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Where Care: A Patient Localization System for Nursing Homes

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Abstract—As the world’s population continues to increase rapidly, there is a growing demand for healthcare services. Nursing homes are becoming more and more populated; the demands placed on care staff continue to grow exponentially. New approaches to care, such as palliative techniques, need to be considered to ensure residents are cared for in years to come. Localization can be used to track changes in behaviour and provide new insights into residents’ palliative needs. Low-cost, reliable systems can be developed to help nurses monitor resident locations within nursing homes. This paper proposes a Bluetooth Low Energy localization system called “Where Care”. The proposed system uses smartphones and wireless Bluetooth beacons to localize residents in a test facility. A novel beacon placement technique and localization algorithm are used to provide real-time resident locations. Data collected is displayed in a graphical user interface (GUI) for ease of use. Heat maps and graphs are available in the GUI to allow care staff to make location predictions based on historical resident data. Nurses can also configure a notification service within the system interface to ensure resident safety. The system is implemented and tested in an experimental university space. Results show that the “Where Care” tool provides sufficiently accurate real-time localization measurements and data summaries. Overall, feedback indicates that “Where Care” is a useful tool with the potential for future use in busy, over-burdened nursing homes.

Index Terms—localization, bluetooth low energy, smartphones, neural network

I. INTRODUCTION

The world’s population is ageing at a rapid rate. According to WHO, one in six people will be at least 60 years old by 2030 [1]. Additionally, the number of people aged at least 80 years is set to triple between 2020 and 2050 [1]. More people are now turning to nursing homes to care for aged adults [2]. As a result, there will be an exponential increase in staff workload in nursing homes. Palliative care caters to

the values and beliefs of dying residents and their family members [3]. Palliative interventions have been suggested to optimise elderly care [4]. However, an increasing population age coupled with a shortage of nurses has led to resource strain in nursing homes [5]. Caregivers do not have enough time to observe residents’ behaviours; subsequently changing palliative needs often go unnoticed [6].

Location monitoring can track changes in resident activity patterns; these changes can provide numerous insights into the palliative care needs of a nursing home resident [7]. General nurses have already shown enthusiasm for sensor-based technologies which can aid them in practice [8]. However, there are very few monitoring systems designed for nursing home contexts at present. Additionally, many existing systems are financially unfeasible for budget-constrained facilities [9]. The use of excessive hardware and complicated device configuration procedures limit the practicality of pre-existing monitoring tools [5]. These circumstances make many technologies unsuitable for the nursing home use case. As a result, there is a need to explore cost-effective solutions to resident localization.

Low-cost smartphone-based solutions are expected to become popular in the future [10]. Cost analysis of various indoor positioning methods reveals Bluetooth to be one of the cheapest localization technologies [11]. Additionally, Bluetooth Low Energy (BLE) localization systems have shown promise within healthcare contexts [12]. In light of these prospective benefits, this paper proposes a resident localization system called “Where Care” for nursing homes. “Where Care” is designed to be low-cost and easy to implement in a wide variety of facilities.

The main contributions of this paper are the successful deployment of the novel crystal-based beacon placement technique, CiP, in a monitoring system, the development of a novel neural network algorithm to successfully localize different Android smartphone devices, and the creation of a visual display to enable nurses to predict resident locations based on

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historical data. The rest of this report will describe past work in the field, the proposed localization system, the experimental deployment setup, and system analysis procedures.

II. RELATED WORK

Localization techniques utilising BLE devices are rising in popularity due to their low cost, simple implementation, and energy efficiency [13]. Furthermore, such systems are capable of discerning positions within closed spaces. BLE distance measurements are usually obtained using Received Signal Strength Indication (RSSI) values from broadcasting beacons [14]. RSSI represents the relationship between the transmission and received powers of devices involved in BLE systems [15]. However, due to NLoS and multipath effects, RSSI values are known to rapidly fluctuate [13], [16]. As a result, RSSI readings can be unreliable.

