room beacons and hub modules varied amongst participants with a majority 50% selecting a level 3 rating of inconvenience. Including an option to detail specific rationale for their selection proved beneficial her as initial feedback showed us that several participants found the beacon’s to be too large and cover outlets entirely. Additionally, participants struggled with Hub setup as older adults are not too familiar with connecting devices via Ethernet to their router directly. Using the feedback we received, the room beacons were redesigned for a smaller form factor while still enclosing the same electronics. For the Hub, a more detailed process on ethernet cable usage and the ability to connect to various ethernet ports around a home was included so older adults were not asked to modify their router as part of the setup procedure.

Similarly, feedback on the tracking devices (smartwatches) was crucial to assess the functionality and quality of the AIP-IPS. Table 4.4 shows 75% of participants found the smartwatch inconvenient to charge as we requested them to charge it overnight every day for the duration of the study. Despite this being inconvenient it’s worth noting that 75% of participants also responded with a 1, when asked about how frequently the smartwatch would run out of charge. Additional questions regarding the smartwatches were asked and most of the feedback we received consisted of participants' discomfort using the smartwatch. We decided that for the remainder of the pilot study, the same smartwatch can be used. Future iterations of the system, however, will allow for user's to either integrate their own smart devices or provide at least three options of wearable devices.

TABLE 4.4
Post-Clinical Survey Device Feedback from Initial Study Participants

Question	Quantitative Rating (Overall % of Responses)					Rationale (Optional)
	1	2	3	4	5	
Inconvenience of wearing the smartwatch during the study	0	25	50	25	0	bulky, heavy, turns off frequently
Inconvenience of charging the smartwatch during the study	0	0	0	25	75	N/A
Frequency of the smartwatch running out of battery before charging	75	0	25	0	0	N/A
Frequency of forgetting to wear the watch after putting it on charge	25	75	0	0	0	N/A
Frequency of removing the watch	0	0	75	25	0	removed during shower, sleep
Frequency of forgetting to wear the watch after removing it for a reason not related to charging it	75	25	0	0	0	N/A
Inconvenience of installing room beacons or hub modules	0	25	50	0	25	difficult hub setup, beacons falling from outlet
Level of user satisfaction with the devices in this study	0	0	25	75	0	bulky watch, invalid time on watch
Willingness to use this tech in the future in collaboration with HCPs to diagnose disability/diseases	25	0	25	0	50	N/A
Interference of devices with daily routine	75	25	0	0	0	bulky watch, beacons falling from outlets
comfort with step count, heart rate, and room positioning being recorded	25	75	0	0	0	N/A

***Ranking Scale: 1 (LOW) – 5 (HIGH), Ex "4" would represent high frequency or high discomfort**

The significance of qualitative data analysis for this system is important because of its intended use case as an AIP smart system. A key research component throughout the development process was ensuring the AIP-IPS would be suitable for use by older adults. It is similar to understanding your target market when developing a successful product in an industrial setting. Additionally, it ties deeply into the motivation behind developing the AIP-IPS and helps us as researchers learn what worked and what didn't work while developing technology for smart AIP. Using the knowledge of design choices that proved beneficial will help improve future designs and inspire more iterations. For example, a positive aspect of the AIP-IPS was its easy installation process using wall plug adapter beacons. The process of simply plugging a device to your wall outlet is much more practical than asking an older adult to physically mount beacons at specific locations within their rooms like traditional IPSs use.

4.3 Collected Quantitative Data

This pilot study consisted of several participants collecting months' worth of positioning and sensor data. Due to the nature of the study involving human participants, it was imperative that the collected data points remain anonymous and follow a logical procedure when recording, saving, and processing any datasets during the study period. The following subchapters will explain the data collection process, data structures and significance of these datasets. Collected datasets are used to validate and assess the performance of the AIP-IPS. Therefore, the data collection and analysis processes are incredibly important components of this system's development process.

4.3.1 Collected Data Structure

As mentioned in **Chapter 3**, all collected sensor and BLE data is stored locally on the Raspberry Pi in the Hub module. Each Hub is equipped with a 64GB micro-SD card that contains the Raspbian OS and stores the collected beacon data in csv files. Figure 4.1 shows us the process of data collection and retrieval in a systematic flow. A corresponding csv file is created and dynamically filled for each room a beacon is actively functioning. The beacons record sensor and BLE data along with the epoch time at which the data was received at the Hub. Additionally in some scenarios (large locations with several unmonitored rooms) we would request to perform this calibration procedure in rooms without beacons as well. This would ensure the false detection of a user in a room without a beacon would be avoided.

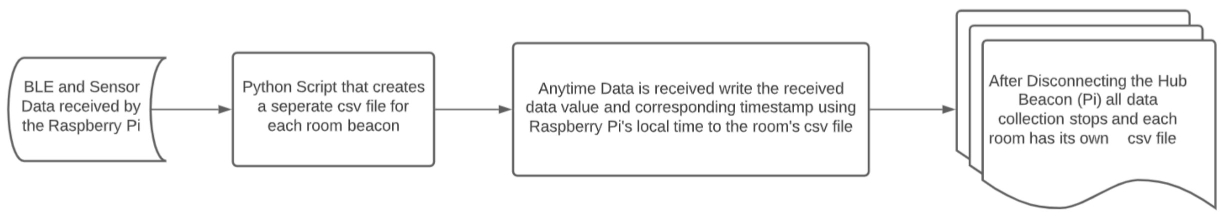

Figure 4.1: AIP-IPS Hub Data Collection and Extraction Process

Table 4.5 shows an example of what a room's collected csv file looks like. This example is a short clipping of data collected in a 1-minute recording period. The entire contents of a room csv file include ambient sensor and BLE RSSI data along with a timestamp of when it was received. The smartwatch's RSSI is measured by beacons at varying time intervals based on the location of the smartwatch. For example, when the smartwatch is closer to a specific beacon it will send RSSI data more frequently. This is due to the process of BLE communications involving the transfer of packets when a device is discovered. By default, the beacons are programmed to scan for devices at the fastest possible rate the microcontroller is capable of which is 1ms at a sampling frequency of 1000Hz. Whereas the sensor data is periodically recorded by the microcontroller in the beacon every 10ms at a sampling frequency of 100Hz. Additionally, the smartwatch collects heart rate and step count data that is not sent to the Hub, instead is saved on the smartwatch itself and extracted separately. Transmitting sensor values to the Hub from the watch would require additional communications and significantly reduce battery life, therefore we made the decision to save these values on the device and extract it along with the data collected from the hub and synchronize their timestamps during the post processing stage.

TABLE 4.5
Sample of Collected Participant Beacon Room Data (SP231, Kitchen.csv)