In BLE localization systems, RSSI smoothing is necessary to prepare raw data for location algorithms on receiving devices. Smoothing methods can help to mask or mitigate unwanted noise using a variety of signal processing techniques. The moving average filter is one of the simplest methods of RSSI smoothing. This method gathers a specified number of RSSI samples and averages the values to create a new value [17]. This new value is quite often more reliable than its component values. Due to its simplicity and lack of computational expense, the moving average filter can be used in a wide variety of localization scenarios.

Once RSSI values are collected and filtered, a BLE system will perform localization. BLE fingerprinting is a relatively new approach to localization which is ripe for exploration. Fingerprinting can provide accurate results and only requires one beacon reading to yield an appropriate output [18]. This localization method involves an offline training phase where data is collected and stored for future use. User location is calculated in a subsequent real-time processing phase by matching received data with values stored in the pre-collected database [19]. This matching process can be done in a variety of ways; the K-nearest neighbour algorithm and Euclidean distance measurements are frequently used [20]. Although not yet in widespread use, machine learning (ML) techniques coupled with fingerprinting have also shown promise [21]. Combining different technologies, such as integrating RSSI with ML algorithms, holds the potential to enhance the accuracy and robustness of indoor localization solutions [22].

Kalikova, Krcal, and Sterba [12] place emphasis on beacon configuration in their work on smartphone applications. Mobile receivers can take up to six seconds to detect a beacon; therefore, broadcast intervals should be set to shorter periods to combat delays. They also [12] outline the importance of using short broadcasting intervals for accurate localization results. Higher transmit powers can also increase localization accuracy. However increased accuracy comes at the cost of battery efficiency; therefore, a balanced approach to accuracy and battery usage must be considered when designing such systems.

While the importance of appropriate beacon distribution is highlighted by Kalikova et al. [12], few studies have assessed the effectiveness of different beacon placement techniques. Rezazadeh, Subramanian, Sandrasegaran, Kong, Moradi and Khodamoradi [23] proposed the CiP placement pattern. Their deployment method is centred on the use of equilateral triangles to create an extensible crystal-like beacon formation. The results of their study indicate that equilateral triangle usage guarantees the shortest distance between beacons for accurate position estimation. However, their technique has yet to be applied to an indoor navigation system.

To create low-cost localization systems, mobile scanners can be implemented on resident smartphones or smartwatches. Using pre-owned mobile devices can limit the excessive purchase of additional sensors. These smart devices can localize with the help of wireless beacons; these beacons can be placed strategically within a target area to broadcast signals at periodic intervals. However, smartphones and smartwatches do not have the computational power to execute many RSSI data processes; hence, mobile systems will usually send collected data elsewhere for processing and storage [14].

Firebase is a scalable NoSQL database with real-time data handling and user authentication capabilities. Aburukba, Sagahyroon, Kamel, Al Shamsi, Surti and Sajwani [24] utilise Firebase in their elderly remote monitoring framework. They highlight the advantages of Firebase's fast and efficient database retrieval operations for smartphone-based nursing home systems. Additionally, Mizan et al. [25] developed an application to save cognitively impaired users and their desired destinations to Firebase before performing an in-app indoor localization and navigation service. Secure data collection and interpretation is facilitated by the use of Firebase authentication. Additionally, this app enables real-time data to be utilised effectively by residents, their family members and clinicians.

Many BLE-based monitoring systems developed for nursing homes focus solely on the accuracy of the localization algorithm used; oftentimes, the presentation of data for nursing home staff is counter-intuitive, overly simplified, or inadequately explained [26]. Aburukba et al. [24] proposed a front-end system to make resident data comprehensible for care staff; they used Bootstrap 4, jQuery, Chart.js and CanvasJS technologies to turn their data into meaningful maps, bar charts, pie charts, and numerical statistics. The system uses colour contrast and spatial information placement to aid staff in realising intuitive insights from the data.

III. SYSTEM DESIGN

The "Where Care" localization tool uses resident smartphones to scan for broadcasting Bluetooth beacons. Detected signals are subsequently sent to a Firebase database for processing. A separate back end localizes residents using recorded signal data and saves results for monitoring interface access. The nurse monitor displays real-time resident location data, generates location summaries, and allows for customizable alerts. All system components are designed with input from nursing experts.