BLE Name	Filtered RSSI (dB)	Unfiltered RSSI (dB)	BLE Time	DHT Humidity, Temperature (%, C)	Light Level	Motion Sensor (Digital)	Ultrasonic Distance (cm)	Sensor Time
['i12D703']	['-87.10']	['-91.00']	['1639533028687']	[37], [26.6]	0	1	0	['1639533028321']
['i12D703']	['-87.02']	['-82.00']	['1639533044153']	[37], [26.4]	23	1	0	['1639533124184']
['i12D703']	['-88.35']	['-83.00']	['1639533065603']	[37], [26.2]	21	1	0	['1639533034124']
['i12D703']	['-88.02']	['-83.00']	['1639533078322']	[37], [26.6]	20	1	0	['1639533078383']
['i12D703']	['-89.45']	['-92.00']	['1639533098547']	[37], [26.4]	21	1	0	['1639533098434']
['i12D703']	['-89.20']	['-90.00']	['1641373628877']	[38], [26.6]	0	1	0	['1639533028321']
['i12D703']	['-91.49']	['-96.00']	['1641373644592']	[37], [26.4]	23	1	0	['1639533124184']
['i12D703']	['-89.03']	['-82.00']	['1641373660461']	[37], [26.2]	21	1	0	['1639533034124']
['i12D703']	['-89.74']	['-91.00']	['1641373679395']	[38], [26.6]	20	1	0	['1639533078383']
['i12D703']	['-88.87']	['-90.00']	['1641373690585']	[37], [26.6]	21	1	0	['1639533098434']
['i12D703']	['-88.75']	['-91.00']	['1641373707696']	[37], [26.6]	20	1	0	['1639533028321']
['i12D703']	['-86.36']	['-82.00']	['1641373721800']	[37], [26.6]	20	1	0	['1639533124184']
['i12D703']	['-88.12']	['-90.00']	['1641374044207']	[38], [26.6]	20	1	0	['1639533034124']
['i12D703']	['-87.24']	['-81.00']	['1641374057171']	[37], [26.6]	20	1	0	['1639533078383']
['i12D703']	['-86.71']	['-82.00']	['1641374090768']	[37], [26.6]	21	0	0	['1639533098434']
['i12D703']	['-87.12']	['-91.00']	['1641374100773']	[37], [26.6]	20	0	0	['1639533028321']
['i12D703']	['-87.37']	['-90.00']	['1639533044153']	[37], [26.4]	23	1	0	['1639533124184']
['i12D703']	['-85.77']	['-82.00']	['1639533065603']	[37], [26.2]	21	1	0	['1639533034124']
['i12D703']	['-84.42']	['-82.00']	['1639533078322']	[37], [26.6]	20	1	0	['1639533078383']
['i12D703']	['-85.82']	['-82.00']	['1639533098547']	[37], [26.4]	21	1	0	['1639533098434']

4.3.2 Data Analysis and Significance

The initial stage of data analysis requires the collected sensor and BLE data to be synchronized with their timestamps. Time synchronization is the process of integrating multiple sources of sensor data within one unified dataset. For the AIP-IPS, this ensures that the collected data from multiple data sources (beacons) can be analyzed with respect to a single timeframe. To perform indoor tracking, these datasets must be time synchronized. The flowchart in Figure 4.2 shows the process of creating a time synchronized dataset from multiple datasets collected by room beacons.

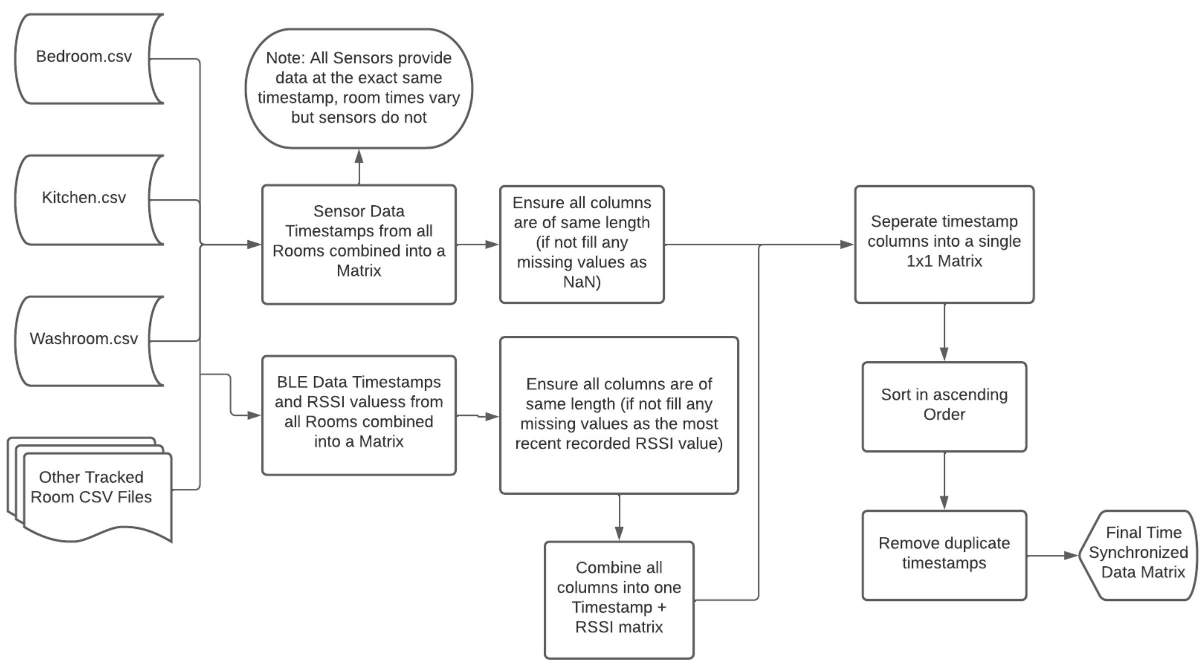

Figure 4.2: AIP-IPS Time Synchronization Process Flowchart

This process consists of first separating the timestamps from the sensor and BLE RSSI data as they arrive at different time points. After completing this step using each room's csv file, you will have timestamp datasets from each individual room file. The next step would be synchronizing these timestamp sets from multiple rooms together and create one chronological time synchronized column. To do this, you need to merge all the timestamp datasets together and removing all duplicate timestamps. This will leave you with a chronological 1x1 timestamp matrix that will act as your reference matrix. Finally, you merge the collected RSSI data from each room's files with this synchronized timestamp matrix. The final dataset will look like Table 4.6 where each room's RSSI value has a designated column followed by a synchronized timestamp column.

TABLE 4.6
Sample of Time Synchronized Dataset from McMaster Smart Home AIP-IPS

Kitchen RSSI	Washroom RSSI	Bedroom RSSI	Basement RSSI	Synchronized Timestamp
['-95.00']	['-73.00']	['-105.00']	['-55.00']	['1638376132652']
['-95.00']	['-75.00']	['-105.00']	['-55.00']	['1638376132659']
['-94.00']	['-71.00']	['-97.00']	['-54.00']	['1638376143792']
['-94.00']	['-74.00']	['-94.00']	['-54.00']	['1638376143795']
['-98.00']	['-88.00']	['-86.00']	['-58.00']	['1638376159149']
['-98.00']	['-87.00']	['-86.00']	['-61.00']	['1638376179417']
['-98.00']	['-81.00']	['-82.00']	['-61.00']	['1638376179424']
['-70.00']	['-86.00']	['-82.00']	['-50.00']	['1638376195073']
['-70.00']	['-80.00']	['-76.00']	['-50.00']	['1638376195078']

4.3.3 Calibration and Room Detection

The calibration process involves the collection and creation of reference datasets during the setup phase of the AIP-IPS remotely. The Hub contains a Raspberry Pi that is connected to the internet via Ethernet. In **Chapter 3**, the process of uploading data to Google Cloud Firestore™ is explained, we use the same cloud platform to send commands that place the AIP-IPS in calibration mode or reboot the system remotely. The calibration procedure involves users wearing a smartwatch to walk around specific location inside rooms that have beacons and collecting RSSI data that is used as a reference. An example of this would be a user notifying us they wish to calibrate their Kitchen beacon. We would then send a command to place the AIP-IPS in calibration mode and specify the room which we would like to start recording a calibration dataset for. In this case it would be the Kitchen, after sending this command the user would walk to specific locations in this room (center of the room, halfway between the center and the entrance to the room and the entrance). While standing in these locations the system would rapidly collect RSSI data for a fixed period of 15 seconds and save these values in the calibration dataset for the corresponding room.

To detect the location of the smartwatch we utilized a modified version of the trilateration algorithm. Using Equation 3.1 from **Chapter 3**, the corresponding Euclidian distance values from each recorded calibration point are calculated and recorded in the same dataset. This same equation is applied to the RSSI values in the generated time synchronized dataset (Table 4.6). The Euclidean distance is determined for each room's RSSI relative to a time point is subtracted from the median Euclidian distance value from each room's calibration dataset. The room with the least difference is determined to be the location of the smartwatch as it is calculated to be the shortest possible distance between a beacon and tracking device thus making it the room it is located.