The nurses involved in informal discussion about the same are employees at a reputable nursing home in Cork, Ireland. All agreed that a resident monitoring system would be hugely useful in their facility. They emphasised that the system should be inexpensive and easy to install in any nursing home. System hardware involved should be easy to deploy in a wide variety of facilities. Additionally, data visualisations should be comprehensible and interactive.

A. System Components

The “Where Care” system involves several key components; data collection, location processing, storage, visualisation and notifications. Figure 1 outlines the architecture of the proposed system.

1) *Component Communication*: The components of the system communicate using Firebase functions. The beacons broadcast Bluetooth signals to be detected by the resident’s smartphone. The resident’s smartphone uses Firebase functions to send data to a Firebase Realtime Database instance. The monitoring platform will also use Firebase functions to get localization data from Cloud Firestore for visualisations and notifications.

2) *Mobile Application*: The Flutter cross-platform UI framework is used to develop the mobile application. This framework ensures that a wide variety of resident devices can be included in the system. Flutter was chosen due to its relevance in the field, high-performance capabilities, and object-oriented programming structure [27].

3) *Beacon Placement Pattern*: The beacons used within the proposed system are deployed in the Crystal-based iBeacon Placement (CiP) pattern developed by Rezazadeh et al. [23]. To the best of our knowledge, this paper describes the first use of this economical deployment technique within a healthcare application.

4) *Beacon Broadcasting Configuration*: The broadcast interval for each beacon is set to 100 milliseconds for optimal accuracy. Beacon transmission power (TX) is set to +4dB for broadcast signal reliability [13]. Calibration power is set to -58dBm as recommended by iBKS105 manufacturers. Under these conditions, detection becomes highly reliable and RSSI signals become relatively stable [12]. Universally Unique Identifier (UUID) values configured for each beacon are used by the localizing smartphone device to distinguish between incoming RSSI signals.

5) *Monitoring Interface*: Ben Shneiderman’s Eight Golden Rules informed the interface design; these rules increase system usability [28]. The colour scheme and system layout remain constant throughout the monitoring interface; this consistency makes the system easy to learn. The usability needs of various nurses were considered when creating some of the system instructions; simple, concise language was used to accommodate a range of literacy levels. Additionally, a user guide is included in the interface to help new users grasp the tool quickly.

Further design features were discussed informally with experts in the field. The nursing home’s preexisting IT infras-

tructure made a browser-based monitoring website necessary. The majority of nurses consulted do not carry mobile devices while working; therefore, the monitoring interface is designed primarily for desktop use. The developed interface comprises a real-time location monitor, a 24-hour summary page, a monthly summary page, a resident profile configuration tool, a user guide, and a sign-out service.

6) *Data Visualisation*: A real-time monitor is presented to the nurse upon system login. This real-time monitor overlays coloured semi-opaque circles on a map of the environment to represent residents. A resident could be located anywhere within the appropriate circle presented. This monitoring view allows nurses to use colour perception to detect any strange resident locations.

24-hour and monthly data summaries are presented using heat maps. These heat maps are designed to present nurses with the most likely resident locations based on either 24-hour or monthly data. These heat maps can be filtered by time, enabling nurses to predict a resident’s location based on their history. Alternative visualisations are also available to increase website accessibility. Figure 2 describes the 24-hour heat map incorporated into the monitoring interface.

7) *Data Storage*: Data needs to be sent from the resident’s mobile device to a database for further beacon processing. The proposed system abstracts raw resident data from nurse monitoring information using server-side functions and a combination of both Firebase Realtime Database and Cloud Firestore features.

The Firebase Realtime Database is used to store raw resident data. This database is structured as a JSON tree; each node within the tree can be extracted as a JSON object. Cloud Firestore is used in this system to store processed data along with information about resident profiles and notifications.