4.3.4 Data Visualization

Two separate visualization platforms were used to receive and visualize the acquired datasets from the AIP-IPS. The first is a real-time visualization interface developed in Python. This program directly connects to the Hub and reports all received data to a custom designed output screen as shown in Figure 4.3. This interface was primarily used for troubleshooting the AIP-IPS and performing the experimental procedures described in **Chapter 3**. Additionally, this interface can enter calibration mode and add new devices. The second visualization platform is used for remote monitoring and calibration. Figure 4.4

shows you what the Google cloud Firestore™ database looks like. The file structure currently allocates separate folders for study participants and is divided into two sub folders: periodic sampling and periodic location updates. The periodic sampling folder contains incoming sensor and RSSI data while the periodic location update folder displays the current location of each device being tracked.

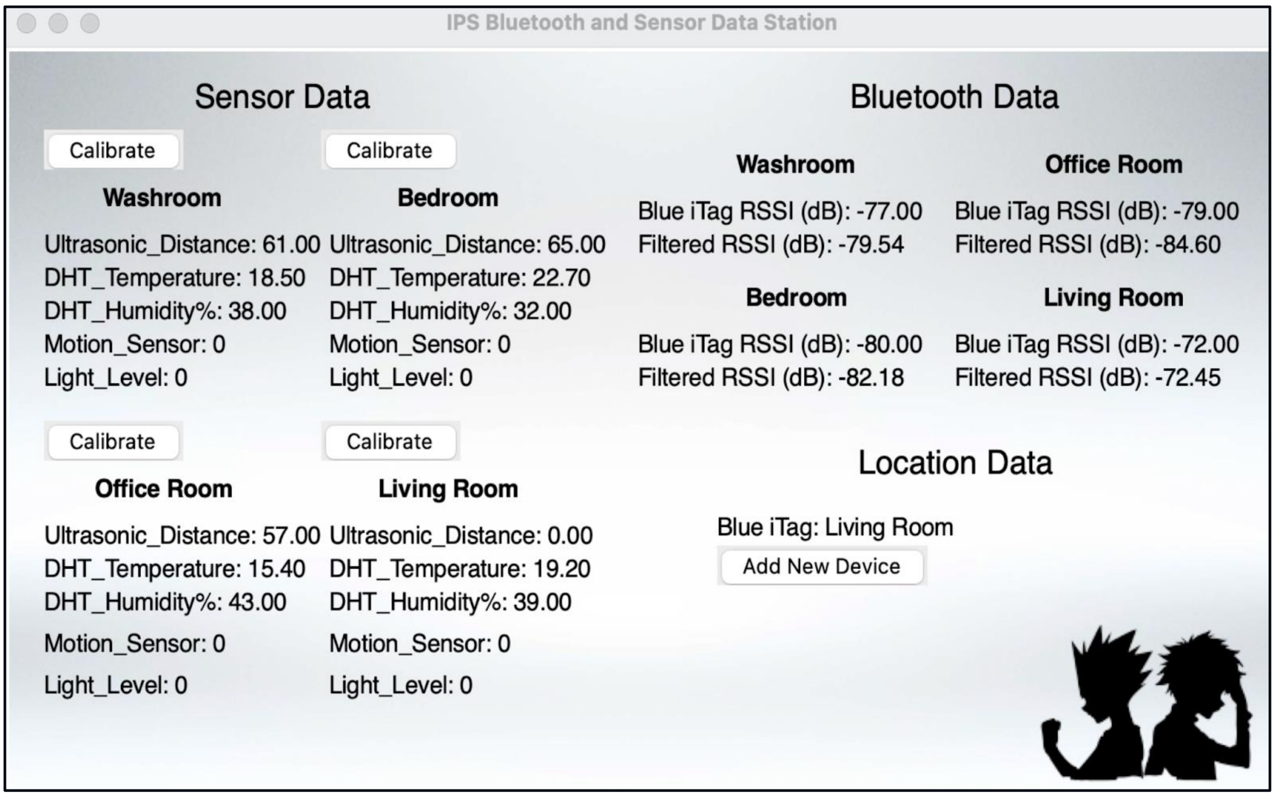

Figure 4.3: Graphical User Interface for the AIP-IPS integrated in a residential home Basement

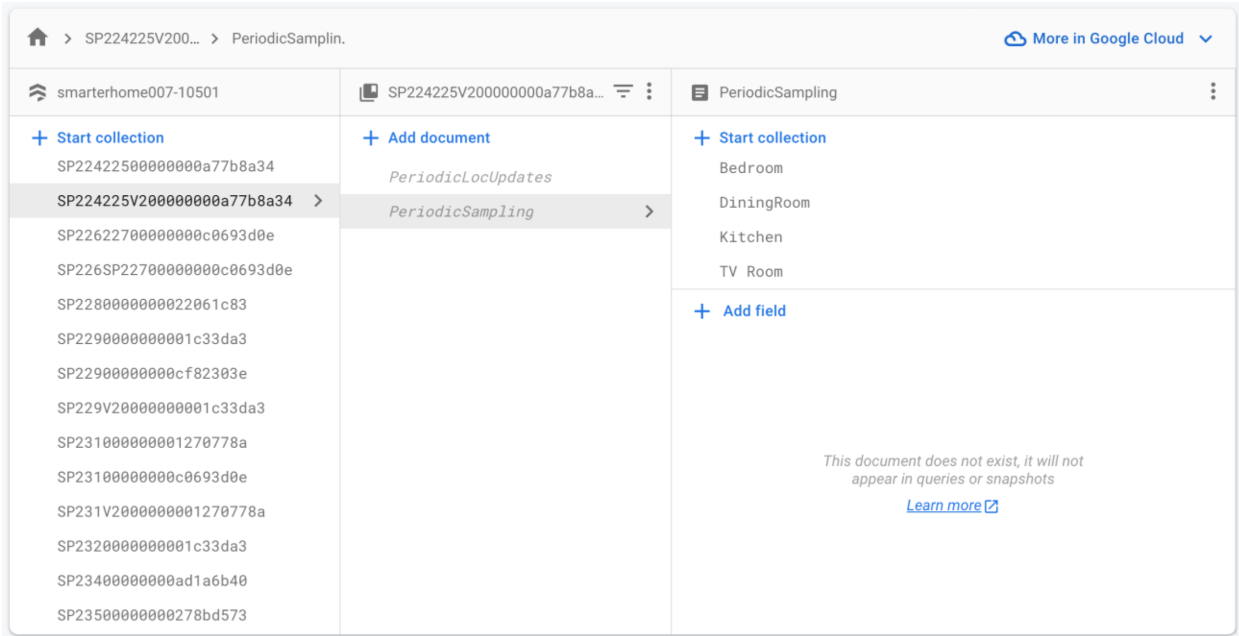

Figure 4.4: Sample View of Google cloud Firestore™ Dashboard for Pilot Clinical Study

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Chapter 5 Conclusions and Discussion

This research focuses on the development of an IPS for AIP applications. The system was designed, tested, and validated for this purpose. The AIP-IPS is an innovation of existing IPS technology and takes inspiration from several systems and becomes its own entity as a state-of-the-art IPS that requires minimal knowledge of its integration location. This research provides readers with an understanding of the motivation and impact behind this research and sets a foundation for future work using the AIP-IPS. The review of existing IPSs and its technology help illustrate that this is an active research field that changes dynamically every year. Then the experimental methodology and results using the AIP-IPS are presented to display our contribution to this research field. This is followed by the implementation of our work in pilot clinical study, which provided an abundance of data in various forms for analysis.