8) *Back End Processing*: Node.js is used for back end processing. It has been shown to have high-performance capabilities when reading and writing data [29]. Raw RSSI data from the Firebase Realtime Database instance is received, smoothed, localized, checked against resident constraints and saved to Cloud Firestore. A ML-based fingerprinting approach using a one-device database was chosen for the optimal balance of accuracy and feasibility. Our back end will also save new resident profiles and device tokens for notifications.

Moving average calculations are made upon the receipt of 10 beacon readings. As there is one group of readings recorded per second, this localization system will come into effect after 10 seconds; this latency still renders the system acceptable for real-time monitoring within nursing homes [5]. The matching model used in this system is a feed-forward neural network which outputs a confidence score for each of the location nodes used.

Fingerprinting issues surrounding one-device databases have been highlighted by Naser, Lam, Qamar, and Zaidan [30]; to tackle a multi-device localization use case, they recommend creating a database using multiple device configurations. However, this approach is time consuming and unlikely to be feasible in busy nursing homes. We propose an alternative

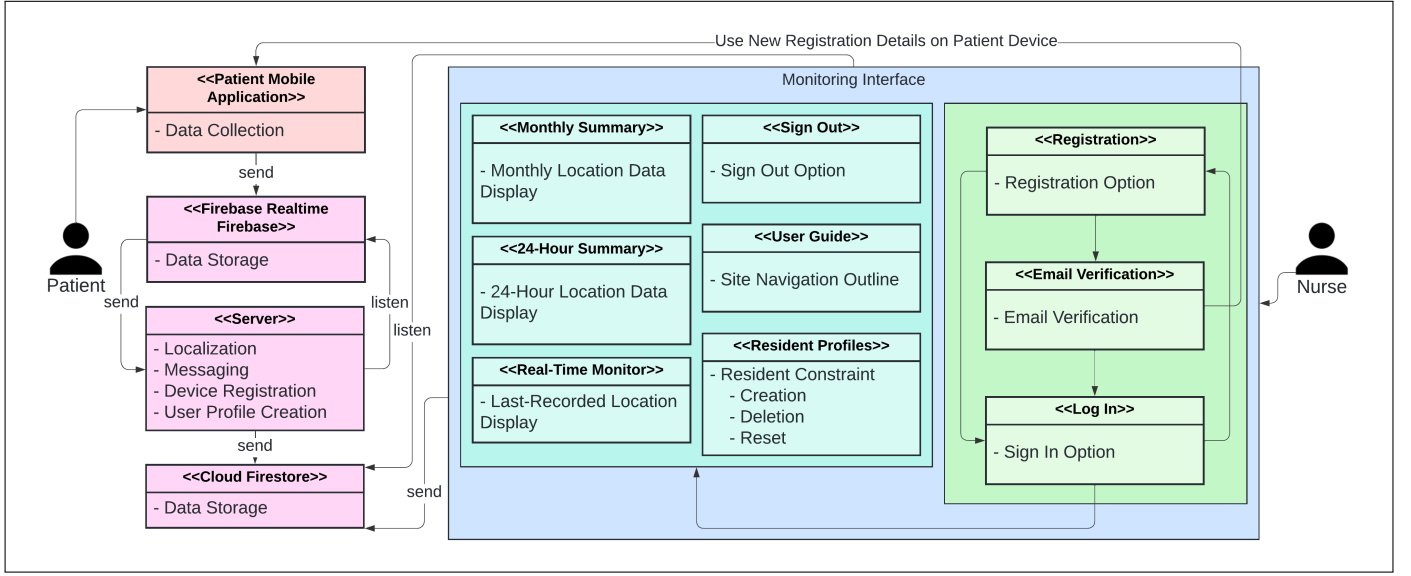


Fig. 1. Component Communication

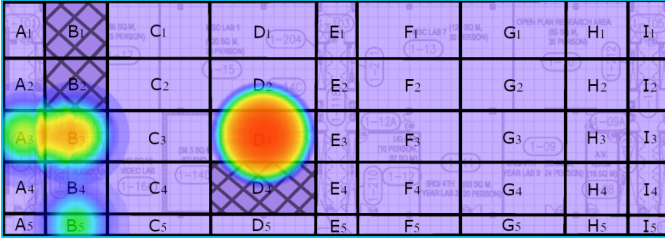


Fig. 2. 24-Hour Heat Map

solution using a device-agnostic normalization procedure. Data is fed to the network from the prerecorded fingerprinting database; for each beacon reading the RSSI measurements are L1 normalized. L1 normalization ensures that a device's Bluetooth sensitivity is not learned by the network; instead, beacon RSSI signals are fed to the neural network based on their proportional strength in relation to other signal values recorded at the same time. Once L1 normalization occurs across rows of beacon signal readings, the data fed to the network is better capable of handling a wide variety of devices.

The neural network implemented within this system is composed of a 20-node input layer with a ReLU activation function, a drop-out layer to prevent overfitting, and a softmax loss function with an Adam stochastic gradient descent optimizer. The 42-node output layer gives a confidence score to each map location; the highest confidence score is decided as the final location. This model builds on the work of Maduranga and Abeysekera [31], who used a similar neural network in a novel approach to Bluetooth localization. However, unlike Maduranga and Abeysekera, our model extends beyond single-device localization estimates, accommodating a wider range of devices for localization purposes.

The Node.js back end generates notifications after checking each predicted location from the localization model against forbidden areas configured for a given resident. If a resident is found to be at a prohibited location, Firebase Cloud Messaging

is used to alert devices registered to the service of the resident's location.