The goal of the AIP-IPS was to maintain accurate room detection while compromising on precision to eliminate the need for a floorplan and invasive installation procedures. In **Chapter 3,** the AIP-IPS we developed to achieve these goals was tested in multiple indoor locations and maintained 96% accuracy in detecting the correct room location of both a BLE tag and smartwatch. Additional tests recorded an average of 1.46 seconds detection speed for room transitions between adjacent rooms. When comparing this detection speed with other IPSs, there is a significant difference as many have achieved less than 500ms adjacent room transition detection speed. The reason for this lack of precision is due to the use of less beacons and not implementing a floorplan-based visualization platform. Moreover, these systems are continuously monitoring the exact coordinate location of devices whereas the AIP-IPS is monitoring specified room locations.

Assembling, testing, and integrating this system in the homes of older adults across the Hamilton region produced a plethora of qualitative and quantitative datasets. **Chapter 4** outlined how this data was collected, how the study was set up, what types of data we collected and included sample datasets to help illustrate its significance. The trial proved advantageous as results from our pre and post clinical survey feedback inspired iterations that improved the AIP-IPS. Feedback regarding prolonged use of our selected smartwatch (TicWatch S2) was negative as 75% of users felt the tracking devices were uncomfortable to wear for long periods of time due to its size and weight. However, this is beneficial as it inspired the inclusion of the ability to dynamically pair a device to the AIP-IPS network. This way a user can integrate their own device with the AIP-IPS in case they were uncomfortable with the smartwatch we provided them. This process will only work if their device is Bluetooth compatible and it will not collect the additional heart rate, step count and IMU data, which do not affect the location tracking. Another key piece of feedback we received was 75% of users did not experience any difficulties with the setup and installation of the AIP-IPS. Considering the users in this case are all older adults, this is excellent feedback and aligns with the goal of developing an easy-to-use IPS that does not have an extensive setup procedure.

Precision and accuracy are two important characteristics of an indoor positioning system that are often used to describe the performance of the system. Precision refers to the degree of consistency or repeatability of a measurement. In an indoor positioning system, precision refers to the ability of the system to consistently determine the location of an object or individual within a certain range or margin of error. For example, a highly precise indoor positioning system might be able to consistently determine the location of an object within a few centimeters, while a less precise system might have a margin of error of a few meters.

Accuracy, on the other hand, refers to the degree to which a measurement or estimate conforms to the true or correct value. In an indoor positioning system, accuracy refers to the ability of the system to determine the true location of an object or individual. For example, an accurate indoor positioning system might be able to determine the true location of an object, while a less accurate system might have a larger margin of error. Overall, an indoor positioning system should strive to be both accurate and precise to provide reliable and useful location data. The AIP IPS is accurate in determining the room location of a tracking device; however, it compromises in precision by restricting its detection capabilities to primarily room detection.

5.1 Future Work and Applications

The AIP-IPS proves to be a self-installable easy to use IPS for a variety of different use cases. Because the AIP-IPS is a smart system, there will always be methods of improvement by integrating it with different technologies. The concept of the IOT is something that fits perfectly when thinking about future work. Based on feedback from the pilot study in **Chapter 4**, the smartwatches we used were not ideal. Thus, the need to either change our tracking device or implement the ability to connect an existing Bluetooth capable device such as a smartphone or smartwatch. This feature is currently implemented in the AIP-IPS however it cannot be done dynamically after the system is setup, it requires changes in the firmware of the Beacon and Hub modules. Due to COVID-19 restrictions we could not implement this feature as part of the clinical study as it would require us to be on site to manually reprogram the devices in person. Future work would consist of developing a remote system that could discover trackable devices and integrate them within the AIP-IPS data collection framework. Additional future work could be a redesign of the electronic components used as they are currently limited to the Bluetooth 4.0 protocol. This would require a change in the microcontroller used for the Beacon modules and a redesign of the printed circuit board for sensor connectivity. Implementing the latest Bluetooth 5.3 capable electronics would create opportunities to enhance our indoor positioning algorithm as well. Bluetooth 5.3 introduces directional sensing capabilities through the measurement of angle of arrival and angle of departure parameters. Recording these values along with RSSI, would allow for increased precision and the ability to detect the orientation of a tracking device without the need for an IMU.