IV. EXPERIMENTAL SETUP

The test space used is a 57.6 x 19.8 metre area of University College Cork's Western Gateway Building. 10 iBKS105 beacons and 42 different graph nodes are used to localize residents. Figure 3 describes the location nodes and beacons used within the test system. This figure also shows the location nodes which are automatically not considered within the system due to building security issues: B1, B2, and D4.

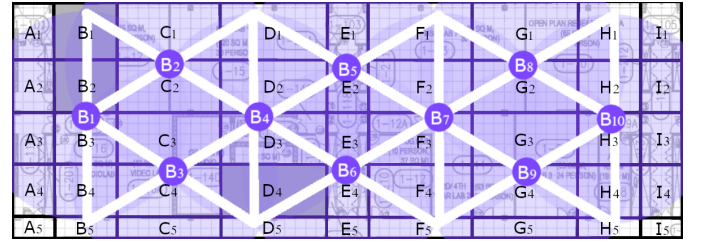


Fig. 3. Location Nodes

The real-time application consists of an authentication procedure and a simple beacon scan-and-save function. The data is sent straight to Firebase Realtime Database; hence, no heavy back end processes are carried out on smartphones. Despite the Flutter framework's cross-platform capabilities, our proposed system is limited to Android devices only due to hardware constraints; one needs the Xcode IDE installed on an unrestricted MacBook or iMac to develop a Flutter application for iOS [27].

An additional Flutter app was built to collect the initial beacon readings for the fingerprinting database. For each location node on the map, 60 seconds of beacon readings were recorded. The Firebase Realtime Database was used as a temporary store for these beacon readings; once these readings were used to create the feed-forward neural network, the database was repurposed for real-time location data.

The feed-forward neural network used in this system is trained using TensorFlow in Python and then loaded into Node.js using TensorFlow.js. The model is a simple Sequential model where each layer has one input tensor and one output tensor. The ten input layers correspond to the ten beacons used in the system; the ReLU activation function is used for its popularity, efficiency, and fast convergence [32]. The dropout layer avoids overfitting when training the model; two of the ten input units are dropped at each step during training. This ensures that the model does not become overly dependent on any node. ReLU is typically used with a Softmax function, which limits the model's output between zero and one. This function ensures that the model's output can be construed as a probability [32].

The model was trained multiple times using the Keras EarlyStopping class; this EarlyStopping instance is configured to return the best epoch at the end of the process. Additionally, 10% of the initial data was set aside before the beginning of training to ensure valid testing procedures. A further 10% of the reduced data was separated for in-training evaluation. The resultant model was trained for 2100 epochs, and the best model returned from the process was from epoch 2050. Test data evaluated after training ensures the resulting model is accurate enough for the proposed system's needs. The final model exhibits 84.59% accuracy. Subsequent use of this model in the back end was facilitated by a series of asynchronous TensorFlow.js and Firebase tasks for localizing residents, saving location predictions, and sending notifications.

The website used as the monitoring interface was created using HTML, CSS, and JavaScript. JavaScript libraries used include simpleheat, Three.js and Plotly to visualise data along with Sweet Alert to display messages.

V. RESULTS AND DISCUSSION

The experimental setup was tested using a variety of qualitative and quantitative measures to assess feasibility within a nursing home context.

A. Beacon Battery Efficiency

Beacon battery efficiency was tested for four days using three beacons from our experimental system. Battery percentage readings were taken from these three beacons (Test A, Test B, Test C) every 24 hours. As shown in Table I, test results indicate that our configuration is very battery-intensive; the beacon batteries would have to be changed on almost a weekly or bi-weekly, basis. A large amount of battery drain and subsequent beacon maintenance time, puts the system at a disadvantage in a busy nursing home setting. Future work may investigate different beacon settings to obtain the optimum balance between practicality and reliability.

B. Mobile Application

Two phones were used to test the real-time Flutter app: a Samsung Galaxy SM-G780F and a Samsung Galaxy SM-A125F. CPU and memory usage were both analysed. Figure 4 represents the CPU flame graph obtained from the SM-G780F

Day	Time	Beacon A	Beacon B	Beacon C
1	9:20	100%	100%	100%
2	9:20	87%	55%	80%
3	9:20	62%	39%	47%
4	9:20	55%	39%	41%

TABLE I
BEACON BATTERY LIFE

application instance. Graph-based observations indicate that while mostly computationally efficient, the system UI takes up a large amount of CPU processing time. As a result, the application can appear slow at times. These results indicate that future iterations of the app need to develop a less computationally intensive front end for optimal usability.

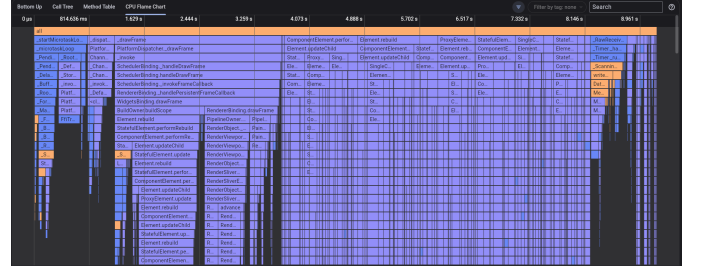


Fig. 4. CPU Profiling SM-G780F

Flutter uses more memory than native Android applications. However, results from testing are in keeping with other studies, indicating an adequate amount of memory is used [33].

C. Node.js Back End

Our neural network was compared against a fingerprinting Euclidean distance matching algorithm as outlined in Table II. All results shown in this table are based on code which was run on a 64-bit Linux server with 24GB RAM and an Intel Xeon Silver 4110 CPU. Accuracy was assessed offline using pre-collected data; future work includes assessing the real-time results of our algorithm. One can discern from this table that our neural network results in a less computationally intensive system, with more reliable localization results. This observation indicates that our back end is suitable for computationally limited nursing home systems.

Measurement	Euclidean Best Match	Neural Network
CPU Percentage	98.7%	10.3%
Memory Percentage	1%	0.6%
Load Average - 1 Minute	224%	57%
Load Average - 5 Minutes	1.41%	48%
Load Average - 15 Minutes	0.62%	36%
Accuracy	42.38%	84.59%

TABLE II
LOCALIZATION ALGORITHM COMPUTATIONAL PERFORMANCE

D. Monitoring Interface

Cross-browser multi-user testing was carried out to ensure the monitoring interface satisfied end-user requirements. The

results indicated that the interface designed was understandable and accessible. End-user feedback suggested that the design was suitable for use in a nursing home.