The AIP-IPS is designed for AIP applications, however it is still capable of functioning for multiple different use cases. A more commercialized example of an application would be the development of an indoor security system, that only allows users with specific tracking devices to enter specific rooms. Another application would be home automation using the IOT and smart sensors. An example of this application could be turning on and off lights based on the AIP-IPSs room detection. Similarly, another automation example could be voice automation in the form of a virtual guidance assistant. For people with visual impairment this would prove beneficial if they cannot determine their current indoor location in large indoor public spaces like a shopping mall. Several applications of indoor position technology exist, and people will continue to create newer, more impactful applications.

The AIP-IPS can be improved with the use of machine learning, it can be integrated into the AIP-IPS in a few ways. One way is to use machine learning algorithms to improve the accuracy and reliability of the system. This can be particularly important in complex indoor environments, where the signal strength and quality of the wireless signals used to determine location may vary significantly. One specific way in which machine learning can be used to calibrate the AIP-IPS is by using it to model and predict the signal strength and quality of the wireless signals used to determine location. This can be done by collecting data on the signal strength and quality at various locations within the building and using this data to train a machine learning model. The model can then be used to predict the signal strength and quality at any given location within the building, which can be used to improve the accuracy and reliability of the indoor positioning system. Another way in which machine learning can be used in an indoor positioning system is to improve the efficiency of the system. For example, machine learning algorithms can be used to optimize the placement of wireless signal transmitters or receivers within the building, to minimize the number of devices required and reduce the overall cost of the system.

Similarly, the AIP-IPS can be improved using edge computing and integration with existing IoT devices and software platforms. Edge computing refers to the processing of data at the edge of a network, rather than in a central location. This can be particularly useful in the AIP-IPS, as it allows data to be processed and analyzed closer to the source, which can reduce latency and improve the responsiveness of the system. One way in which edge computing can be integrated into this system is by using it to process and analyze location data in real-time. For example, sensors and other devices within the building can collect data on the location and movement of individuals or objects and send this data to an edge computing system for analysis. The edge computing system can then use this data to determine the location of the devices or objects within the building and transmit this information back to a central server or another system for further processing or analysis. The Internet of Things (IoT) refers to the use of connected devices and sensors to collect and transmit data over the internet. In the AIP-IPS, IoT devices can be used to collect data on the location and movement of individuals or objects within the building and transmit this data to a central server or other system for processing and analysis. This can be done using a variety of wireless communication technologies, such as Zigbee, LoRaWAN, Bluetooth, or WIFI.

5.2 Conclusion

In conclusion, the present work describes the development, testing and validation of an IPS that requires minimal setup procedures and little knowledge of its integration location. This dissertation includes a comprehensive literature review in **Chapter 2** that illustrates the current state of research in AIP applications, specifically focusing on indoor positioning systems and their use in healthcare monitoring platforms. The engineering component of designing the AIP-IPS is presented in the form of a manuscript that includes methodologies for testing and validation of the AIP-IPS in **Chapter 3**. Technical details involving the hardware and software used to develop this system are also included to aid anyone who wishes to develop their own IPS of this design. Lastly, **Chapter 4**, validates the AIP use case by implementing the AIP-IPS in a pilot clinical study for older adult participants. This chapter covers qualitative, quantitative data analysis and collection. It illustrates the significance of the data collected by the AIP-IPS and its correlation the smart AIP. Datasets we have currently collected and future datasets we will acquire from new and continuing study participants, will be used for further analysis to identify room transition patterns, room frequency, room occupancy and context awareness sensing algorithms. This will ultimately lead to the development of a context aware smart healthcare monitoring system tailored for older adults.