Usability tests were conducted online using Microsoft Forms. A range of people were asked to participate based on their capacity and understanding of nursing software. 20 people undertook the usability survey. These people were a mixture of nursing professionals and students. Likert-style questions based on the System Usability Scale (SUS) were posed to participants [34]. All participant data was anonymised upon submission. The overall results shown in Figure 5 indicate that the majority of website elements are user-friendly. This user-friendliness enhances the applicability of such design in a nursing home context.

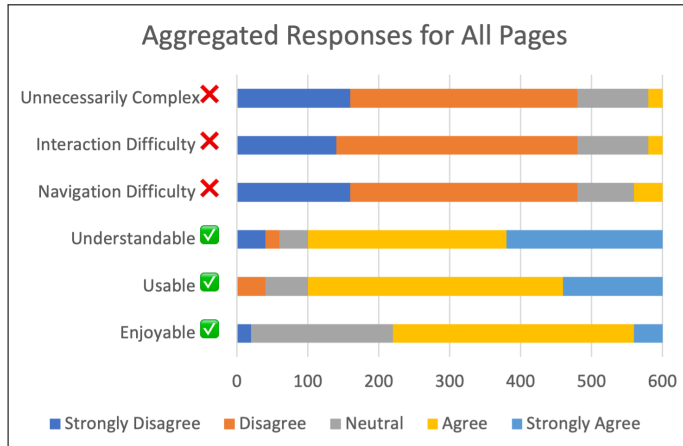


Fig. 5. Overall Usability Chart

E. System Limitations

While the proposed system is capable of delivering real-time user location information, there are several potential challenges and limitations to address.

Firstly, although using a smartphone app to collect beacon RSSI values is economically feasible, it is assumed that the nursing home resident is continually carrying their phone. However, in reality, they will not be always carrying their devices. Therefore, continuous smartphone-based monitoring may not be contextually feasible.

Additionally, beacon scanning in the background on Android devices can consume a lot of battery. Some studies have opted to avoid background beacon scanning altogether, focusing only on foreground services [35]. Android permissions make such services increasingly more difficult to access for mobile developers. As a result of these issues, this system cannot scan for beacons while the application is in the background, further limiting the feasibility of continuous location monitoring.

The Bluetooth beacons used in this system are set to highly optimised settings; while this configuration makes the beacons more reliable, they will also be drained of battery quickly. This system therefore requires constant battery maintenance to operate effectively; this requirement increases the workload for busy nursing home staff.

VI. CONCLUSION

Few studies have focused on the importance of Bluetooth beacon deployment methods, this paper sheds new light on the importance of beacon placement in monitoring systems. This system presents one of the first applications of the Crystal-based iBeacon Placement (CiP) pattern proposed by Rezazadeh et al. [23]. By using the CiP pattern, the proposed tool could potentially be implemented in a wide variety of different nursing facilities [23]. The resultant localization system demonstrates that CiP enables sufficient beacon coverage in a sparse deployment situation. Future iterations of similar systems could focus on using less battery-intensive beacon configurations; this improvement could help to reduce beacon maintenance time for care staff.

The localization algorithm developed for this paper extends the work of Maduranga and Abeysekera [31]. The feed-forward neural network described in their study inspired the use of a similar model within our proposed system. This paper outlines a novel solution to multi-device fingerprinting issues by using L1-normalized neural network inputs. These inputs ensure that the beacon readings are assessed based on relativity, not based on device RSSI signal sensitivity. As a result, the proposed model produces consistent localization predictions across multiple tested devices [30].

The monitoring interface was carefully designed with the help of healthcare professionals; an iterative development process ensured that “Where Care” is user-friendly. Subsequent user testing corroborated design choices made by consulted experts. The proposed system demonstrates the value of end-user input from the very beginning of the development process.

This paper outlines a flexible, low-cost indoor localization system using Bluetooth beacons and smartphones. The resultant system received positive feedback from potential end-users. The system also used existing smartphone technology to avoid unnecessary purchases such as additional Bluetooth tags or scanners. Systems such as this one may have a future impact on the quality of resident care within nursing homes. As the demands placed upon healthcare workers increase, new technology like “Where Care” needs to be implemented to help elderly adults live comfortably.

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